

Designing Effective Welfare Programs: Evidence from SNAP's BBCE Expansion

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Abstract

Welfare programs in the United States aim to target beneficiaries and combat fraud through means-tested approaches. This paper evaluates the efficiency of income and asset limits in the Supplemental Nutrition Assistance Program (SNAP) in the United States, with a focus on the state option "Broad-Based Categorical Eligibility (BBCE)." BBCE allows states to eliminate asset limits and raise income thresholds to broaden eligible populations. Analyzing state variations from 1996 to 2007, I find that the states adopting BBCE reduced SNAP administration costs by nearly 20% without an increase in fraud cases. Moreover, the eligible population only increased by about 2%, implying that 20% of the costs were spent to rule out 2% of the eligible population. Additionally, there is suggestive evidence of increased program take-up among households already eligible under previous rules, potentially driven by the simplified requirements. These findings indicate that existing asset limits and income thresholds impose unnecessary restrictions, incurring high costs for government agencies and deterring participation without effectively targeting or preventing fraud.

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1 Introduction

Transfer programs in the United States are often designed with complex requirements and rules. Policy-makers use such designs as a screening mechanism to target those who would benefit the most from income redistribution. This is rationalized in economic theories as optimal program designs, which suggest imposing certain restrictions to transfer programs for targeting efficiency (Kleven & Kopczuk, 2011; Nichols & Zeckhauser, 1982). On the other hand, theories also emphasize that these restrictions should balance the costs that come with them, as it takes resources for government agencies to enforce the rules and for potential beneficiaries to comply. However, theories do not provide precise guidelines for achieving this balance, leaving us with only glimpses of insight through empirically examining the rules we currently implement.

Several empirical studies have examined different aspects of program designs. For instance, recertification processes are consistently found to be inefficient in the sense that most beneficiaries who drop out during the process remain eligible (Gray, 2019; Homonoff, Rino, & Somerville, 2022; Unrath, 2021). It is also found that the current program designs create information barriers and difficulties in navigating the application processes for eligible individuals (Currie, 2006; Ko & Moffitt, 2022). Nevertheless, the extent to which we should remove the program restrictions and their consequences remains to be determined.

This paper evaluates how relaxing the income and asset limits would affect program administrative costs, fraud incidents, and the eligible population. Income and asset limits are the most ubiquitous requirements for transfer programs. While the limits are set to screen out more well-off households and prevent fraud, they constitute a large portion of the administrative burdens. Potential beneficiaries are asked to provide various documentation of their income and assets. Completing the paperwork requires physical time and effort and creates mental stress and confusion. In addition, caseworkers spend a tremendous amount of time verifying the information. Sometimes, the banks are not cooperative or even charge fees for documentation (GAO, 2012). Due to a lack of variation over time, these income and asset limits are rarely examined in terms of achieving their goals and collateral costs. This paper is one of the first to provide such analyses utilizing a state option to expand eligibility for the Supplemental Nutrition Assistance Program

(SNAP), formerly the Food Stamp Program.

Authorized by the federal government in 2000, the “Broad-Based Categorical Eligibility (BBCE)” allows states to relax the income and asset limits for a more general set of low-income households to be qualified for SNAP. States also choose to qualify any household through this category, including those already eligible. I focus on the states that eliminated asset limits, raised income thresholds, and applied them to every household. Under such changes, admitting a household to the program is much simpler than traditional eligibility rules. I measure the changes in administrative costs, the number of fraud cases, the size of the newly eligible households and their characteristics, and the take-up behaviors of households who were already eligible before BBCE.

My research design exploits the variation across states and years in BBCE adoptions. Observation periods range from 1996 to 2007. During this period, thirteen states adopted any BBCE policies, and six adopted the most generous form I am interested in. The comparison group consists of states that adopted BBCE between 2008 and 2012, which includes 28 states¹. I employ an event study specification using the interaction-weighted estimator proposed by Sun and Abraham (2021).

To analyze changes in eligible households, I use a micro-simulation dataset that includes simulated eligibility for various programs on the sample of the Current Population Survey — Annual Social and Economic Supplement (CPS-ASEC). The data is published as the Transfer Income Model, Version 3 (TRIM3)², maintained by the Urban Institute. In Appendix B, I show that this dataset performs well in correcting the under-reporting issue of program participation in CPS (Meyer, Mok, & Sullivan, 2009, 2015), and captures similar profiles of SNAP participants with the administrative data³. Building on the SNAP eligibility provided by TRIM3, I identify the already-eligible households by predicting the likelihood of a household satisfying the traditional

¹The rest of the states only adopted after 2015 or have never adopted, suggesting a very different behavior from most states. I choose the states most likely to satisfy the parallel trends assumption, formally justified in later sections.

²Information presented here is derived in part from the Transfer Income Model, Version 3 (TRIM3) and associated databases. TRIM3 requires users to input assumptions and/or interpretations about economic behavior and the rules governing federal programs. Therefore, the conclusions presented here are attributable only to the author of this paper.

³SNAP Quality Control Dataset published by USDA

rules of SNAP based on pre-expansion characteristics. This way, I resolve the problem that households might change their behaviors once BBCE is implemented; therefore, their observed income post-BBCE does not represent how they would behave had BBCE not been implemented. From here on, I will call these households “already-eligible” or “always-eligible” interchangeably.

Results show that adopting the most generous form of BBCE reduced state administrative costs by almost 20%, equivalent to over 100 million dollars. Meanwhile, there was no indication of an increase in fraudulent cases but a slight decrease in the overall trend. Moreover, the size of households eligible only through BBCE constitutes only about 2% of all eligible households, implying that the reduced 20% of administrative costs was targeted at these 2% households. Their characteristics show that these are larger-sized households and are more likely to have children — not necessarily more “well-off” households. I also find suggestive evidence of increases in program take-up of the already-eligible households, which are most likely driven by the streamlined administrative processes. The increase in take-up is particularly observed among those eligible for short-term periods, spanning one to six months in the year. These households are more prone to income fluctuations, and could benefit from consumption smoothing utility by enrolling in SNAP. Across all outcomes, the effects from the most generous form of BBCE are more prominent than any BBCE, further suggesting that the effects stem from changes in rules rather than other channels, such as raising awareness due to new policies.

This study contributes to three strands of the literature. Firstly, within the optimal program design literature, I provide one of the first empirical evidence showcasing the generally efficiency-improving outcomes resulting from the relaxation of income and asset limits. Studies on this strand rely on structural models and calibrations (Golosov & Tsyvinski, 2006; Wellschmied, 2021), and rarely leverage quasi-experiments. Thus, this research acts as a bridge between program design in theory and its real-world implementation. Secondly, within the incomplete take-up literature, the study provides another piece of evidence illustrating how administrative burdens can potentially hinder program take-up. The term “administrative burdens” generally refers to the costs of applying to a public program, including the learning costs and the psychological costs (Herd & Moynihan, 2018). Causal evidence on how administrative burdens affect take-

up is manifold. For example, lack of information or assistance (Aizer, 2003, 2007; Finkelstein & Notowidigdo, 2019), in-person interviews (Homonoff & Somerville, 2021), attitudes of caseworkers (Cook & East, 2023), and physical distance from local offices (Deshpande & Li, 2019) are all found to affect take up. I measure the effects of the income and asset limits on take-up, which are the most common burdens across programs yet have not been widely studied. Lastly, in the policy evaluation papers of BBCE, I conduct a thorough causal estimation of the most general population. I also differentiate between the already and newly eligible populations, a departure from prior studies that predominantly focused on very poor households defined by observed income. Additionally, this paper comprehensively examines the determinants of BBCE adoptions across states and establishes the quasi-random nature of BBCE variations. Notably, the findings align with previous research by not rejecting an increase in take-up, reinforcing consistency with prior empirical observations (Anders & Rafkin, 2022; Dickert-Conlin, Fitzpatrick, Stacy, & Tiehen, 2021; Jones, Courtemanche, Denteh, Marton, & Tchernis, 2021; Klerman & Danielson, 2011; Ratcliffe, Mckernan, & Finegold, 2008).

The paper proceeds as follows. Section 2 discusses the institution of SNAP eligibility and BBCE. Section 3 examines states' adoption decisions and the quasi-random nature of adoption decisions. Section 4 introduces the data and how the sample is constructed. Section 5 describes the methodology and specification. Section 6 presents the results. The final section concludes.

2 The Broad-Based Categorical Eligibility (BBCE)

The Supplemental Nutrition Assistance Program (SNAP), also known as the Food Stamp Program, is the third largest in-kind transfer program in the United States (following Medicaid and Medicare). Despite the scale of the program, the take-up rate of SNAP has been stagnant at around 70%; still millions of individuals are eligible for the program but do not participate. BBCE was one of the many state options granted by the federal government in the post 1996 welfare reform era. Although it was a collateral change with the re-structuring of the previous Aid to Families with Dependent Children (AFDC) to the Temporary Assistance for Needy Families (TANF), BBCE has become a major tool for states to expand SNAP eligibility as well as simplifying administration process. This section discusses how BBCE changes eligibility rules and the expected effects on take-up.

2.1 Existing eligibility rules for SNAP

As per federal law, citizens of the United States have two pathways to qualify for SNAP. The first is to pass the “income and asset tests”, meaning that the household has income and assets that fall below the federally specified thresholds. For a household without any elderly (60 years old) or disabled members, two separate income tests apply — the gross and net income tests. Gross income refers to the sum of earned and unearned income, including cash benefits from other public programs. Net income is gross income minus allowed deductions such as child care and medical expenses. The federal law sets the income limits at 130% times the federal poverty guideline (FPL) for gross income, and 100% of FPL for net income. A household with elderly or disabled members only has to satisfy the net income limit.

On top of the income limits, the federal law also sets limits for countable resources (also referred to as “assets”), which includes cash and bank accounts⁴, at \$2,750 for households without elderly or disabled members and \$4,650 for households with at least one member who is elderly or disabled.

⁴The federal law also sets a vehicle limit at \$4,650, but almost all states set their own vehicle rules nowadays because the federal limit is considered outdated.

The second way to qualify for SNAP is to be “categorically” eligible, namely to gain eligibility automatically if already qualified for another cash assistance program. More specifically, categorical eligibility should be given to households with all members eligible for cash assistance from means-tested programs including the Supplemental Security Income (SSI), General Assistance (GA), Aid to Families with Dependent Children (AFDC)/Temporary Assistance for Needy Families (TANF), and state maintenance-of-effort (MOE) programs. This is to reduce the burden of these households because they already went through similar income and asset tests when determining eligibility for other programs. Note that, however, the food stamp benefit is a function of the aforementioned net income, therefore the categorically eligible households could still end up with no benefits if their net income is too high.

2.2 Changes of eligibility by BBCE

The Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) of 1996, also known as the Welfare Reform, replaces AFDC with TANF. This largely affects the categorically eligible households because of two reasons: 1) AFDC is an entitlement program that does not limit the amount of benefits issued, and TANF is a block grant, which is a fixed amount of federal grant; 2) AFDC is entirely cash benefits, but TANF benefits can be noncash, which is not deemed categorically eligible for SNAP in the federal law at the time. However, in 1996 there was no further modification of the categorical eligibility section in the Food Stamp law except for simply substituting the term AFDC by TANF.

It was not until 2000 that the USDA amended the regulation⁵ on how states can choose to extend categorical eligibility to those who are qualified for noncash TANF/MOE benefits. In such “broad-based categorical eligibility⁶” options, states are allowed to include households with at least one member eligible for these noncash benefits which are at least partially funded by TANF/MOE . This means that in the broadest sense, states can deem a household with one member qualified to receive a brochure printed by a sufficient portion of TANF/MOE funds to

⁵A letter was first issued on July 14th, 1999, but the regulations were promulgated in 2000 (7 CFR §273.2(j)).

⁶The term “broad-based categorical eligibility” was made official in a USDA policy guidance — “Improving Access to SNAP through Broad-Based Categorical Eligibility” issued on Sep 30th, 2009.

be automatically eligible for SNAP; which is what most states that adopt the BBCE option end up implementing.

By adopting BBCE, states now have discretion over who they would like to extend SNAP eligibility to. Most states set higher gross income limits than the regular 130% FPL. Some exempt asset tests in BBCE qualification and some other states only apply BBCE to specific groups such as households with dependents (see Figure 2). Regardless of the specific designs, BBCE generally expands eligibility beyond the federal income and asset tests for at least some groups of households. As a result, those who would have failed the income and asset tests could become eligible.

2.3 Changes of program operation by BBCE

Aside from expanding eligibility, perhaps a more salient change by BBCE is reducing administrative burdens. In an official letter from USDA to state administrators in 2009, states were encouraged to adopt BBCE to streamline the application process in coping with the surge of demand from the Great Recession (USDA, 2009). By “streamlining” the process, the letter was referring to the elimination of asset tests, so that the states would not have to verify the asset information, which appeared to be quite costly for state agencies. During the site visits to 5 states and 18 local SNAP offices by the U.S. Government Accountability Office, the staff raised the problem that verifying assets took a considerable amount of time because it required cooperation from banks, who sometimes would even charge fees for documentation (GAO, 2012). Eliminating asset limits in states’ BBCE policies saves the time and efforts of caseworkers, and perhaps of the households as well because they do not have to provide asset information anymore.

Even if the state did not eliminate the asset test, adopting BBCE could also change how the administrators process an application. Under the regular federal eligibility determination, the caseworkers look at the household composition (such as having elderly or disabled members), and then apply the gross income and asset limits of relevant cash assistance programs to qualify the applicant through the regular categorical eligibility. If not, the caseworkers apply the federal income and asset tests, in which an extra net income test is added. After BBCE is implemented,

the caseworkers only need to assess whether the applicant’s gross income and assets satisfy the BBCE limits when received an application (CRS, 2022; GAO, 2012) since most states define their BBCE eligibility in the broadest sense.

For the above reasons, BBCE was found to reduce SNAP administrative costs by 7 percent during FY1999-FY2016 (Geller, Zic, Isaacs, & Braga, 2019). This suggests that BBCE should be seen as a more general treatment that is not restricted to those who are made newly eligible, but all eligible households who now have a different experience with application. In fact, in 2014, the newly eligible participants only made up 8 percent of all SNAP participants, and 1.2 percent of all benefits issued (Cunyngham, 2016). Therefore looking at the already-eligible households should provide a larger interest in take-up behaviors.

2.4 Expected effects of BBCE on take-up

For those who are always eligible before and after BBCE implementation, the policy creates no financial incentives or disincentives in their take-up decisions. For all eligibility types, the benefit levels are calculated by the same formula, which is a function of a federally determined maximum allotment and household net income. One might think that the higher gross income limit lowers the opportunity costs of labor supply for the marginal households who could choose to be eligible or not, but this would have led to a change in the always-eligible population, and I find no such changes either in the characteristics or the size of them.

Administrative burdens are the most plausible reason for BBCE to have effects on take-up. The term generally refers to the costs of applying to a public program. In the three types of administrative burdens defined by Herd and Moynihan (2018) (learning costs, compliance costs, and psychological costs), BBCE directly reduces the compliance costs if the state exempts asset tests. The caseworkers could also become more available due to the simpler eligibility rules and less verification, thus reducing the learning and psychological costs of the applicants. For BBCE that raises gross income limits, Anders and Rafkin (2022) found that each 10 percentage points of FPL higher limits, take-up rates could increase by 1 percent. They argued that the channel is most likely through reducing information friction rather than through stigma. Although in

this paper I do not find states increasing their outreach efforts, alleviating stigma and easing information barriers are both in the realm of psychological costs and learning costs.

In sum, BBCE is expected to increase the take-up rate by reducing administrative burdens in general, and BBCE that eliminates asset tests and/or raises gross income limits should have larger effects than more restrictive ones.

3 State Adoptions of BBCE

As of July 2023, 44 states and the District of Columbia (DC) have adopted some form of BBCE. The SNAP Policy Database provides the exact timing of adoption for 41 states and DC. Figure 1 shows that a bulk of the states — more specifically, 22 of them — adopted BBCE between 2009 and 2010, the period of the Great Recession. South Carolina was the first state to adopt BBCE in October 2000, followed by Oregon, Maryland, Delaware, Michigan, and North Dakota. Looking at the distribution of first adoption timing geographically in Figure 3, there is no obvious correlation within regions or the politically “blue” or “red” states such as the East/West Coasts or the South. That said, studying the effects of BBCE during the Great Recession could still be challenging, as the eligible population was expanded by the economy, and the American Recovery and Reinvestment Act of 2009 raised SNAP benefits together with many other stimulus measures. Therefore, I focus on the states that adopted BBCE before 2008, which covers 13 states observed from 1996 to 2007. Another merit of focusing on this period is that the treatment is monotone within states, meaning that these states never retrieve or modify their BBCE policies once adopted, whereas many states made their BBCE policies more restrictive after the Great Recession.

Because states make different BBCE policies, I group the states that adopted the most generous form of BBCE: setting a gross income limit higher than the federal gross income limit (130% FPL) while also eliminating asset test, and name them as “BBCE Max”. The ideal grouping is to isolate the states that only eliminated asset tests or only raised gross income limits with no other changes from the federal rules, but unfortunately, the two policies were almost always implemented together. Figure 2 shows that only one state solely raised gross income limits (Texas), and only one state solely eliminated asset tests (Washington). All the other seven states that eliminated asset tests also raised their gross income limits. Nevertheless, the two policies jointly reduce administrative burdens in a broad sense, and grouping them ensures homogeneity of treatment.

3.1 Examining the exogeneity of BBCE adoption

To establish the quasi-random nature of states' BBCE adoption, it is beneficial to test if states adopt BBCE for particular reasons. For example, if states adopt BBCE because they are suffering from too many administrative errors in eligibility and benefit determination, then the high error rates could be correlated with some inherent characteristics of the state government, such as low efficiency, which also affects take-up. In Lin (2022), I tested five plausible reasons for state variations in SNAP policies: voters' preferences for welfare programs, voters' attitudes against blacks, state economic wellness, states' SNAP administrative costs, and states' SNAP error rates. None of these factors significantly predict states' BBCE adoption, but only the contemporaneous unemployment rate. In this paper, I focus on the states that adopted BBCE between 2000 and 2007, and tested three more specifications.

The first model is inspired by Hoynes and Schanzenbach (2009), in which the authors use county characteristics in 1960 to predict the roll-out month of the Food Stamp Program from 1961 to 1975. Analogously, I use state characteristics averaged between 1996 and 1999 to predict states' adoption of BBCE:

$$adopt_s = \alpha + \mathbf{X}_s\gamma + u_s \quad (1)$$

$adopt_s$ is an indicator of whether the state adopted BBCE before 2008. X_s includes the aforementioned five main factors, some relevant state demographics, the take-up rate, and the share of eligible population averaged between 1996 and 1999. Only states that have ever adopted BBCE by 2012 are included in the regression. Table 1 shows that none of the factors individually predicts whether the states would adopt BBCE before the Great Recession, nor do they jointly explain the adoption of BBCE.

To account for some other unobserved state fixed effects, I test another specification using state-month level of observations:

$$bbce_{sym} = \alpha + \mathbf{X}_{s,y-1,m}\gamma + \theta_s + \sigma_y + u_{sym} \quad (2)$$

$bbce_{sym}$ is an indicator of whether the state s has BBCE in place in month m of year y . The

predictors are the same sets of variables as equation 1, but is time-varying and observed in the same month in the previous year. State and year fixed effects are represented by θ_s and σ_y , respectively. Table A.1 shows that even the time-varying circumstances of states do not systematically explain states' adoption decisions before 2008.

One more concern is that there are some unobserved time-varying factors still not controlled for by demographics, economics, and politics. The likely scenario is that the states are simultaneously implementing other policies that also affect take-up. I find no change in state welfare expenditures (Figure C.9), and at most 0.27 Pearson's correlation coefficient between BBCE and other SNAP policies. These policies, including application aid, vehicle limits, outreach spending, and electronic benefit issuance, are also controlled for in the take-up analyses.

4 Transfer Income Model, Version 3 (TRIM3)

TRIM3 is a microsimulation model maintained by the Urban Institute under primary funding from the Department of Health and Human Services. Based on the Current Population Survey – The Annual Social and Economic Supplement (CPS-ASEC), TRIM3 simulates eligibility and participation for several federal transfer programs, including Medicaid, Supplemental Security Income (SSI), and Temporary Assistance for Needy Families (TANF). A major strength of TRIM3 is its detailed modeling of program rules. This includes state-varying policies as well as cross-program interactions. Moreover, for crucial variables that are not available from CPS-ASEC such as immigration status, TRIM3 matches its imputation with reliable external sources of data. With these efforts, TRIM3 performs well in correcting the under-reporting issue with CPS-ASEC. Figure B.1 compares the counts of the total number of SNAP participants between TRIM3, CPS-ASEC, and the administrative data published by USDA. It is apparent that TRIM3 fits the true counts much better than using CPS-ASEC directly.

To further examine the performance of TRIM3, I compare some characteristics of SNAP participants in TRIM3 to the administrative data — the SNAP Quality Control Database⁷. Although the administrative data is accurate in eligibility and benefit-related information, other household characteristics that are not required to be collected are often missing (for example, education levels and race). In Table B.1, I compare some selected characteristics between TRIM3 and QC. Because the sample sizes are large, all the characteristics are significantly different between the two data at 5% significance level. Most characteristics are different at a very small magnitude except for gross income — TRIM3 is 50% higher than QC.

Nevertheless, based on the similar benefit levels at the mean between the two data, the high gross income in TRIM3 may not be too much of a concern in determining eligible benefits. To test this, I construct a benefits calculator following the federal formula — Benefits = maximum allotment - $0.3 \times$ unit net income. The maximum allotment is issued by USDA each year and

⁷In each month, the state agencies randomly select a sample of SNAP participating units to USDA for quality control review. Approximately 50,000 of these reviewed cases will be published for public use as the SNAP Quality Control Data (QC). According to the 2016 Technical Documentation of the SNAP Quality Control Data, units that were determined as eligible and received benefits of at least \$1 will be made into the SNAP Quality Control Data, which is then edited by Mathematica for public use.

increases with household size. I input the income data of TRIM3 recipients and QC samples in the calculator and estimate the eligible benefits. Figure B.2 plots the resulting kernel density and cumulative distribution of eligible benefits for SNAP recipients. The higher income at the mean for TRIM3 does not lead to more participants at the lower end of benefits. In fact, TRIM3 is able to construct a distribution that is similar to the administrative data, especially above about 100 dollars of monthly benefits. This exercise reassures the quality of the TRIM3 data.

4.1 Sample - the always-eligible households

Supposedly, households with income and assets below the corresponding thresholds are eligible without BBCE in place. However, BBCE might affect household behaviors such that their observed income and asset levels are not what they would have behaved without BBCE. For example, eliminating asset limits could encourage more savings, so those who would have saved less now hold more savings than the federal threshold. To address this, I try to predict whether a household would have passed the income and asset tests had there not been BBCE using the observations from the years when states have not adopted BBCE. The predictors include several household characteristics as well as the states' time-varying characteristics:

$$pass_{isy}^m = \alpha + \mathbf{head}_{isy} + \mathbf{unit}_{isy} + \mathbf{economy}_{sy} + \mathbf{policy}_{sy} + \theta_s + \sigma_y + \epsilon_{isy} \quad (3)$$

$pass_{isy}^m$ is a binary indicator of whether household i in state s passes the income and asset tests for m months in year y , $m \in \{\geq 1, \leq 6, 12\}$. While CPS-ASEC collects annual-level observations, TRIM3 provides monthly levels of income. This is because that TRIM3 allocates the reported total number of weeks worked in the past year into each month by matching with the monthly employment published by the Bureau of Labor Statistics (BLS)⁸. I utilize this monthly information to distinguish households who are eligible for at least 1 month, at most 6 months, and 12 months, as the last group may be affected by the policy more than the 6 months group.

⁸More explanation on the allocation and a comparison of the simulated monthly unemployment to the BLS statistics can be found in here: <https://boreas.urban.org/documentation/input/Concepts%20and%20Procedures/Modifications%20to%20the%20Underlying%20Surveys.php#AllocInc>

$head_{isy}$ is a vector of household head characteristics, including age, age², female indicator, race, education, employment status, marital status, and disabilities status. $unit_{isy}$ is a vector of household characteristics, including household size, have members who are children (0-4 years old and 5-17 years old, respectively) and proportions of children, have members who are elderly (more than 60 years old) and proportions of elder members, have members who have disabilities and proportions of such members, have members who are non-citizens and proportions of such members, have able-bodied adults without dependents and proportions of such members, whether the households are receiving SSI/TANF cash assistance, and the decile rank of unearned income among national distribution in year y .

$economy_{sy}$ is the BLS published state unemployment rate in year y , $y - 1$, $y - 2$, and $y - 3$. $policy_{sy}$ includes whether the state has adopted other food stamp policies that change eligibility rules in year y , such policies include vehicle limits, non-citizen eligibility, proportion of participants who are only certified for 1-3 months of benefits and need to re-certify after that. In addition to food stamp policies, I also include the state minimum wage rate in year y . Some other food stamp parameters in year y are also included: state administrative costs, error rates, standard deduction of income, and maximum shelter deduction⁹.

I exclude households that only have children members and households that only have noncitizen members from my sample to ensure that these characteristics can represent decision-making for the majority of the households.

Some of the variables in my specification are not available in the public users data: unit asset for all years, unit gross income before 2005, unit net income before 2005, and individual disability status¹⁰. For income and asset variables, I follow the documentation of TRIM3 and construct the variables using their approach. Figure B.3 compares my imputation to TRIM3 data in available years (2005-2015). I am able to construct mostly consistent distributions with TRIM3. Although for gross income there is a small interval between \$500 to \$1,000 that shows some deviation, my imputation appears to allocate the differences to nearby income intervals, which does not cross the eligibility threshold (\$1,265 for one member household in 2015).

⁹These deductions are used when calculating net income.

¹⁰Disability questions are included in CPS-ASEC since 2008.

For the disability status, I refer to the SNAP QC Technical Documentation of the year 2015, which thoroughly explains how the QC team constructs individual disability status because this information is not always needed in eligibility determination. Note that I use the 2015 version of the document, and over the years, Mathematica has been modifying and improving the imputation methods. That is why in Figure B.4, my total counts of households with disabled members are very different from QC in years 1996-2002, but are much closer in later years. Despite the differences, my imputation has a much smoother increasing trend, which corresponds to the overall trend of SNAP caseloads.

Equation 3 is able to identify 96.8% of those who actually passed the income and asset tests for the at least 1 month group in the years and states that BBCE was not adopted (77.9% for the 12 months eligible group and 83.6% for the 6 months group). I define the “always-eligible” households as eligible households in TRIM3 who are identified to likely pass the income and asset tests by equation 3. On the other hand, the “newly-eligible” households are defined as those who are predicted to not likely pass the income and asset tests while also observed to fail the tests.

Table 2 and 3 report the mean characteristics of each type of eligible household. In general, in the years and states that have not adopted BBCE (labeled as “Pre BBCE”), the always-eligible households and the observed eligible households are mostly alike. Even though some characteristics are statistically different, the magnitude is rather small. The proportion of those who are newly eligible due to BBCE is roughly consistent with other studies: about 2-3% of eligible households have observed income above the federal threshold (GAO, 2012; Laird & Trippe, 2014). The profile of these newly eligible households is also consistent: larger household size, more likely to have earnings and higher income.

It is of great importance that the always-eligible households do not systematically change after BBCE implementation. If BBCE is correlated with some population shifts, then the take-up behaviors observed in pre and post-periods are incomparable. In Table 4, I run a state and year fixed effect regression on the always eligible households. The dependent variable is whether the state has adopted BBCE/BBCE Max in the year, and the independent variables are some time-invariant population characteristics likely to be relevant to program take-up. This specification

is to examine if there is some within-state change in population composition with the adoption of BBCE/BBCE max. Although virtually none of the characteristics are individually different between BBCE/BBCE Max states and years, the joint tests of these household demographics are significantly different. However, in the event study section, I find that the population shift happens after 5-7 years of BBCE/BBCE Max adoptions. Therefore, I focus on the first five years of adoption and measure the dynamic effects.

5 Empirical Strategy: Sun & Abraham (2021) Event Study Estimator

The identification strategy builds on the quasi-random adoptions of BBCE/BBCE Max across states and years. To estimate the dynamic effects of BBCE while dealing with the differential timing of BBCE adoption, I use the interaction-weighted estimator developed by Sun and Abraham (2021). Their approach resolves the issues of contaminated weights in the traditional two-way fixed effect specification, and is robust under treatment effect heterogeneity. The estimator is constructed as first separately estimates the treatment effect in each event time for each treatment cohort, and then uses the sample share of cohorts as weights to calculate the weighted average event coefficients. In the first step, I estimate the cohort-specific event study coefficients by equation 4.

$$y_{isy} = \alpha + \sum_{c \in C} \sum_{k \neq -1} \pi_{c,k} 1(\tau_{sy} = k) \cdot Cohort_s^c + \theta_s + \sigma_y + \mathbf{X}_{isy} \mathbf{\Gamma} + \mathbf{W}_{sy} \mathbf{\Phi} + e_{isy} \quad (4)$$

y_{isy} represents the outcome of interest. When the outcome is take-up, it is measured by the share of eligible benefits took up by household i in state s in year y , $y_{isy} \in [0, 1]$. $1(\tau_{sy} = k)$ is the event indicator, which equals to 1 if state s in year y is k years apart from the first adoption year. $Cohort_s^c$ is the cohort indicator of whether state s first adopts BBCE/BBCE Max in year c . $\pi_{c,k}$ estimates the difference of outcome from the base year and comparison states in event time k for cohort c . In the second step, each cohort c is weighted by its sample share in event time k when calculating a single event time coefficient. θ_s and σ_t represent state and year fixed effect, respectively.

X_{isy} controls household characteristics relevant to take-up decisions, including household size, indicators and proportions of household composition (elder members, disabled members, children, able-bodied adults without dependents (ABAWD), noncitizens), whether household is receiving SSI/TANF, and household head characteristics (age, citizenship, disability status, ABAWD status, gender, race/ethnicity, education, marital status). Two additional control variables are the

federally assigned standard deduction and maximum benefit levels, which vary by household size and years.

W_{sy} controls state varying factors such as other SNAP policies that also affect take-up. These policies include vehicle limits, application aids¹¹, duration of each certification (and lag one year), outreach spending (and lag one year), and electronic benefit issuance. Aside from SNAP policies, I also controlled for states' minimum wage levels as well as unemployment rates (y and $y - 1$).

For state-level observations, I control for \mathbf{W}_{sy} , state and year-fixed effects.

5.1 States that adopts between 2008 and 2012 as comparison group

The above identification requires the parallel trend assumption and the no anticipatory behavior assumption (Sun & Abraham, 2021). The latter assumption refers to no treatment effects in pre-treatment periods, which is unlikely to be violated because even if the households anticipate BBCE to be adopted, there is no reason for them to take up prior to the actual implementation of the policy. The parallel trend assumption, on the other hand, does not easily hold for any choices of comparison groups. The treatment group in this paper is the 13 states that adopted BBCE/BBCE Max before the year 2008. This makes the rest of the states “never-treated” during the observation period from 1996 to 2007. However, 28 of them adopted between 2008 and 2012, i.e. the Great Recession periods, while the rest of the 10 states either adopted later than 2015 or never adopts to date (July, 2023). Such deviation in adoption decisions may signal some fundamental differences between the two types of “never-treated” groups. I chose the 2008 to 2012 adoption states as my comparison group.

¹¹Application aids include waiving face-to-face interviews, waiving reporting of changes if not related to eligibility change, joining the federally-initiated Combined Application Project to simplify application for SSI recipients, operating call centers, and having online application portals.

6 Results

Figure 4 shows that both BBCE and BBCE Max significantly reduced state administrative costs. Note that all of the event times (11 years in pre-periods and 8 years in post-periods) are included in equation 4, and the full event study plot can be found in Appendix C. The flat pre-trends in at least four years before the adoption show that the adoptions of BBCE/BBCE Max were not correlated with changes in total administrative costs. In Table 5, the aggregate effects in event time 3 to 5 are 3.7 dollars (15%) and 4.4 dollars (18%) reduction in the administrative costs. In Figure 5, I find no increase in fraud cases or fraud amount, and even observe decreases for BBCE Max. Note that in Figure C.5, the total number of fraud investigations did not decrease, therefore, the decrease in confirmed fraud cases was not due to a decrease in fraud investigation efforts.

Before we interpret the results of the already-eligible households, we need to confirm if the eligible population in the post-treatment periods is the same one as the pre-treatment periods. If the eligible populations are fundamentally different in the two periods, then the results could be led by the selection of households instead of changes in household take-up decisions. An example of how BBCE can change the always-eligible population is that the higher income thresholds allow the households to work more and remain eligible. The higher earnings could then make the total income surpass the federal threshold, therefore, those who can work are selected out of the sample. It turns out that households earned a bit more after BBCE was implemented (Figure 9), but this did not change the general composition of the always-eligible population. Figure 6 formally tests this by using equation 4 with the always-eligible indicator as y_{isy} and includes all households nationwide (except for children or noncitizen-only households). Conditional on household characteristics and relevant state factors, BBCE/BBCE Max did not systematically change the likelihood of the same households being always eligible. Figure 6 shows no trend or discontinuity between the pre- and post-adoption periods. The example of working more would have led to negative coefficients in post-periods, and such a scenario does not seem to occur, the same for the “at most 6 months” and the “12-months” always eligible groups.

Figure 7 presents the suggestive evidence that BBCE Max increased take-up rates for the

general always-eligible households. After one year of BBCE Max adoption, the take-up rate started to rise and increased by up to 9 percentage points (or about 18%) in the second year. It is unclear why the take-up rates dropped in the fourth year, given that even the balanced panel, which has the exact same states in all event times, also shows the same pattern (see Figure C.11). Nevertheless, the aggregate effects¹² of BBCE Max from event 0 to 3 is about 5-6 percentage points increase (about 10%) for the at least 1-month eligible group. In Figure 8, it appears that the increase was majorly led by the short-term eligible group (at most 6 months). The aggregate effect from event time 0 to 3 was 9-10 percentage points (almost 20%), while no significant increase for the long-term eligible group (12 months) was observed. This suggests that the simpler program rules are more meaningful for those with more income variability. Perhaps due to the unpredictable income or an expectation for only temporary needs, these households did not find it worthy to apply for the program.

To further examine the channel of effects from BBCE/BBCE Max, I examine whether the states increased their outreach expenditure on SNAP. More outreach spending could increase awareness and reduce learning costs, which means that the increase in take-up was caused by decreased information friction instead of simpler application processes. Note that the spending on outreach is deducted from total administrative costs. In Figure 10, the outreach spending did not increase significantly with adopting BBCE. Although there appear to be positive point estimates for event times 1 and 2, the magnitude is identical for BBCE and BBCE Max, yet only BBCE Max increases take-up. If it was entirely due to a lack of awareness, then there should not be heterogeneous effects between BBCE and BBCE Max.

6.1 Robustness of Estimates

Appendix C provides different specifications of the event study estimation for both the state-level and household-level outcomes. For consistency of treated states, I run balanced panel analyses in which the treated states are the same across all event times. The effects are even larger than the unbalanced panel (Figure C.2, C.7, C.11). Excluding covariates also does not change

¹²Simple average of linear combinations of the event coefficients.

the estimates much, but standard errors are smaller (Figure C.3, C.8, C.12). For state total administrative costs, because the data for 1996 is not available, I use the federal share of SNAP administrative costs as an alternative outcome and run estimation from 1996 to 2007. The mean and coefficients are almost exactly half of those from total administrative costs, which makes perfect sense because the federal government shares 50% of states' administrative costs in most cases.

6.2 Labor Supply Responses

One additional finding is that BBCE Max also increases average weekly earnings. In Figure 9, both the 6-month and the 12-month always eligible groups increased earnings, with the 12-month group increasing more persistently. In Table 6, the aggregate effects in event time 0 to 5 for the 12-month group increased about 50 dollars per week (or 17%), and 90 dollars (or 12%) for the 6-month group. This does not come with changes in the overall profile of the always-eligible households, which means that these are virtually the same set of households changing their labor supply decisions. A potential explanation is that higher income thresholds may allow more room for households to work more without losing eligibility.

7 Conclusion

The results of this study offer valuable insights into the impact of relaxing income and asset limits within transfer programs. The findings indicate a significant reduction in state administrative costs with the adoption of both BBCE and the more generous BBCE Max, while dispelling concerns of potential fraud increases. Notably, the observed decrease in fraud cases is not attributed to a reduction in investigative efforts, emphasizing the robustness of the results.

A crucial aspect addressed in this study is the stability of the eligible population over time, ensuring that observed effects are not driven by changes in household composition. The analysis reveals that, despite a slight increase in earnings post-BBCE adoption, there is no systematic change in the composition of always-eligible households. This confirms the reliability of the findings and dispels concerns related to the selection of households.

Moreover, BBCE Max demonstrates a suggestive increase in take-up rates, particularly among short-term eligible households, highlighting the significance of simplified program rules, particularly for those with income variability. I rule out the channel of effects from enhanced awareness, as evidenced by the absence of significant increases in outreach spending.

In essence, this research contributes to the literature by bridging theoretical propositions with empirical evidence within the optimal program design framework. The nuanced examination of incomplete take-up and the causal estimation of BBCE effects on a broader population underscore the multifaceted implications for policy and program design. These findings provide valuable guidance for policymakers seeking to optimize program efficiency while ensuring accessibility for those in need.

For future work, it is worth noting that my findings did not distinguish the effects from income thresholds and asset limits, as these two measures are often simultaneously applied during my observation periods. Additionally, my sample size for the newly eligible households is insufficient to conduct a comprehensive analysis of their behavior. These constraints give rise to intriguing questions regarding the optimization of program rules.

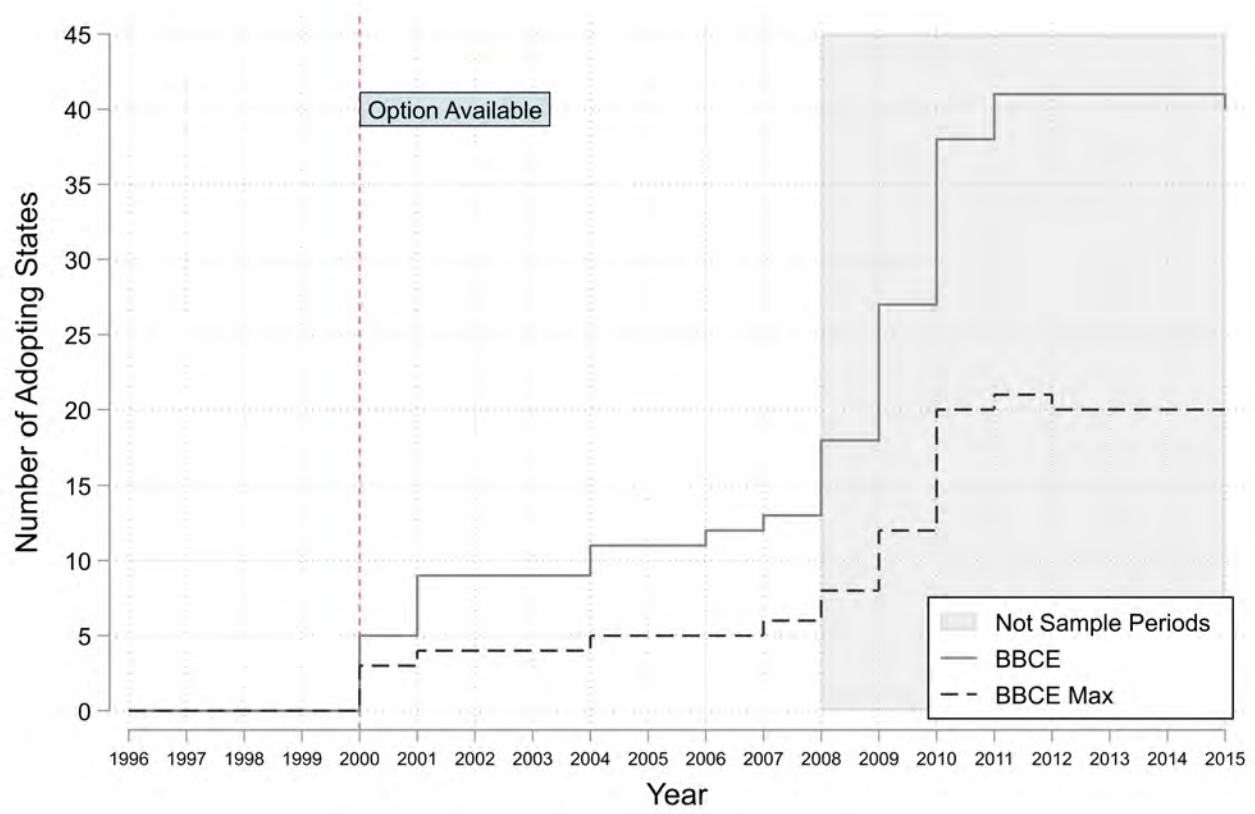
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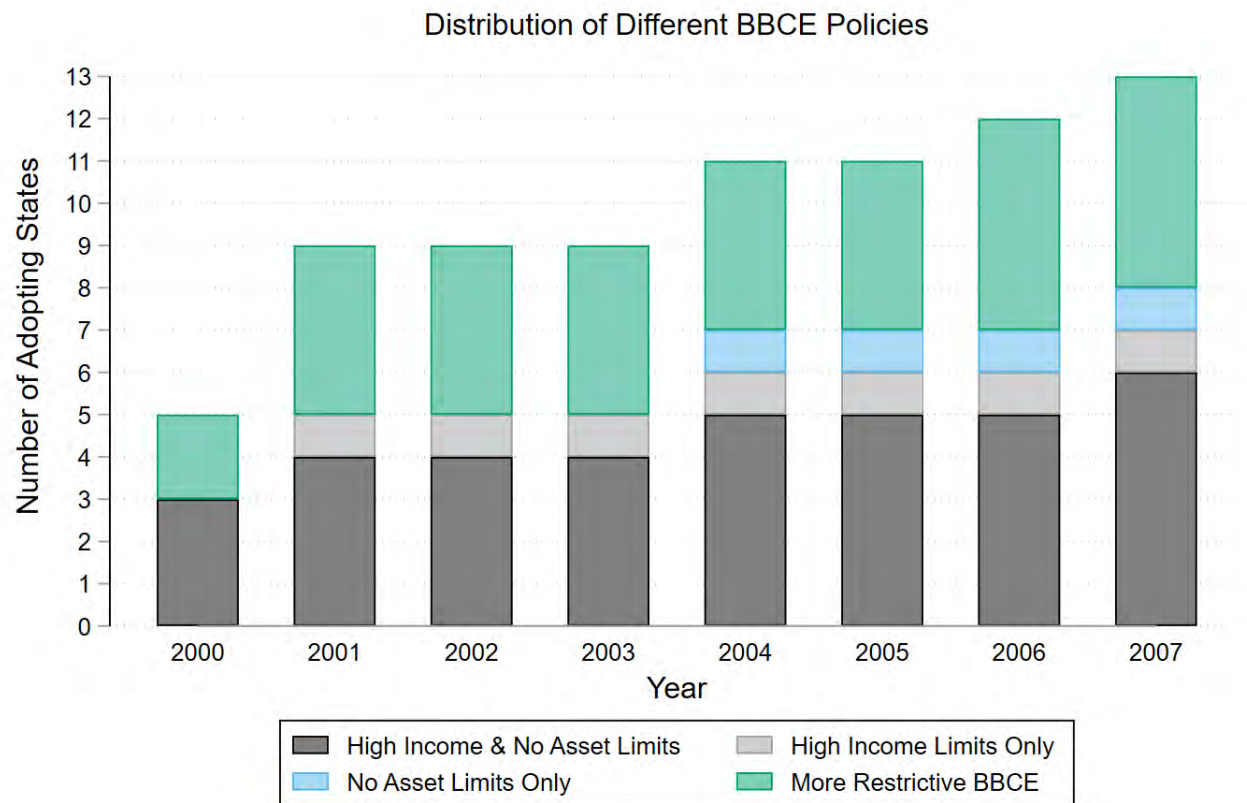
Figure 1: Number of States Adopting BBCE By Year 1996 to 2015



BBCE indicates whether the states adopt any form of BBCE policies. BBCE Max indicates the states adopt the most generous form of BBCE: gross income limits above 130% FPL and eliminating asset tests.

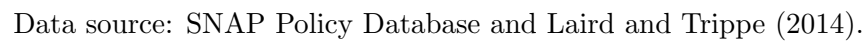
By the end of 2015, a total of 41 states had adopted BBCE. 13 of them adopted before the Great Recession (between 2000 and 2007). This paper studies the effects between 1996 and 2007 because effects during the Great Recession are likely confounded with other factors, such as other stimulus policies. States that adopted BBCE post-2008 also made changes or reversed their BBCE policies within a few years, while none of the states that adopted before 2008 made any changes.

Figure 2: Types of BBCE Policies Adopted by States



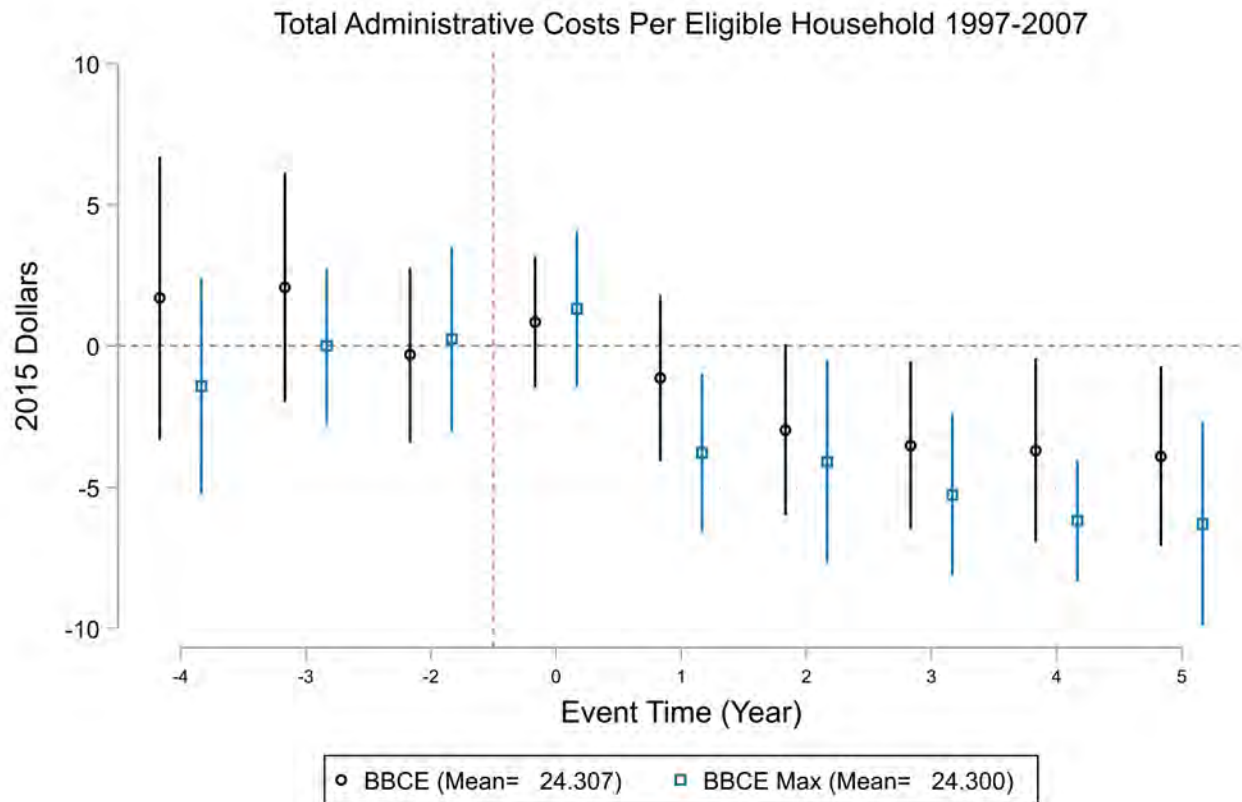
Almost all states that adopt high gross income limits (above 130% FPL) also eliminate their asset limits except for two states. Texas only adopted a high gross income limit, and Washington only adopted no asset tests. The “More Restrictive BBCE” states adopted BBCE conditional on households with elderly members or dependents. By the year 2007, a total of 13 states adopted any BBCE, and 6 of them adopted BBCE Max (high income & no asset limits).

Year of BBCE adoption through 2015



There does not seem to be apparent geographical correlations in the timing of adoption. The darkest shade of green represents the comparison group of this paper — those who did not adopt BBCE during 2000 to 2007 but adopted during 2008 to 2012. The three lighter shades of green are the treatment states of this paper. The gray states that did not adopt BBCE by the year 2015 are not studied in this paper.

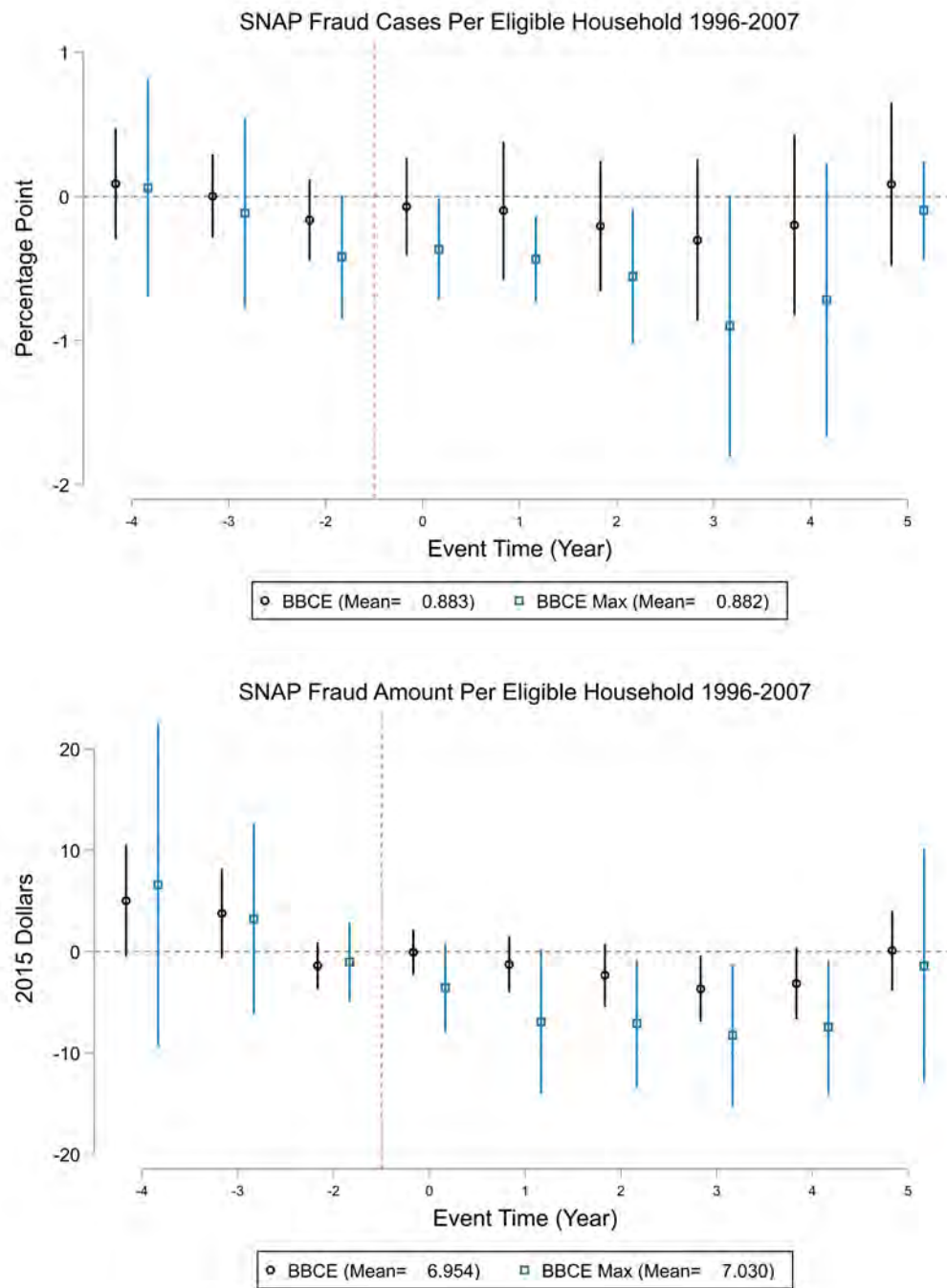
Figure 4: Event Study Estimates: State Total Administrative Costs for SNAP



Sun & Abraham (2021) estimators using equation 4, state-level version. Standard errors clustered at the state level. The dependent variable is the total SNAP administrative costs divided by the number of always eligible (for any month) households. All monetary values are adjusted to the December 2015 consumer price index. The state-year level of observations is weighted by states' always eligible (for any month) populations. Mean administrative costs at event time lead 1 and the comparison group is marked in the legend. State total administrative costs in 1996 are not available

This figure shows a major reduction in SNAP administrative costs by adopting BBCE, especially through BBCE Max. In event lag 3 to 5, state administrative costs decreased by 4.6-5.5 dollars (about 23%) for BBCE, and 5.2-6.5 dollars for BBCE Max (about 27%).

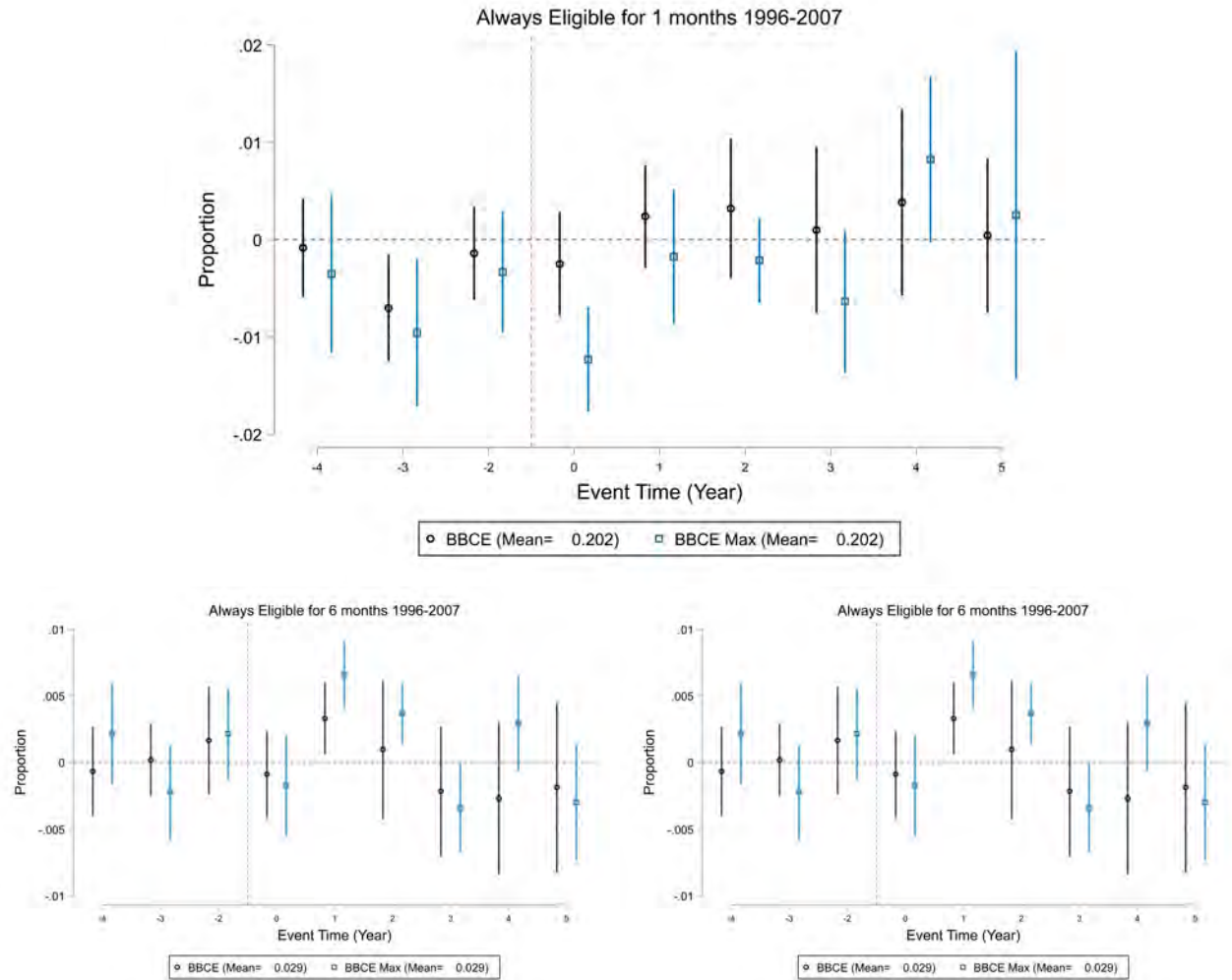
Figure 5: Event Study Estimates: SNAP Fraud Cases and Benefit Amount



Sun & Abraham (2021) estimators using equation 4, state-level version.. Standard errors clustered at the state level. The dependent variables are the number of fraud cases and the amount of benefits, both divided by the number of always eligible (for any month) households. All monetary values are adjusted to the December 2015 consumer price index. The state-year level of observations is weighted by states' always eligible (for any month) populations. The means of the dependent variables at event time lead one and the comparison group are marked in the legend. State total administrative costs in 1996 are not available

This figure examines whether BBCE/BBCE Max increased SNAP fraud incidence. The upper panel shows decreases in fraud cases, and the lower panel also shows a decrease in fraud amounts. The fraud cases include fraud conducted before and after the certification, and the fraud amounts are only determined for cases that have completed the certification.

Figure 6: Event Study Estimates: Likelihood of Being Always-Eligible

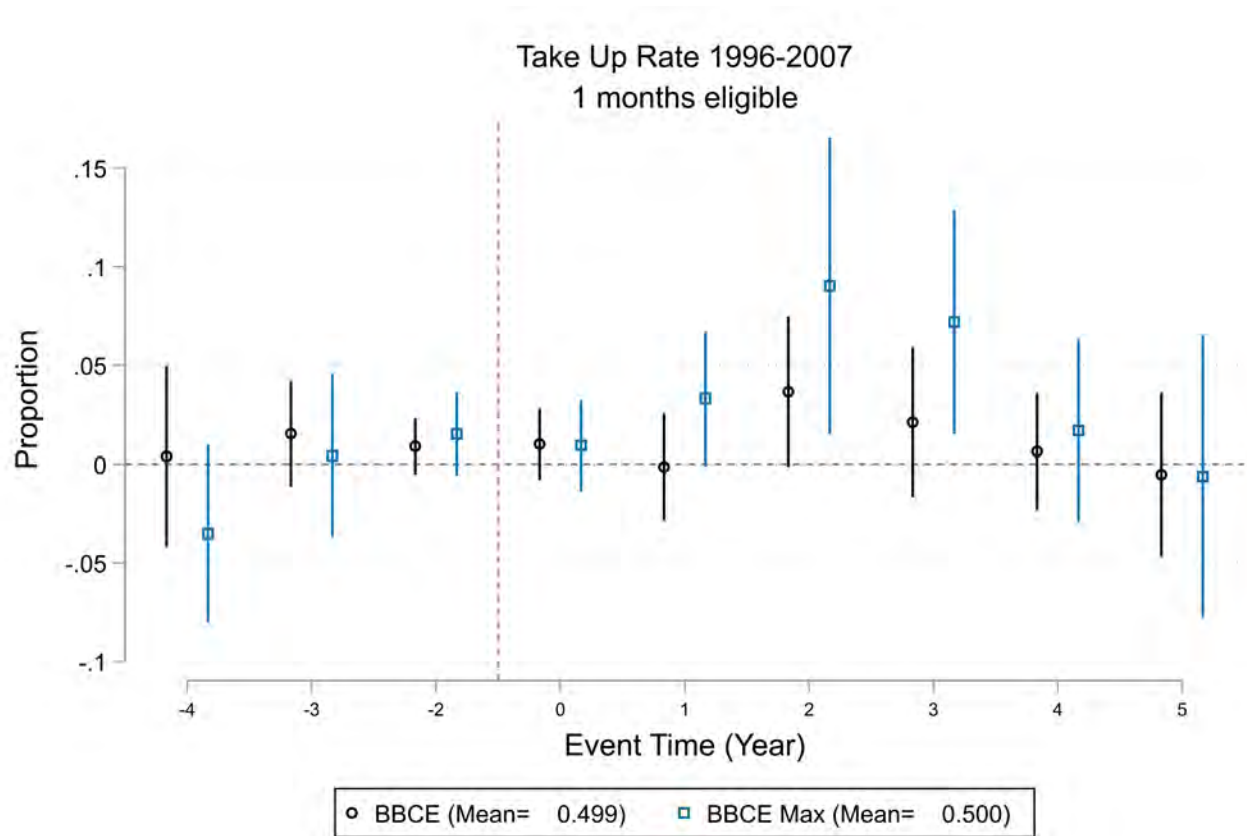


Sun & Abraham (2021) estimators using equation 4. Observations weighted by household sampling weight. Standard errors clustered at the state level.

The dependent variable is an indicator of being always eligible for at least one month in the year. The sample includes all populations, eligible or not.

This figure shows no change in the size of the always-eligible population after BBCE/BBCE Max adoption. It also implies no drastic or trending changes in the composition of the always eligible population; otherwise, the probability of a household with the same characteristics being always eligible would change.

Figure 7: Event Study Estimates: Take-Up Among Always Eligible

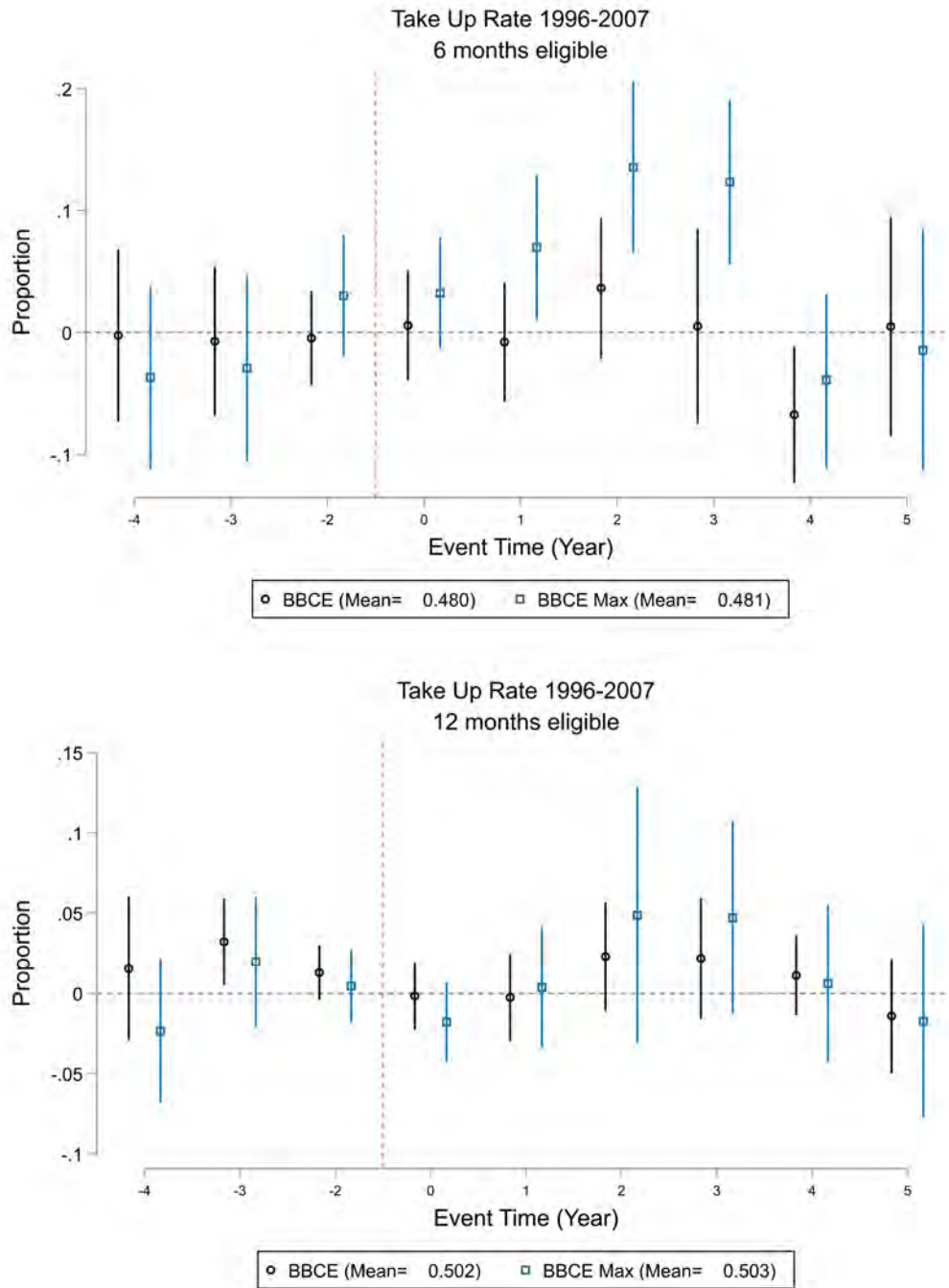


Sun & Abraham (2021) estimators using equation 4. Observations weighted by household sampling weight. Standard error clustered at the state level.

The dependent variable is whether or not the household is receiving nonzero SNAP benefits. Sample includes households always eligible for any month in the year.

Event time ranges from -11 to 7. The complete vector of estimates are plotted in Appendix ???. This figure includes 94% of the sample.

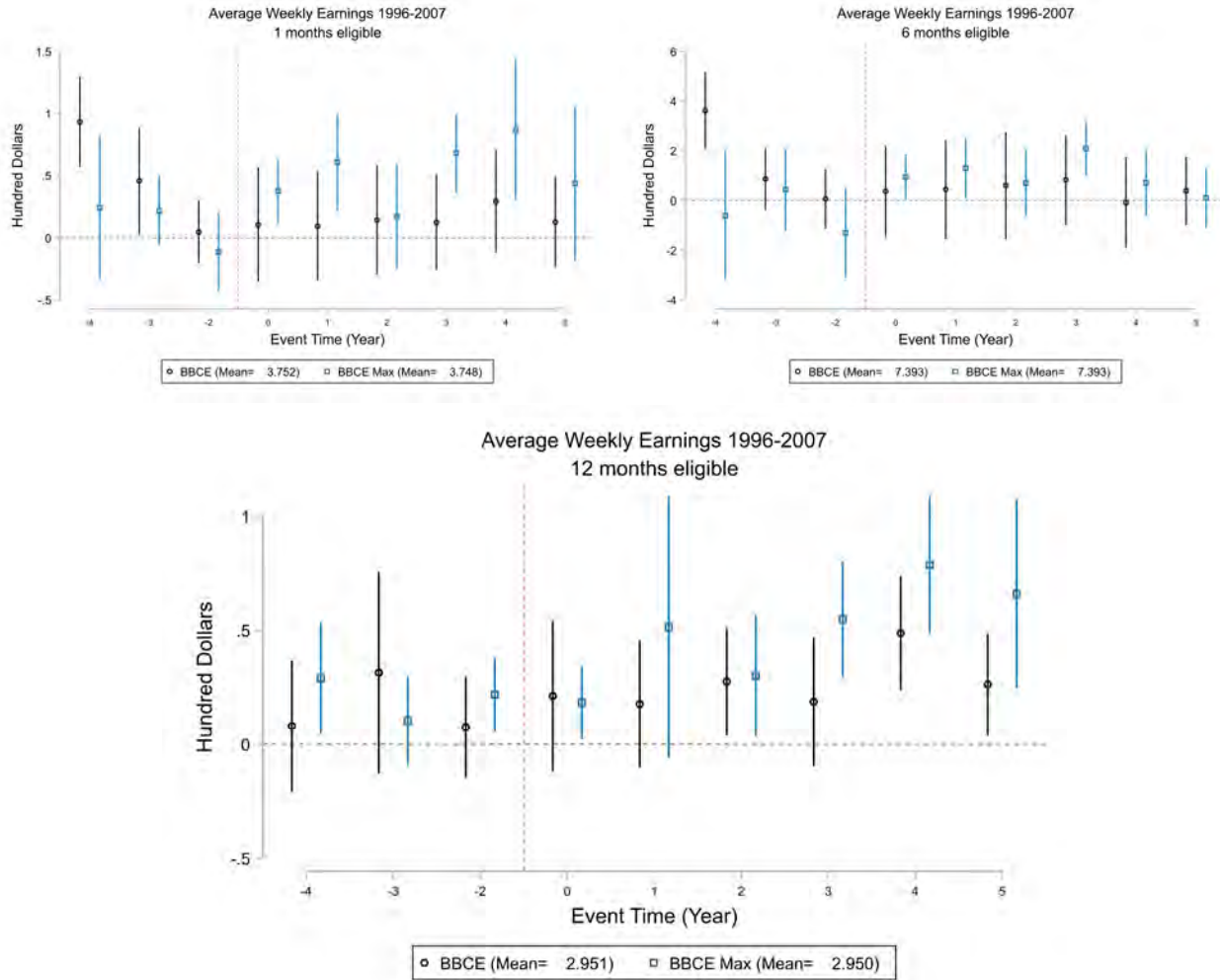
Figure 8: Event Study Estimates: Take-Up Among Subgroups



Sun & Abraham (2021) estimators using equation 4. Observations weighted by household sampling weight. Standard error clustered at the state level.

The dependent variable is whether or not the household is receiving nonzero SNAP benefits. The sample includes households always eligible for at most 6 months in the year and for every month in the year. This figure analyzes heterogeneous responses by short-term and long-term eligible households. The simplified eligibility rules affect the short-term eligible groups much more than the long-term eligible groups.

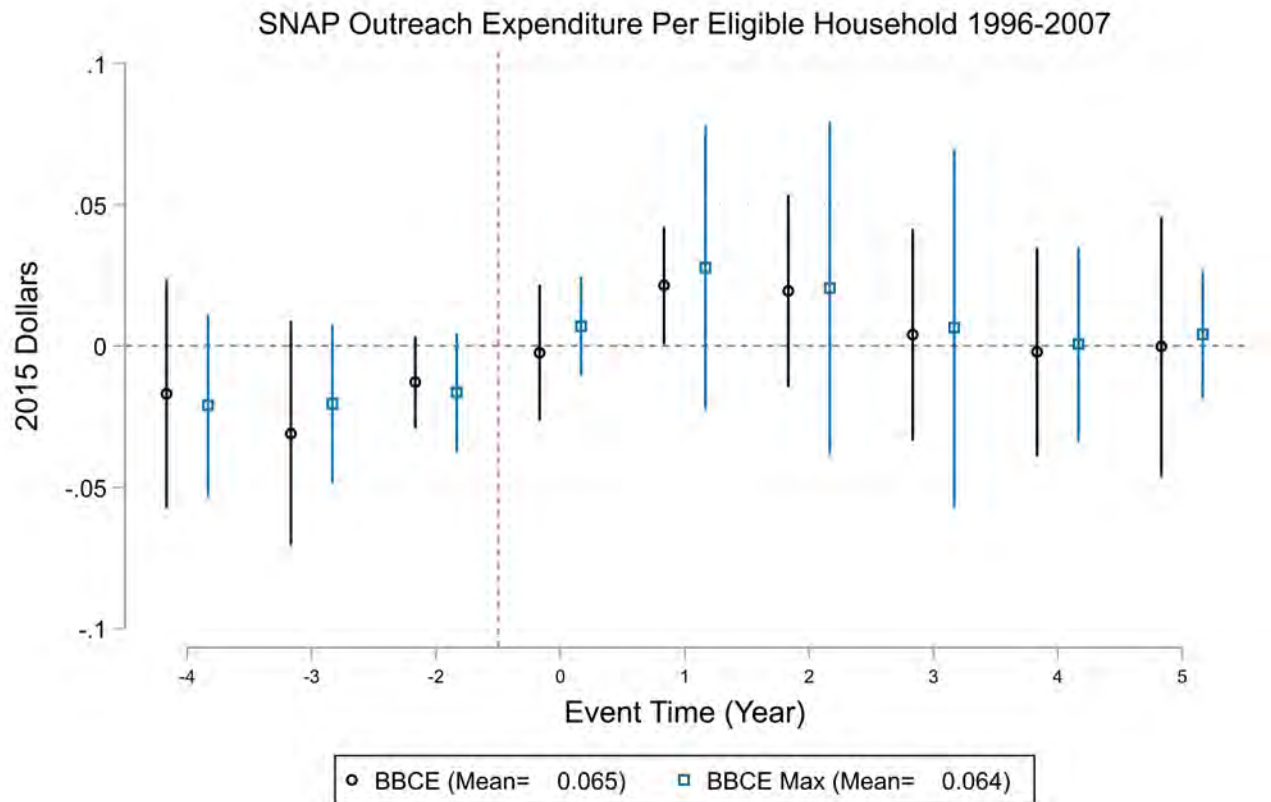
Figure 9: Event Study Estimates: Average Weekly Earnings



Sun & Abraham (2021) estimators using equation 4. Observations weighted by household sampling weight. Standard error clustered at the state level.

This figure analyzes whether BBCE/BBCE Max affects labor supply outcomes. The first row shows some increases in the average weekly earnings for the general and the short-term always-eligible households. The bottom panel shows that the 12 months always eligible group consistently increased their earnings in post periods.

Figure 10: Event Study Estimates: State Outreach Expenditure



Sun & Abraham (2021) estimators using equation 4, the state-level version. The dependent variable is the amount of expenditures on SNAP outreach programs divided by the number of always eligible (for any month) households. All monetary values are adjusted to the December 2015 consumer price index. The state-year level of observations is weighted by states' always eligible (for any month) populations. Mean of the dependent variable at event time lead 1 and the comparison group is marked in the legend.

This figure investigates another channel of effects from BBCE/BBCE Max — the outreach efforts. If the states are increasing outreach efforts due to adopting BBCE, then increased awareness/information could be an alternative explanation for the household responses rather than the simplified eligibility requirements. There does not seem to be a significant increase in outreach.

Table 1: Determinants of State Adoption of BBCE Before 2008: Fixed Pre-BBCE Option State Characteristics

	(1) BBCE	(2) BBCE Max
Take up rate	0.0216 (0.0235)	0.0143 (0.0177)
Share of Eligible Population	0.0579 (0.222)	-0.0905 (0.168)
Population Age < 18	-0.394 (0.290)	-0.363 (0.219)
Population Age ≥ 65	-0.275 (0.176)	-0.194 (0.133)
Share of Hispanic	0.0233 (0.0282)	0.0255 (0.0213)
Share of Black	-0.0163 (0.0201)	0.0111 (0.0152)
Share of Other Race/Ethnicity	-0.0101 (0.0185)	0.0120 (0.0140)
Education HS or Below	-0.0434 (0.0454)	-0.00150 (0.0342)
Share of Population with Disability	-0.343 (0.294)	0.0224 (0.222)
Non-disabled Adults without Dependent	-0.258 (0.207)	-0.237 (0.157)
Share of Married Persons	-0.141 (0.0966)	-0.102 (0.0729)
Share of Citizens	0.0500 (0.0571)	0.0593 (0.0431)
Unemployment Rate	-0.273 (0.253)	-0.235 (0.191)
Median Household Income (Dec. 2015\$)	-0.00457 (0.0364)	-0.0441 (0.0275)
Share of Voters Support Welfare	-0.0304 (0.0680)	-0.105 (0.0513)
Share of Voters Have Racism	0.0190 (0.0387)	-0.0216 (0.0292)
Share of Expenditure Covered by Own Revenue	-0.00312 (0.0202)	-0.0142 (0.0153)
Total SNAP Admin Costs Per Case	0.00559 (0.0120)	0.0109 (0.00908)
SNAP Error Rate	-0.0343 (0.0469)	0.0403 (0.0354)
Observations	41	41
R^2	0.500	0.385
Prob > F	0.411	0.789
Mean	0.25	0.09

Ordinary least squared regression estimates. Observations weighted by eligible population size averaged from 1996 to 1999. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Dependent variable is an indicator of states ever adopting BBCE/BBCE Max before 2008, 0 if the states adopted BBCE between 2008 and 2012. Independent variables are the average of 1996 to 1999 levels of potential determinants of states' policy choices.

Variables are gathered from multiple sources of data. See Appendix B

Table 2: Mean Characteristics of SNAP Eligible Units: Always Eligible for At Least 1 month

	Pre BBCE	Post BBCE	
	Always-Eligible (1)	Always-Eligible (2)	Newly-Eligible (3)
Take-up rate	0.510 (0.492)	0.569*** (0.486)	0.642*** (0.475)
Gross Income	1414.8 (1533.8)	1387.4* (1511.4)	3435.3*** (2670.3)
Net Income	833.0 (1138.5)	810.3** (1073.3)	2044.3*** (2213.5)
Eligible Benefit	147.9 (161.0)	149.8 (164.7)	148.3 (181.3)
Age of Head	46.41 (19.27)	46.88*** (19.07)	42.90*** (15.00)
Head Female	0.616 (0.486)	0.620 (0.485)	0.739*** (0.440)
Head White	0.710 (0.454)	0.741*** (0.438)	0.800** (0.400)
Head Black	0.238 (0.426)	0.213*** (0.410)	0.152*** (0.359)
Head Hispanic	0.187 (0.390)	0.222*** (0.416)	0.0948*** (0.293)
Head HS or below	0.708 (0.455)	0.681*** (0.466)	0.488*** (0.500)
Head unemployed	0.804 (0.397)	0.824*** (0.381)	0.841 (0.366)
Head married	0.363 (0.481)	0.350*** (0.477)	0.286** (0.452)
Head Disabled	0.0936 (0.291)	0.105*** (0.307)	0.0864 (0.281)
Unit Size	2.293 (1.539)	2.218*** (1.499)	3.026*** (1.662)
Have Earnings	0.582 (0.493)	0.580 (0.494)	0.631* (0.483)
Has Disabled Member	0.152 (0.359)	0.154 (0.361)	0.124 (0.330)
Has Elderly Member	0.293 (0.455)	0.300 (0.458)	0.161*** (0.368)
Has Children 0-4	0.224 (0.417)	0.217* (0.412)	0.206 (0.405)
Has Children 5-17	0.339 (0.474)	0.324*** (0.468)	0.579*** (0.494)
Has Noncitizen Member	0.116 (0.321)	0.114 (0.317)	0.0109*** (0.104)
Observations	125839	23591	478

Weighted by household sampling weights. Columns (2) and (3) mark mean difference t-tests between columns (1) versus (2) and columns (2) versus (3), respectively. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. “Pre BBCE” includes never adopting states and adopting states in pre-periods. “Post BBCE” includes adopting states in post-periods. “Always-eligible” is defined as eligible for at least 1 month in the year. “Newly-eligible” is defined as eligible but not always eligible. The share of newly eligible is 2%.

Table 3: Mean Characteristics of Always Eligible Units: Short- versus Long-term Eligible

	12 months		At most 6 months	
	Pre BBCE (1)	Post BBCE (2)	Pre BBCE (3)	Post BBCE (4)
Take-up rate	0.525 (0.494)	0.550*** (0.492)	0.464 (0.485)	0.598*** (0.470)
Gross Income	1160.0 (1341.2)	1144.6 (1148.6)	2462.5 (3245.5)	2215.8*** (2337.1)
Net Income	634.0 (800.6)	634.0 (721.8)	1587.4 (2409.8)	1430.1*** (1805.6)
Eligible Benefit	157.4 (166.6)	159.2 (172.2)	103.3 (125.3)	106.6 (126.5)
Age of Head	50.43 (20.48)	50.68 (19.96)	37.07 (11.51)	36.91 (11.80)
Head Female	0.680 (0.467)	0.677 (0.468)	0.401 (0.490)	0.410 (0.492)
Head White	0.680 (0.467)	0.716*** (0.451)	0.824 (0.381)	0.838* (0.369)
Head Black	0.267 (0.442)	0.237*** (0.426)	0.130 (0.336)	0.121 (0.327)
Head Hispanic	0.226 (0.418)	0.269*** (0.444)	0.0677 (0.251)	0.0770* (0.267)
Head HS or below	0.793 (0.405)	0.772*** (0.419)	0.424 (0.494)	0.406* (0.491)
Head unemployed	0.794 (0.405)	0.801* (0.399)	0.951 (0.215)	0.966*** (0.180)
Head married	0.344 (0.475)	0.344 (0.475)	0.408 (0.492)	0.361*** (0.480)
Head Disabled	0.130 (0.337)	0.144*** (0.351)	0.00475 (0.0688)	0.00444 (0.0665)
Unit Size	2.252 (1.516)	2.208*** (1.511)	2.199 (1.518)	2.118** (1.437)
Have Earnings	0.470 (0.499)	0.479* (0.500)	0.860 (0.347)	0.848 (0.359)
Has Disabled Member	0.211 (0.408)	0.209 (0.406)	0.0111 (0.105)	0.0110 (0.104)
Has Elderly Member	0.413 (0.492)	0.410 (0.492)	0.00987 (0.0989)	0.00882 (0.0935)
Has Children 0-4	0.242 (0.429)	0.233* (0.423)	0.127 (0.333)	0.132 (0.338)
Has Children 5-17	0.352 (0.478)	0.334*** (0.472)	0.234 (0.424)	0.234 (0.424)
Has Noncitizen Member	0.157 (0.364)	0.153 (0.360)	0.0119 (0.109)	0.00918 (0.0954)
Observations	94183	17447	18587	4029

Weighted by household sampling weights. Columns (2) and (4) mark the mean difference t-test between pre- and post-BBCE periods. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. “12 months” means always eligible for 12 months in the year. “At most 6 months” means always eligible for 1 to 6 months in the year.

Table 4: Regression of BBCE/BBCE Max Implementations Over Characteristics of Always-Eligible Households

	At least 1 month		At most 6 months		12 months	
	BBCE	BBCE Max	BBCE	BBCE Max	BBCE	BBCE Max
Age of Head	-0.0000834 (0.0000606)	-0.0000153 (0.0000445)	-0.000475* (0.000193)	-0.0000862 (0.000147)	0.00000583 (0.0000587)	-0.0000182 (0.0000446)
Head Female	0.000876 (0.00145)	-0.000793 (0.00142)	-0.00574* (0.00230)	-0.00412 (0.00248)	0.00196 (0.00143)	0.000423 (0.00154)
Head Black	0.00319 (0.00195)	0.00148 (0.00157)	0.00136 (0.00564)	0.00182 (0.00409)	0.00294 (0.00208)	0.00160 (0.00195)
Head Hispanic	0.00153 (0.00182)	0.000129 (0.00143)	0.00130 (0.00389)	-0.000910 (0.00385)	0.00171 (0.00210)	0.0000615 (0.00169)
Head Others	-0.00274 (0.00309)	-0.00166 (0.00257)	-0.00838 (0.00591)	-0.0144* (0.00691)	-0.00265 (0.00366)	0.000951 (0.00309)
Head HS or below	-0.000319 (0.00101)	-0.0000229 (0.000678)	-0.00502 (0.00269)	-0.00340 (0.00225)	0.00111 (0.00139)	0.00123 (0.00106)
Head married	-0.00167 (0.00107)	-0.000400 (0.000914)	-0.00124 (0.00271)	-0.00333 (0.00188)	-0.00153 (0.00131)	0.0000751 (0.00107)
Head Disabled	0.0106*** (0.00290)	0.00693* (0.00259)	0.0175 (0.0290)	0.0376 (0.0208)	0.0101** (0.00313)	0.00568* (0.00226)
Head unemployed	0.00234 (0.00125)	0.000723 (0.000921)	0.00482 (0.00564)	0.00781 (0.00555)	0.00337 (0.00205)	0.000634 (0.00109)
Unit Size	0.000528 (0.000622)	-0.000434 (0.000374)	-0.000159 (0.00171)	-0.0000546 (0.00115)	0.000969 (0.000720)	-0.000278 (0.000507)
Has Disabled Member	-0.00172 (0.00220)	-0.00128 (0.00149)	-0.0231 (0.0181)	-0.0304 (0.0197)	-0.00225 (0.00247)	-0.000728 (0.00104)
Has ABAWD Member	0.000417 (0.00189)	0.00124 (0.00120)	0.00177 (0.00497)	0.00560 (0.00389)	-0.00119 (0.00215)	0.000157 (0.00114)
Has Elderly Member	0.00443 (0.00219)	0.00336 (0.00207)	0.0168 (0.0110)	-0.00625 (0.00785)	-0.000269 (0.00279)	0.00197 (0.00157)
Has Children 0-4	-0.000332 (0.00169)	0.000423 (0.00123)	-0.00444 (0.00474)	0.00461 (0.00336)	-0.00171 (0.00185)	-0.00216 (0.00122)
Has Children 5-17	-0.000566 (0.00209)	0.00295 (0.00154)	0.00416 (0.00545)	0.00632 (0.00467)	-0.000763 (0.00216)	0.00184 (0.00175)
Has Noncitizen Member	-0.000718 (0.00307)	-0.00428 (0.00335)	0.0165 (0.0141)	0.00542 (0.0120)	-0.00240 (0.00343)	-0.00452 (0.00374)
Observations	149430	124375	22616	18720	111630	93306
Adjusted R^2	0.759	0.733	0.736	0.753	0.779	0.741
Prob > F	0.0539	0.5075	0.1361	0.5016	0.0338	0.6681
Mean	0.151	0.0714	0.160	0.0970	0.155	0.0673

State and year fixed effects regression estimates. Sample weighted by household sampling weight. Standard errors clustered at the state level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The dependent variable is an indicator of BBCE/BBCE Max adoption. Independent variables are unit characteristics, controlling for other SNAP policies, unemployment rates, state fixed effects and year fixed effects.

"Prob > F" conducts the joint test of the listed characteristics.

Table 5: Aggregated Effects on State Outcomes

All Observations	Event -4 to -2		Event 3 to 5		Event 0 to 5	
	BBCE	BBCE Max	BBCE	BBCE Max	BBCE	BBCE Max
Total Administrative Costs	1.153 (1.859)	-0.392 (1.357)	-3.702* (1.443)	-4.432*** (0.807)	-2.395* (1.152)	-4.047*** (0.986)
SNAP Fraud Cases	-0.0237 (0.124)	-0.158 (0.220)	-0.139 (0.215)	-0.428 (0.239)	-0.131 (0.160)	-0.511* (0.217)
SNAP Fraud Amount	2.459 (1.736)	2.934 (3.906)	-2.249 (1.535)	-4.293 (2.305)	-1.736 (1.276)	-5.795* (2.325)
Balanced Panel	Event -4 to -2		Event 3		Event 0 to 3	
	BBCE	BBCE Max	BBCE	BBCE Max	BBCE	BBCE Max
Total Administrative Costs	1.233 (1.981)	-0.274 (1.689)	-3.552* (1.532)	-5.138*** (1.406)	-1.726 (1.206)	-3.091** (1.160)
SNAP Fraud Cases	-0.0213 (0.130)	-0.233 (0.260)	-0.351 (0.268)	-0.912* (0.456)	-0.177 (0.175)	-0.575** (0.207)
SNAP Fraud Amount	2.898 (1.793)	4.049 (4.672)	-4.450* (2.010)	-8.746* (3.488)	-2.024 (1.384)	-7.066** (2.342)

Aggregated Sun & Abraham event study estimates. Standard error in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Balanced panel includes the same set of states observed from event -4 to 3: 11 out of the 13 states treated for BBCE (87% of the sample), and 5 out of the 6 states treated for BBCE Max (93% of the sample).

Table 6: Aggregated Effects on Always Eligible Household Outcomes

	Event -4 to -2		Event 0 to 3		Event 0 to 5	
	BBCE	BBCE Max	BBCE	BBCE Max	BBCE	BBCE Max
<i>Panel A - At least 1 month</i>						
All Observations						
Take up	0.00938 (0.0131)	-0.00524 (0.0149)	0.0166 (0.0129)	0.0512* (0.0217)	0.0112 (0.0130)	0.0359 (0.0232)
Average Weekly Earnings	0.479*** (0.132)	0.117 (0.179)	0.117 (0.201)	0.458** (0.161)	0.148 (0.184)	0.522** (0.199)
Balanced Panel						
Take up	0.0177 (0.0323)	-0.0305 (0.0210)	0.0347 (0.0194)	0.0637* (0.0279)	0.0267 (0.0178)	0.0442 (0.0268)
Average Weekly Earnings	0.197 (0.251)	0.584* (0.241)	0.291 (0.267)	0.689** (0.225)	0.277 (0.246)	0.677** (0.239)
<i>Panel B - At most 6 months</i>						
All Observations						
Take up	-0.00470 (0.0247)	-0.0120 (0.0255)	0.00982 (0.0252)	0.0903*** (0.0236)	-0.00389 (0.0222)	0.0513 (0.0280)
Average Weekly Earnings	1.512** (0.545)	-0.492 (0.957)	0.551 (0.941)	1.252** (0.481)	0.417 (0.849)	0.967* (0.452)
Balanced Panel						
Take up	-0.0239 (0.0607)	-0.0720* (0.0320)	0.0409 (0.0429)	0.102*** (0.0294)	0.0232 (0.0291)	0.0591 (0.0309)
Average Weekly Earnings	-0.532 (0.855)	0.230 (0.764)	0.148 (0.946)	1.584* (0.632)	-0.309 (0.849)	1.187* (0.533)
<i>Panel C - 12 months</i>						
All Observations						
Take up	0.0202 (0.0138)	0.000306 (0.0166)	0.0101 (0.0128)	0.0204 (0.0242)	0.00627 (0.0126)	0.0117 (0.0241)
Average Weekly Earnings	0.155 (0.114)	0.203* (0.0910)	0.212* (0.106)	0.385** (0.135)	0.266** (0.102)	0.498*** (0.144)
Balanced Panel						
Take up	0.0452 (0.0335)	-0.0185 (0.0242)	0.0355 (0.0216)	0.0319 (0.0316)	0.0304 (0.0208)	0.0194 (0.0285)
Average Weekly Earnings	0.400* (0.185)	0.716*** (0.129)	0.345* (0.160)	0.490** (0.162)	0.445** (0.154)	0.568*** (0.161)

Aggregated Sun & Abraham event study estimates. Standard error in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Balanced panel includes the same set of states observed from event -4 to 5: eight out of the thirteen states treated for BBCE (80% of the sample), and four out of the six states treated for BBCE Max (92% of the sample).

A BBCE Adoption Appendix

Table A.1: Determinants of State Adoption of BBCE Before 2008: Analysis of Time-Varying Characteristics from the Previous Year

	(1) BBCE	(2) BBCE Max
Take up rate	-0.00319 (0.00192)	-0.000473 (0.000577)
Share of Eligible Population	-0.00970 (0.0106)	-0.00159 (0.00765)
Population Age < 18	-0.0179 (0.0137)	-0.0192 (0.0100)
Population Age ≥ 65	0.00657 (0.0108)	-0.00173 (0.00593)
Share of Hispanic	0.0186 (0.0135)	0.00231 (0.00478)
Share of Black	0.000908 (0.00993)	-0.00252 (0.00433)
Share of Other Race/Ethnicity	-0.00354 (0.0101)	-0.00349 (0.00319)
Education HS or Below	0.00768 (0.00894)	0.00499 (0.00274)
Population with Disability	-0.0147 (0.0223)	-0.00313 (0.0117)
Non-disabled Adults without Dependent	0.00129 (0.000746)	0.000548 (0.000432)
Share of Married Persons	0.0130 (0.00985)	0.00698 (0.00488)
Citizens	-0.00424 (0.00945)	0.00818 (0.00555)
Unemployment Rate	0.0186 (0.0207)	0.0188 (0.0171)
Median Household Income (Dec. 2015\$)	-0.00103 (0.00360)	0.0000279 (0.00124)
Share of Voters Support Welfare	0.0246 (0.0175)	0.00239 (0.00691)
Share of Voters Have Racism	0.0114 (0.0264)	0.0171 (0.0207)
Share of Expenditure Covered by Own Revenue	-0.000827 (0.00151)	-0.000263 (0.000912)
Total SNAP Admin Costs Per Case	-0.00212* (0.000877)	-0.000702 (0.000379)
SNAP Error Rate	0.00583 (0.00391)	0.000320 (0.00163)
Observations	4401	4742
Adjusted R^2	0.293	0.254
P > F	0.407	0.944
Mean	0.03	0.01

Monthly observations of state adoption decisions starting from January 1996 until the first adoption month. State and year fixed effect regression estimates. Observations weighted by eligible population size averaged from 1996 to 1999. Standard errors clustered at the state level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Dependent variable is an indicator of BBCE/BBCE Max adoption observed at the monthly level. Independent variables are observed in the same month in the previous year.

B Data Appendix

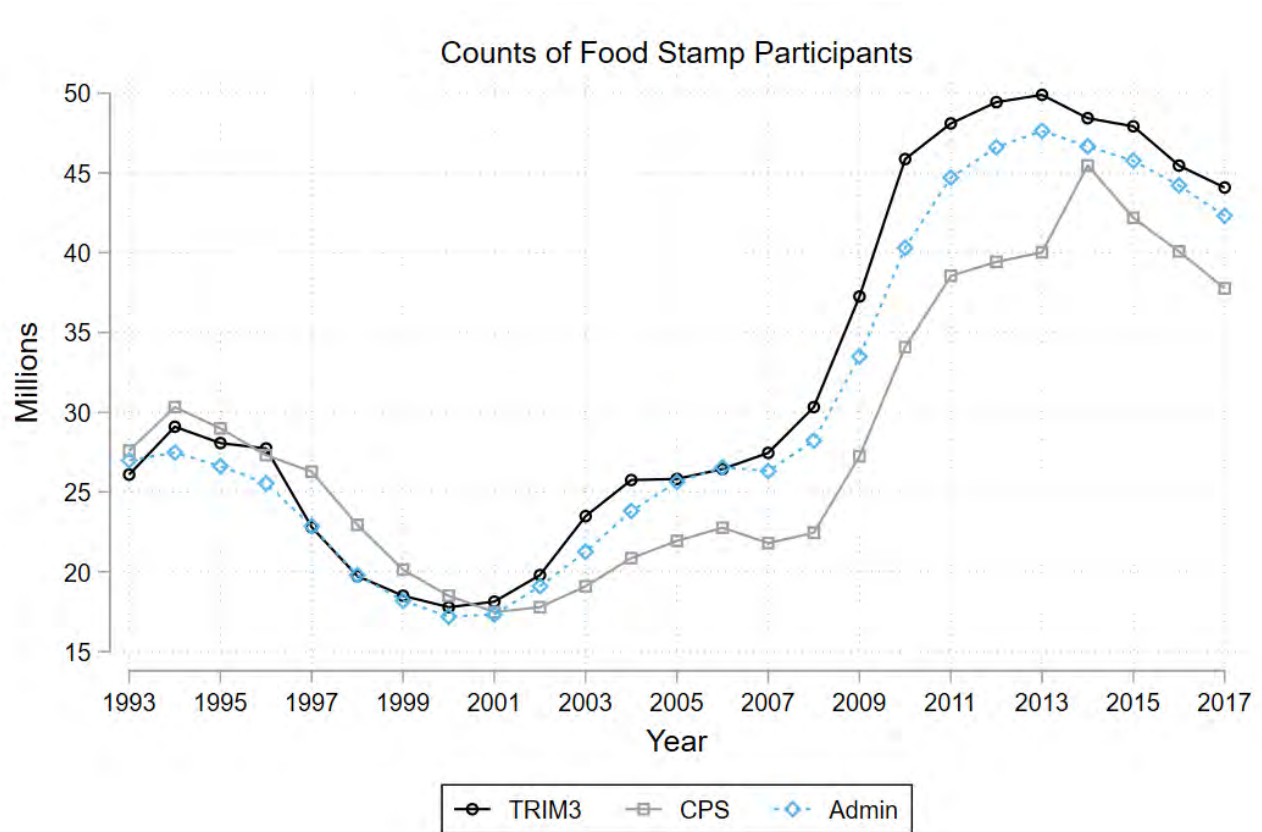
B.1 Sources of factors explaining state policy variation

- **Unemployment rate:** monthly, seasonally adjusted. Current Employment Statistics, the Bureau of Labor Statistics
- **Median Household Income:** calculated by author using TRIM3 (based on CPS-ASEC)
- **Voters' Preference for Welfare:** the Voting and Registration Supplement of the Current Population Survey (VRS), the General Social Survey (GSS).
 - VRS: predict the likelihood to vote or register using a set of individual characteristics including age, sex, natural-born citizenship, education, race, marital status, household size, household income, region, and year indicators. The coefficients are used in the next step.
 - GSS: predict potential voters, construct a welfare attitude indicator according to the following questions (questions rotated):
 - * if the government should be helping the poor
 - * if the national expenditure on assistance to the poor/welfare is too little
 - predict the likelihood of supporting welfare among all the potential voters on TRIM3 samples. Collapse into state average (weighted by person sampling weights).
- **Voters' Having Racism:** same procedure and data as the welfare preference. Questions used are:
 - if agree to the statement “Most (Negroes/Blacks/African-Americans) just don’t have the motivation or willpower to pull themselves up out of poverty”
 - if scored at least five out of seven on the tendency of blacks to be lazy
- **State Finance:** Annual Survey of State Government Finances, US Census Bureau

- **SNAP Administrative Costs:** State Activity Reports, Food and Nutrition Services, USDA
- **SNAP Error Rates:** Quality Control Annual Report, Food and Nutrition Services, USDA

B.2 Comparing TRIM3 to Administrative Data

Figure B.1: Total Number of SNAP Participants: TRIM3 versus Administrative Data



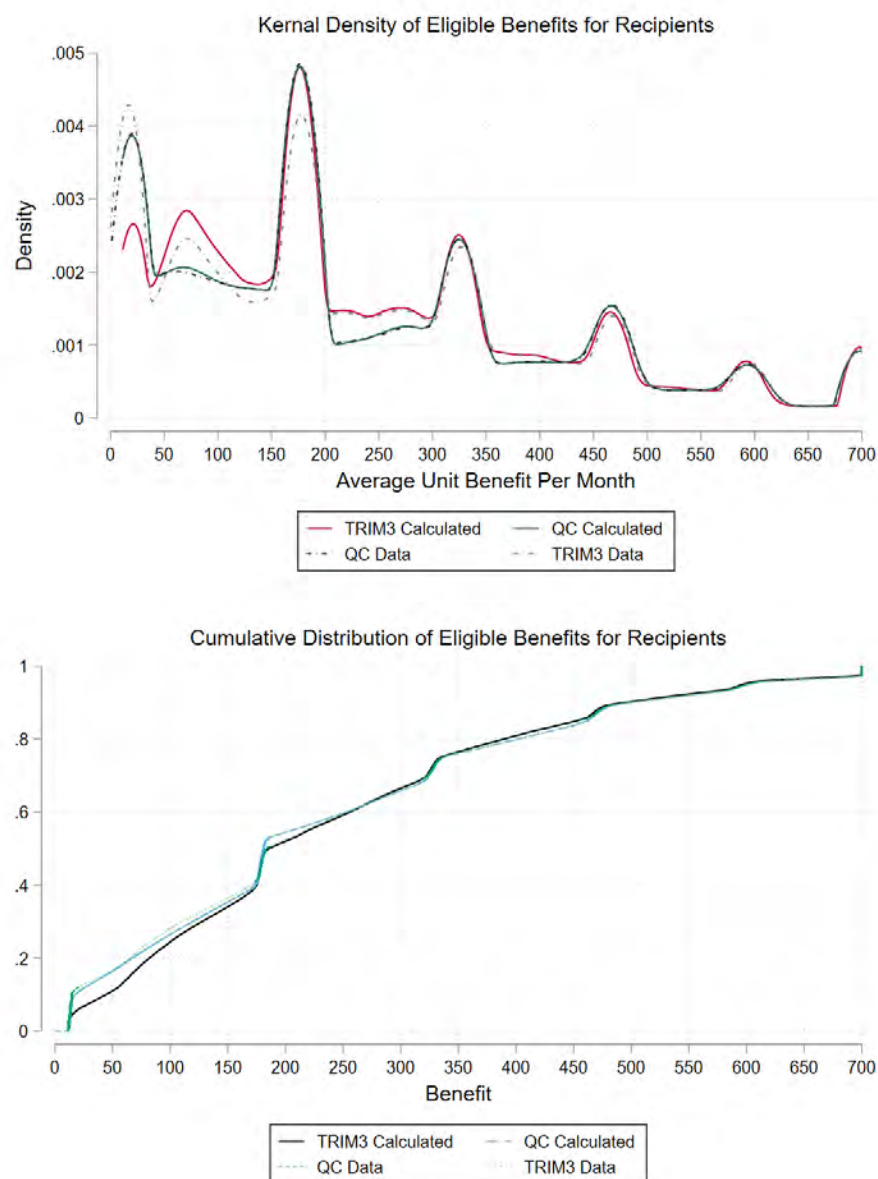
The figure plots the time series of SNAP total number of participants estimated using TRIM3 and CPS ASEC data. Official counts published by the Food and Nutrition Service, USDA is also plotted as a benchmark of the true values. It is apparent that TRIM3 counts are closer to the administrative counts in almost every year than using CPS ASEC directly.

Table B.1: Characteristics of SNAP Participating Households: TRIM3 versus QC (Admin Data)

	(1) TRIM Recipient	(2) QC
Monthly Benefits	231.5 (188.7)	241.7 (185.3)
Gross Income	959.5 (2691.7)	626.7 (448.7)
Net Income	375.6 (475.4)	328.1 (351.8)
Unit Asset	151.8 (4927.4)	133.6 (697.4)
Unit Size	2.463 (1.548)	2.335 (1.536)
Unit with Elder Members	0.190 (0.393)	0.183 (0.386)
Unit with Disabled Members	0.248 (0.432)	0.241 (0.428)
Unit with Kids	0.576 (0.494)	0.547 (0.498)
Age of Head	42.15 (17.53)	41.04 (18.56)
Observations	968606	573856

Mean coefficients; sd in parentheses. Observations weighted by household sampling weights. All monetary values are adjusted to the December 2015 consumer price index.

Figure B.2: Distribution of Received Benefits Calculated by TRIM3 and QC Income



The eligible benefits calculated by TRIM3 income data and QC income data have very similar distributions. This means that the differences in income do not cause differences in SNAP recipients in terms of benefit levels.

B.3 Imputation of TRIM3 Data

- **Household Gross Income (pre 2005):** follow TRIM3 documentation <https://boreas.urban.org/documentation/input/Concepts%20and%20Procedures/UsingIncomeVariables.php>

1. Sum up all monthly income sources of the each household member. Income sources include asset income, earnings, unearned income, unemployment compensation, child support, workers' compensation, alimony, and public assistance (each item mutually exclusive).
2. Divide by number of people in the household
3. Sum up eligible household only — ineligible means cash-out individuals (SSI recipients in California) or non-citizens

- **Household Net Income (pre 2005):** use eligible benefit in data, apply the benefits calculator reversely:

$$\text{Net Income} = (\text{Maximum allotment} - \text{eligible benefit}) / 0.3$$

Maximum allotment varies by household size. Household size includes eligible household only.

- **Household Countable Asset:** following TRIM3 documentation, assume an asset return rate of 0.06

1. Sum up the monthly asset income of all members of the household
2. Sum over all months in the year
3. Divide by 0.06

- **Individual Disability Measure:** follow SNAP QC Documentation FY 2015

1. If the individual is nonelderly (< 60 years old) and is an SSI recipient

2. If the individual is nonelderly and is working < 30 hrs a week and is receiving social security/worker's compensation/veteran's compensation or is coded as not working due to illness or disability
3. If the household has medical expense deductions (modeled by TRIM3) and there is no elderly member in the unit, follow the steps until locating at least one member:
 - (a) coded not working due to illness or disability
 - (b) work < 30 hours per week and has social security, veteran's benefits, or worker compensation
 - (c) has social security, veteran's benefits, or worker compensation
 - (d) Child work < 30 hrs/week
 - (e) Adult work < 30 hrs/week
 - (f) All individuals

Figure B.3: Imputation of Income and Asset in Unavailable Years and Comparison with Available Years

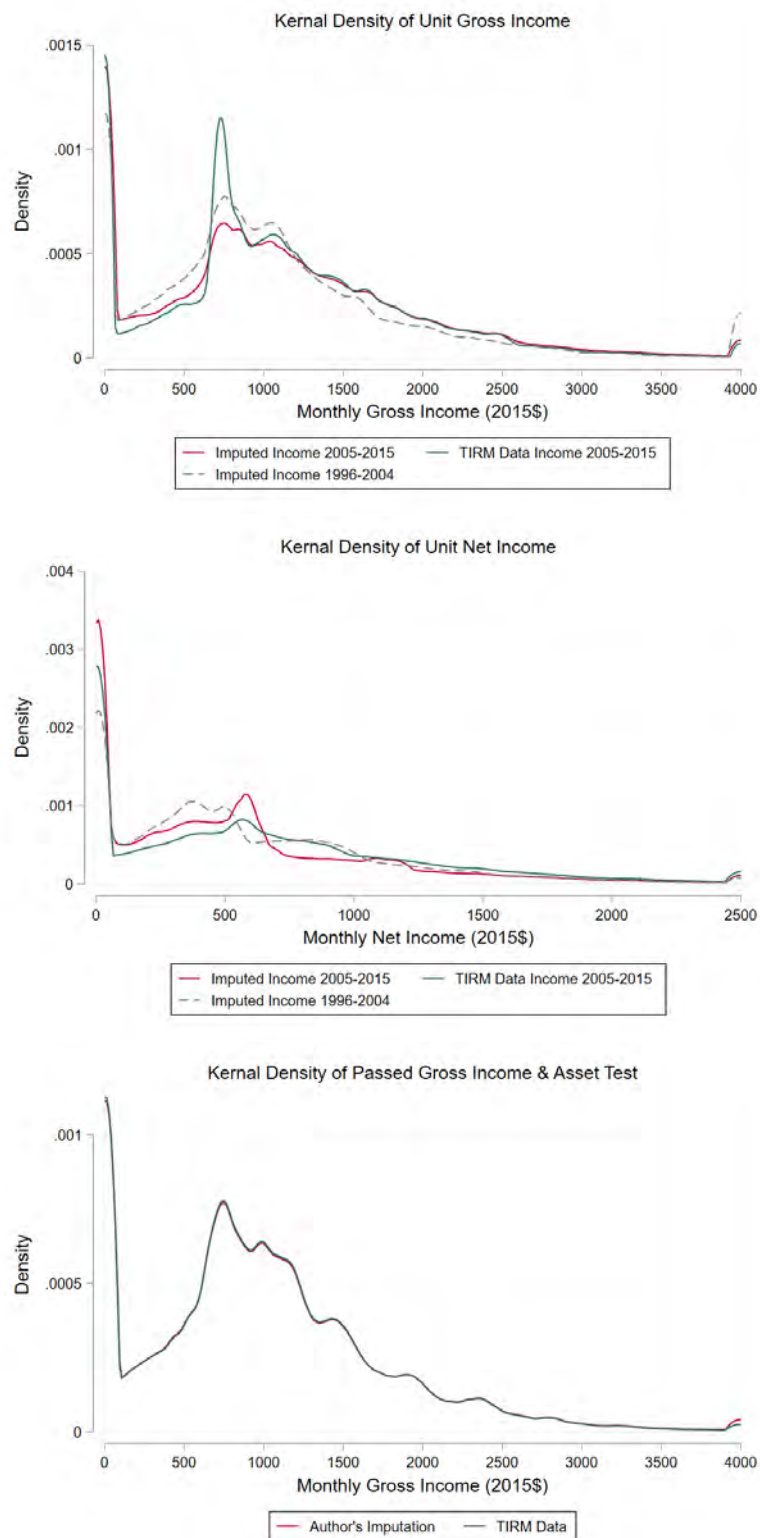
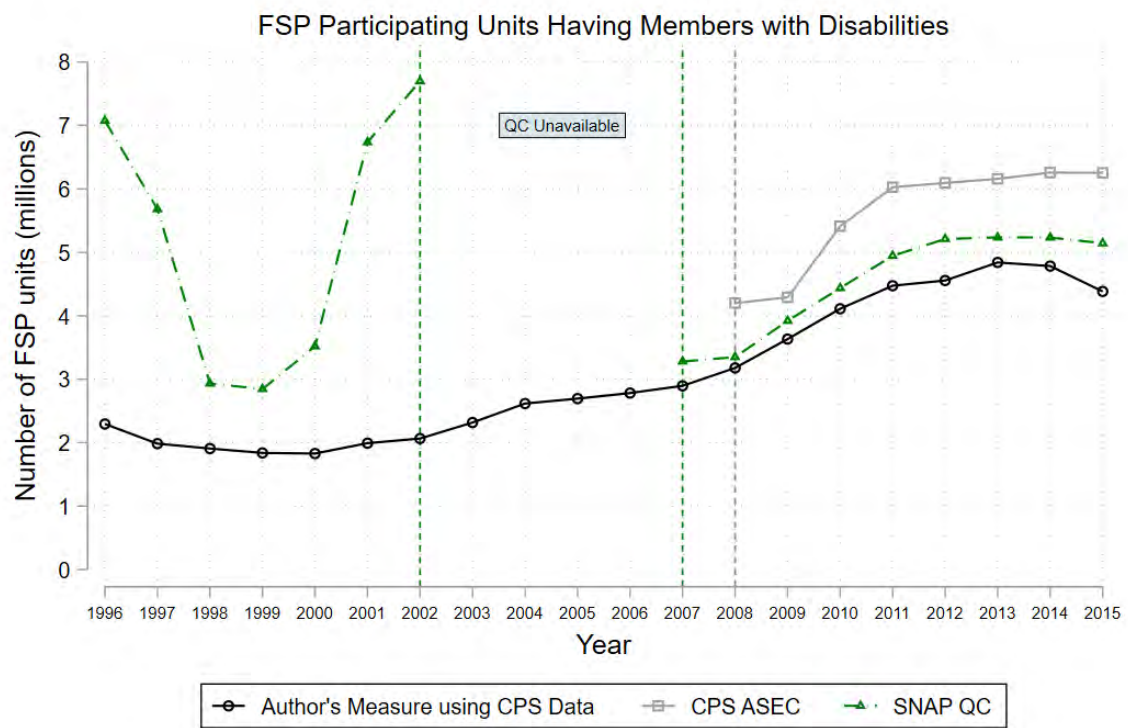
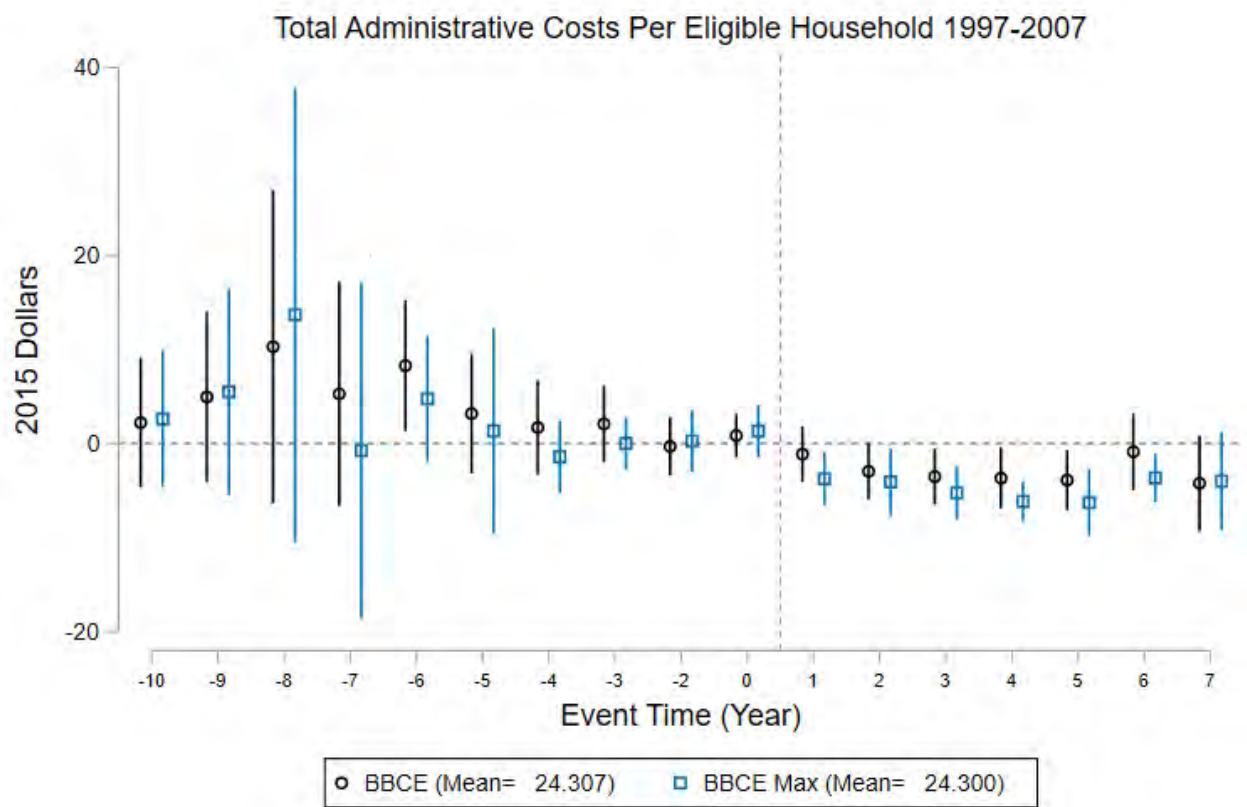


Figure B.4: Disability Measures



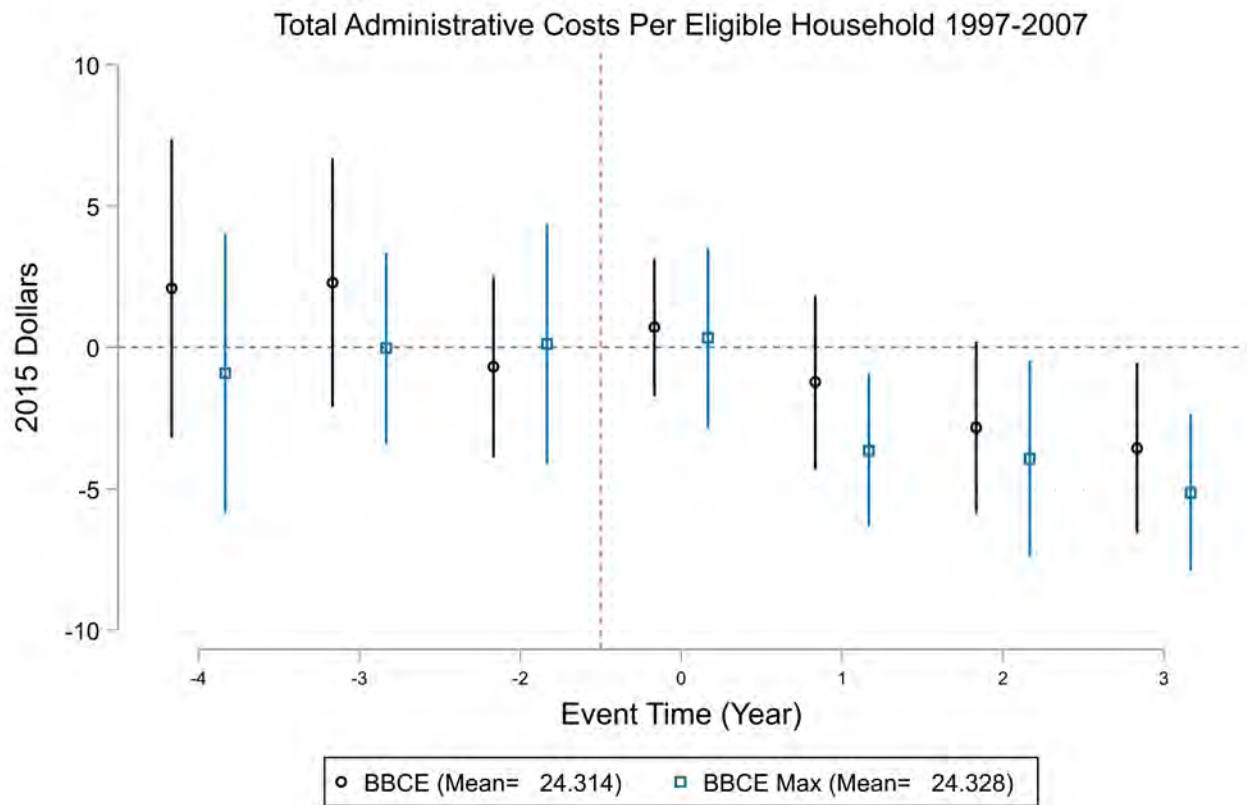
C Result Appendix

Figure C.1: Total SNAP Administrative Costs: All Event Time Estimates



Sun & Abraham (2021) Event Study Estimates. Weighted by the size of always eligible (for any month) households. Clustered standard errors at state level.

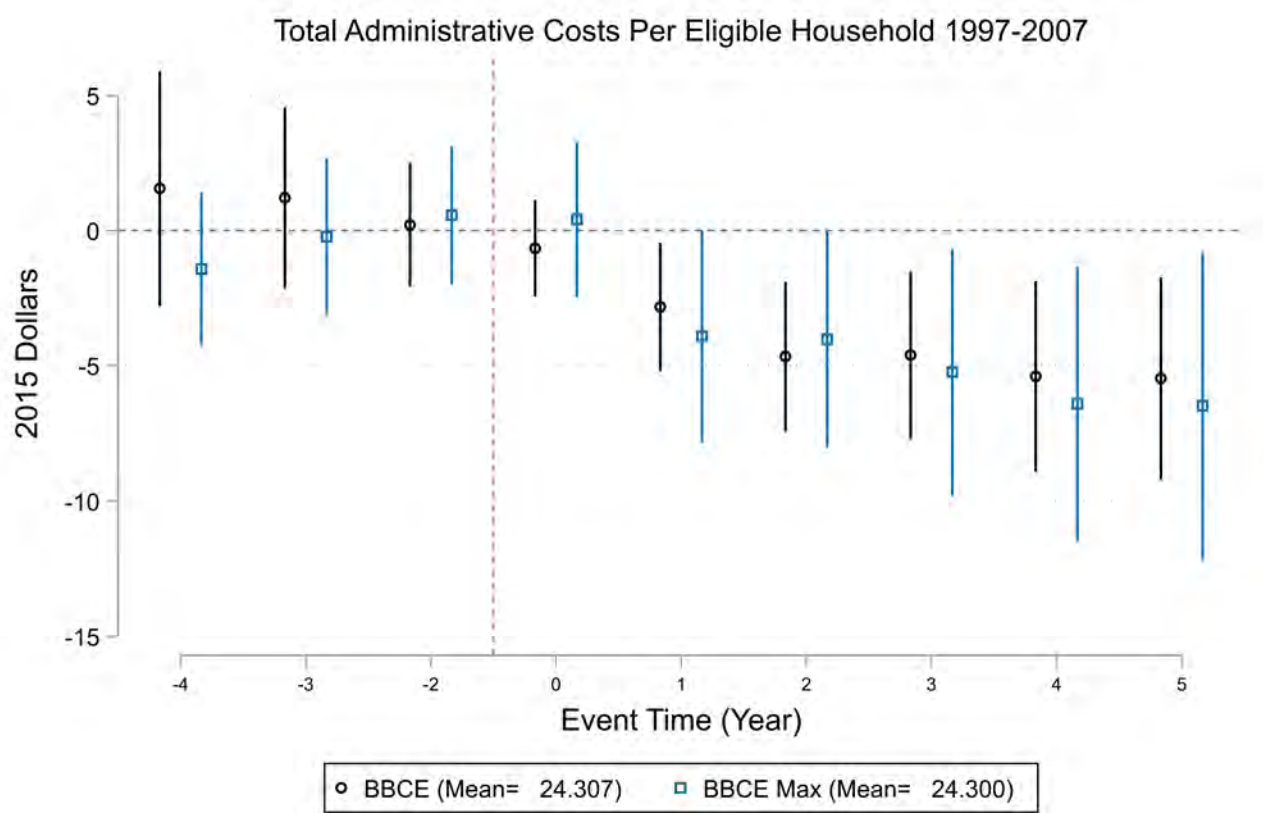
Figure C.2: Total SNAP Administrative Costs: Balanced Panel



Sun & Abraham (2021) Event Study Estimates. Weighted by the size of always eligible (for any month) households. Clustered standard errors at state level.

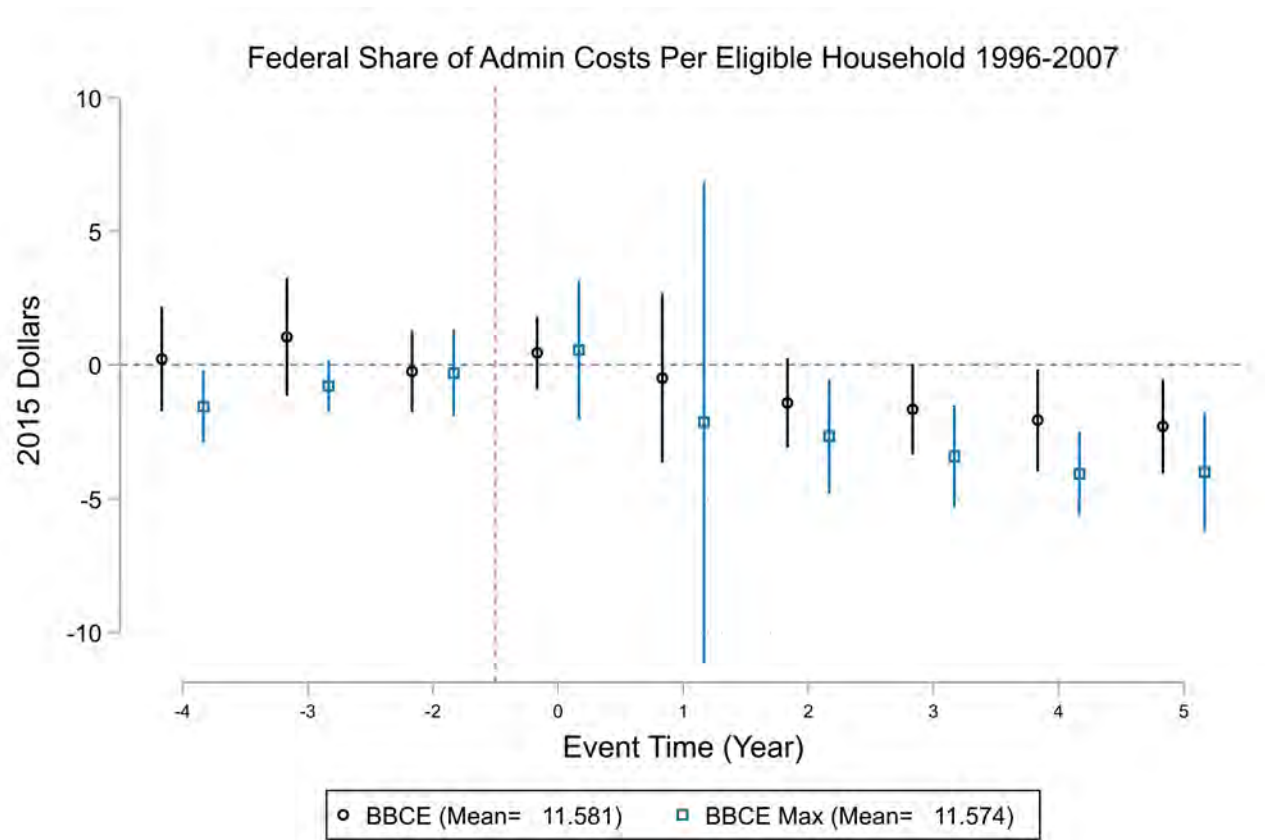
Eleven out of thirteen treated states (about 87% of the sample) are included in the balanced panel of BBCE. Six out of seven treated states (about 93% if the sample) are included in the balanced panel of BBCE Max.

Figure C.3: Total SNAP Administrative Costs: Unconditional Estimates



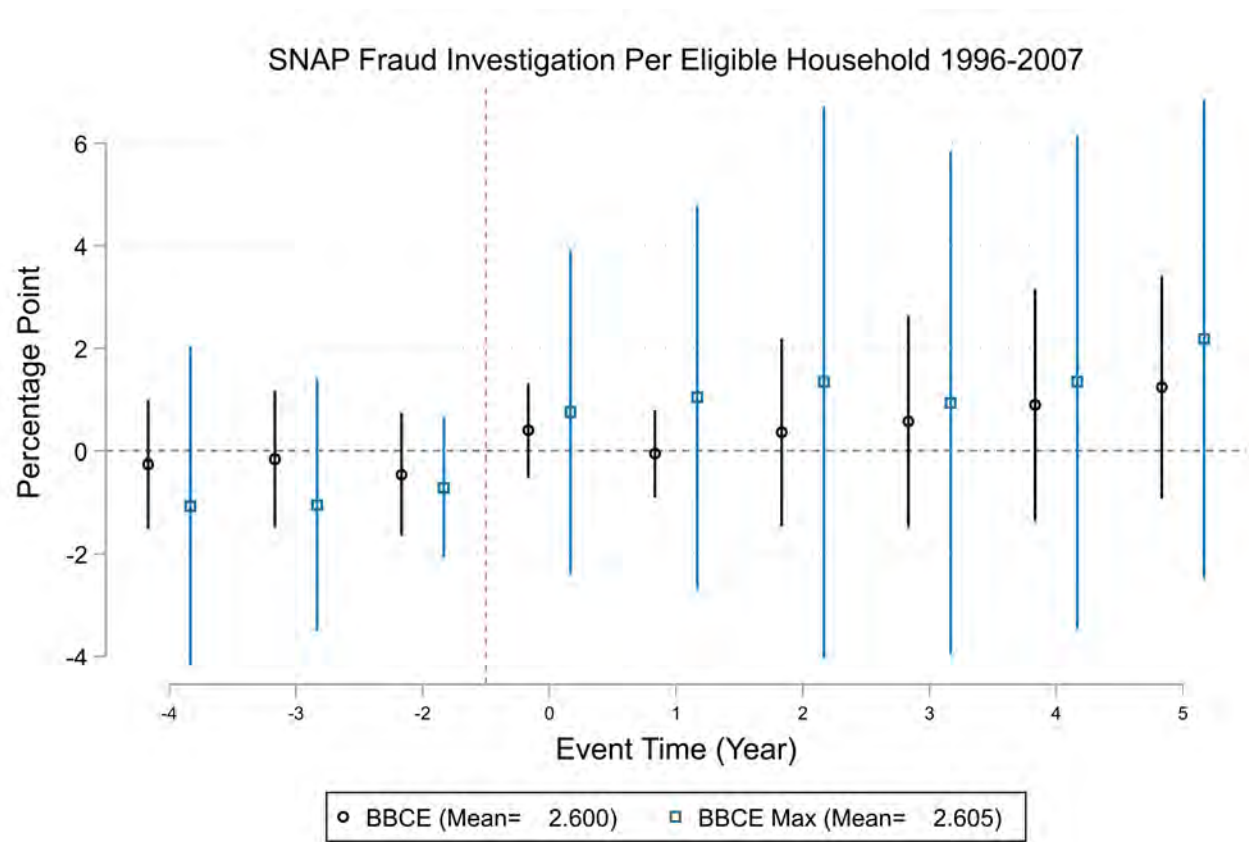
Sun & Abraham (2021) Event Study Estimates. Weighted by the size of always eligible (for any month) households. Clustered standard errors at state level.

Figure C.4: Federal Share of SNAP Administrative Costs



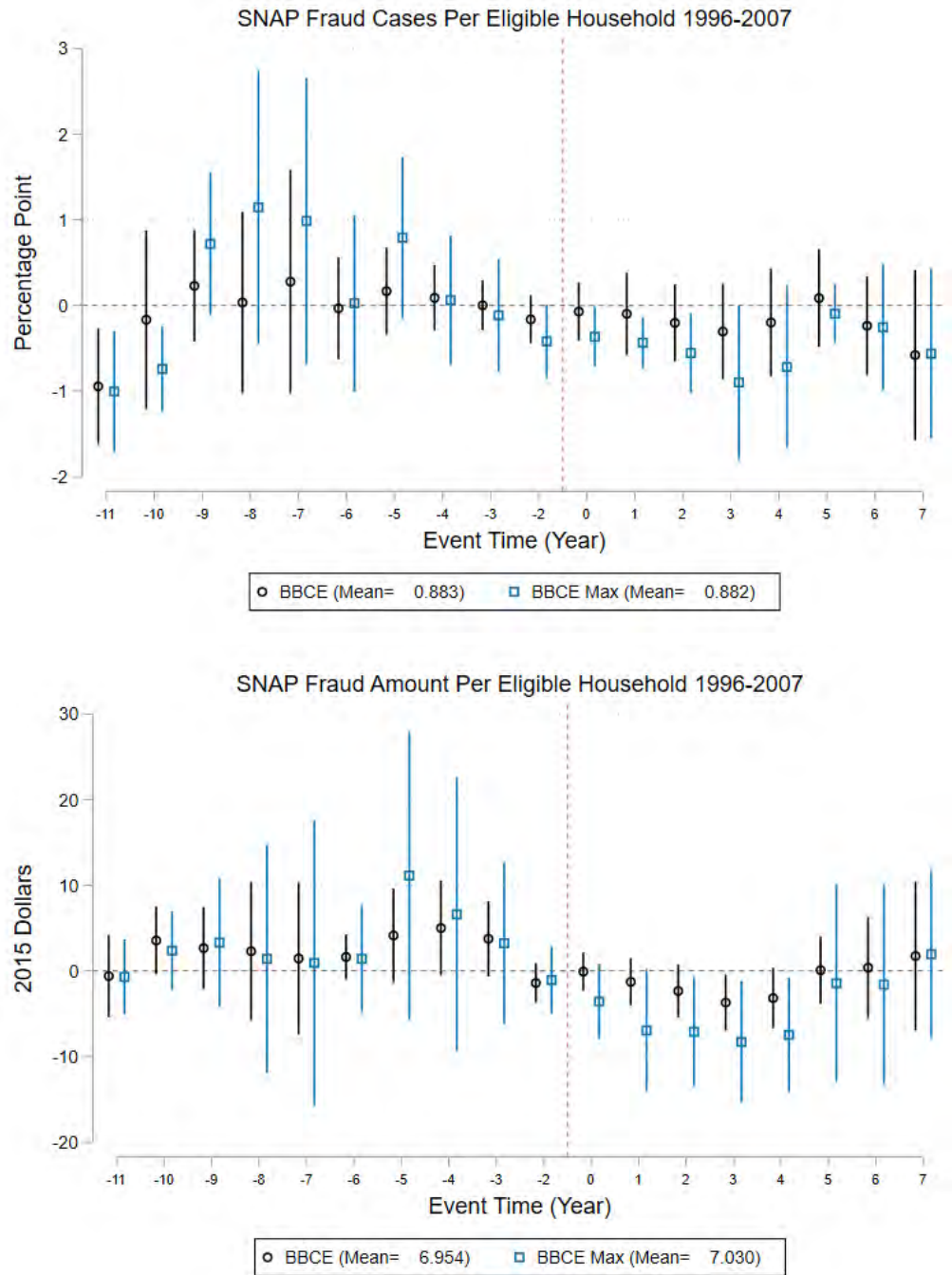
Sun & Abraham (2021) Event Study Estimates. Weighted by the size of always eligible (for any month) households. Clustered standard errors at state level.

Figure C.5: SNAP Total Fraud Investigation



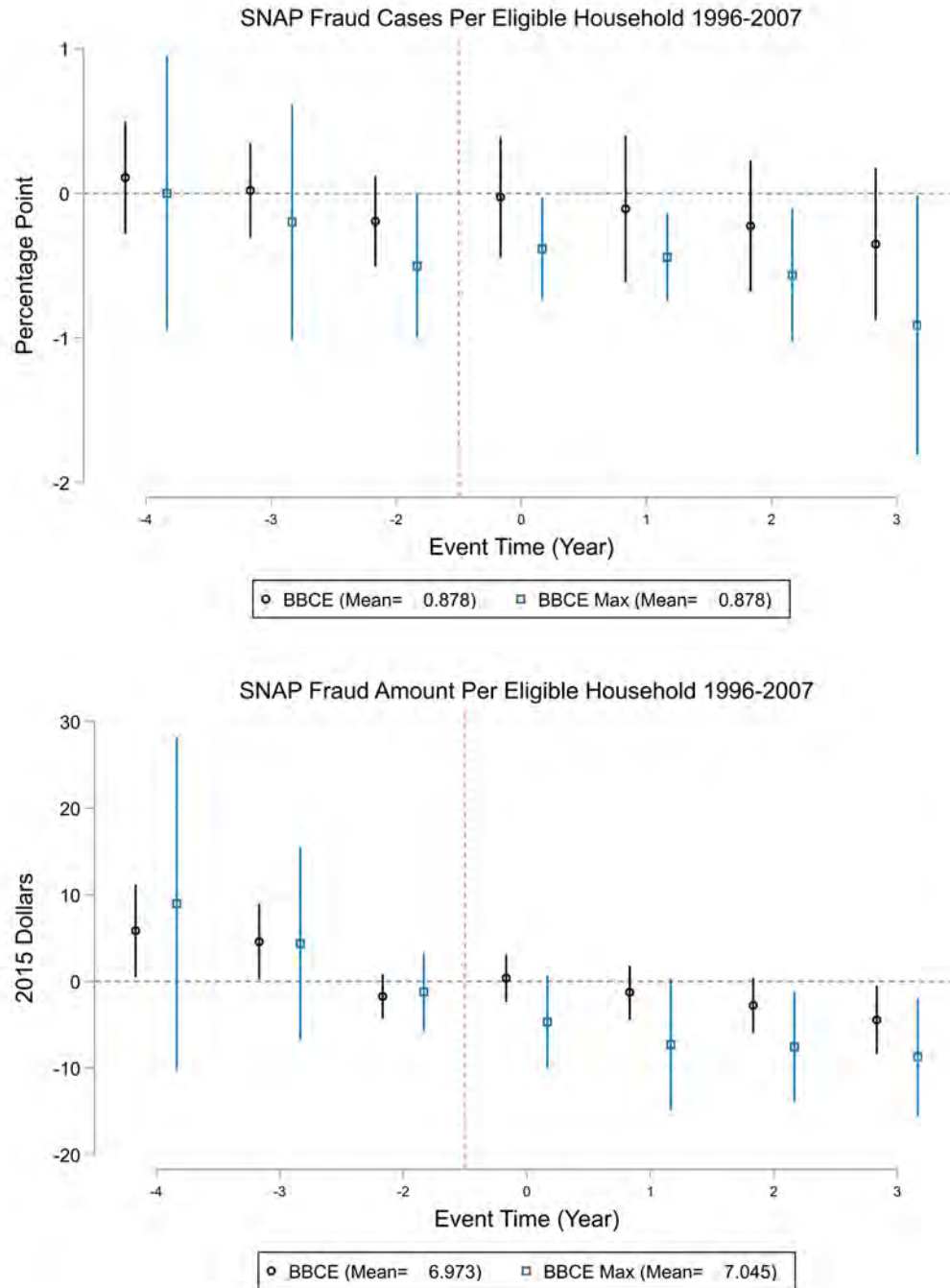
Sun & Abraham (2021) Event Study Estimates. Weighted by the size of always eligible (for any month) households. Clustered standard errors at state level.

Figure C.6: SNAP Fraud Cases and Benefit Amount: All Event Estimates



Sun & Abraham (2021) Event Study Estimates. Weighted by the size of always eligible (for any month) households. Clustered standard errors at state level.

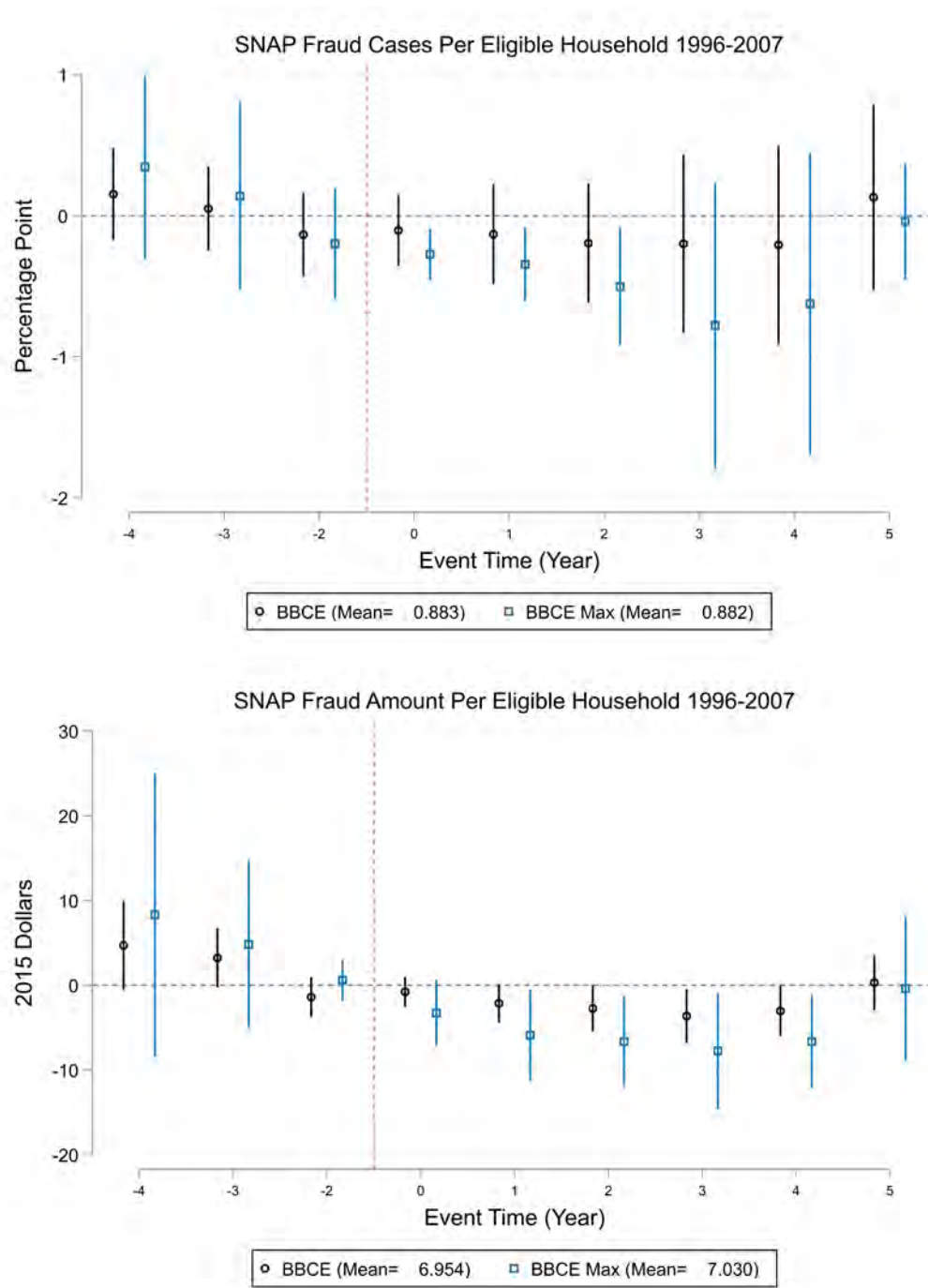
Figure C.7: SNAP Fraud Cases and Benefit Amount: Balanced Panel



Sun & Abraham (2021) Event Study Estimates. Weighted by the size of always eligible (for any month) households. Clustered standard errors at state level.

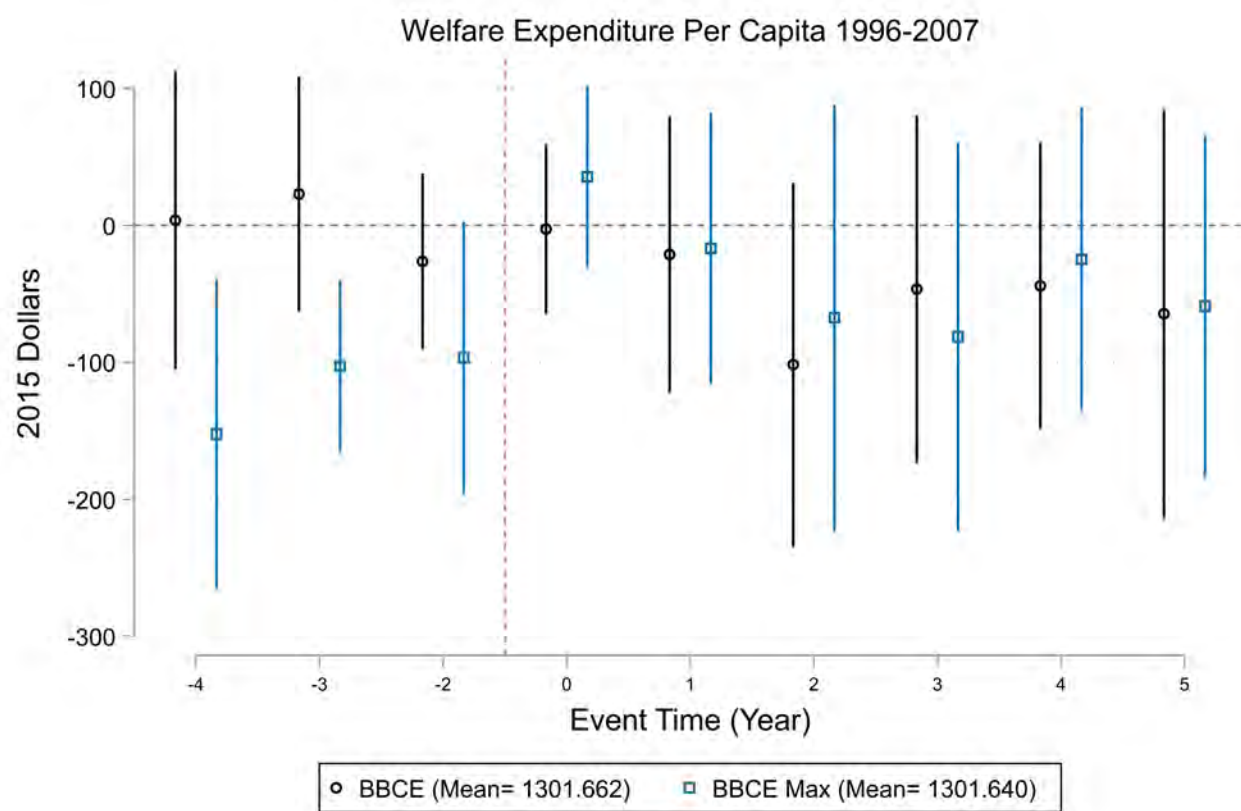
Eleven out of thirteen treated states (about 87% of the sample) are included in the balanced panel of BBCE. Six out of seven treated states (about 93% if the sample) are included in the balanced panel of BBCE Max.

Figure C.8: SNAP Fraud Cases and Benefit Amount: Unconditional Estimates



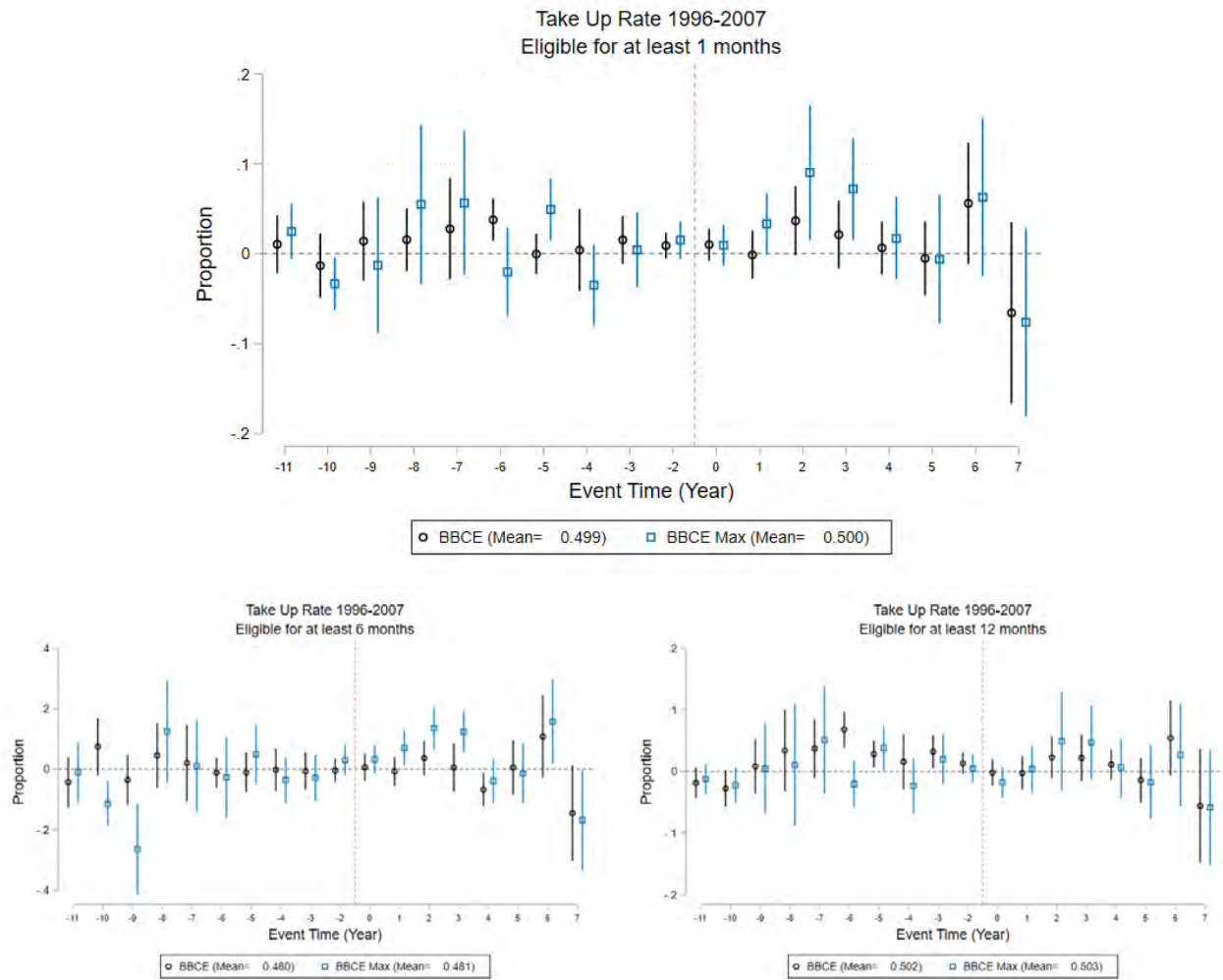
Sun & Abraham (2021) Event Study Estimates. Weighted by the size of always eligible (for any month) households. Clustered standard errors at state level.

Figure C.9: State Welfare Expenditures



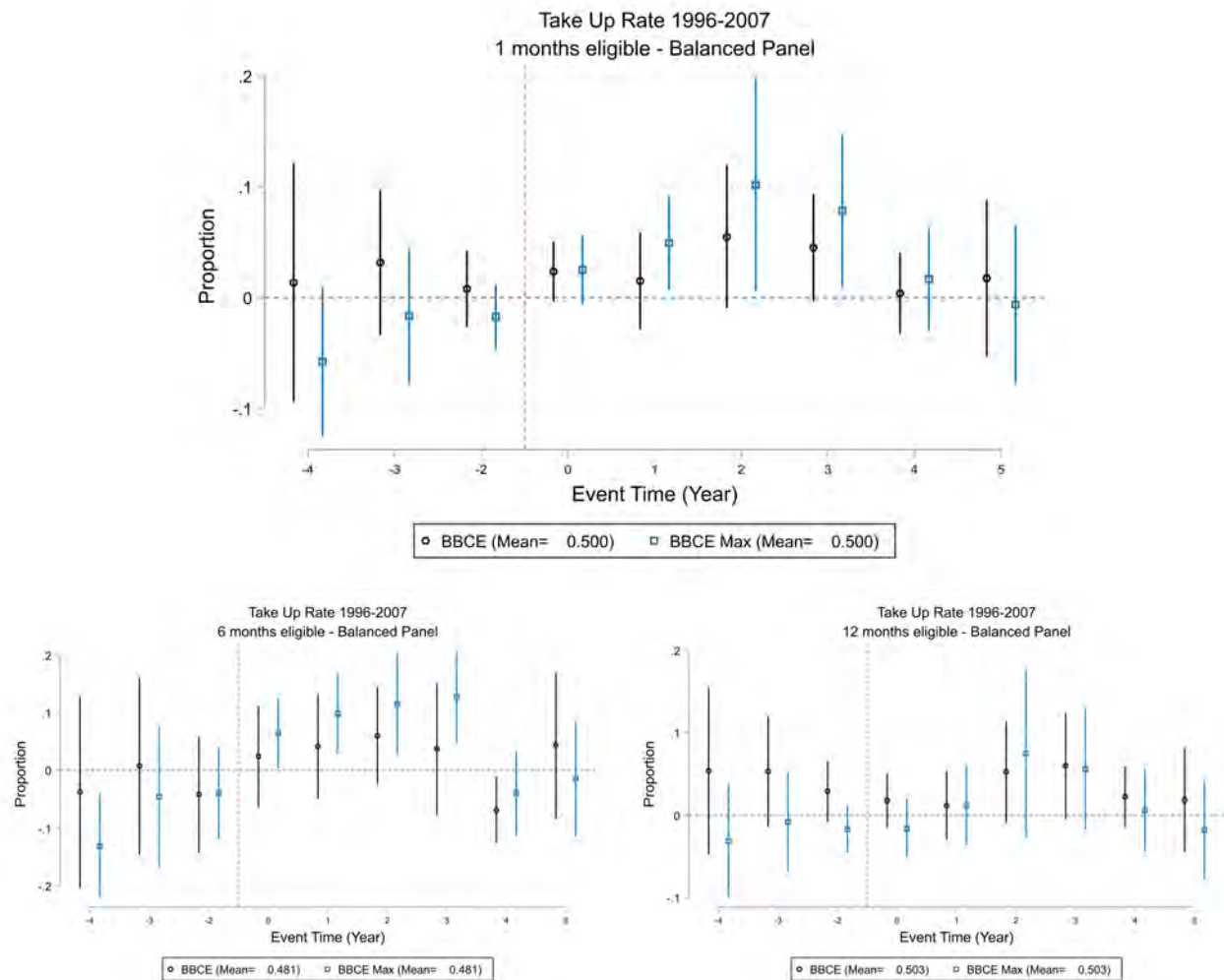
Sun & Abraham (2021) Event Study Estimates. Weighted by the size of always eligible (for any month) households. Clustered standard errors at state level.

Figure C.10: Take-Up Among Always-Eligible: All Event Time Estimates



Sun & Abraham (2021) Event Study Estimates. Weighted by household sampling weights. Clustered standard errors at state level. All covariates as well as state and year fixed effects included.

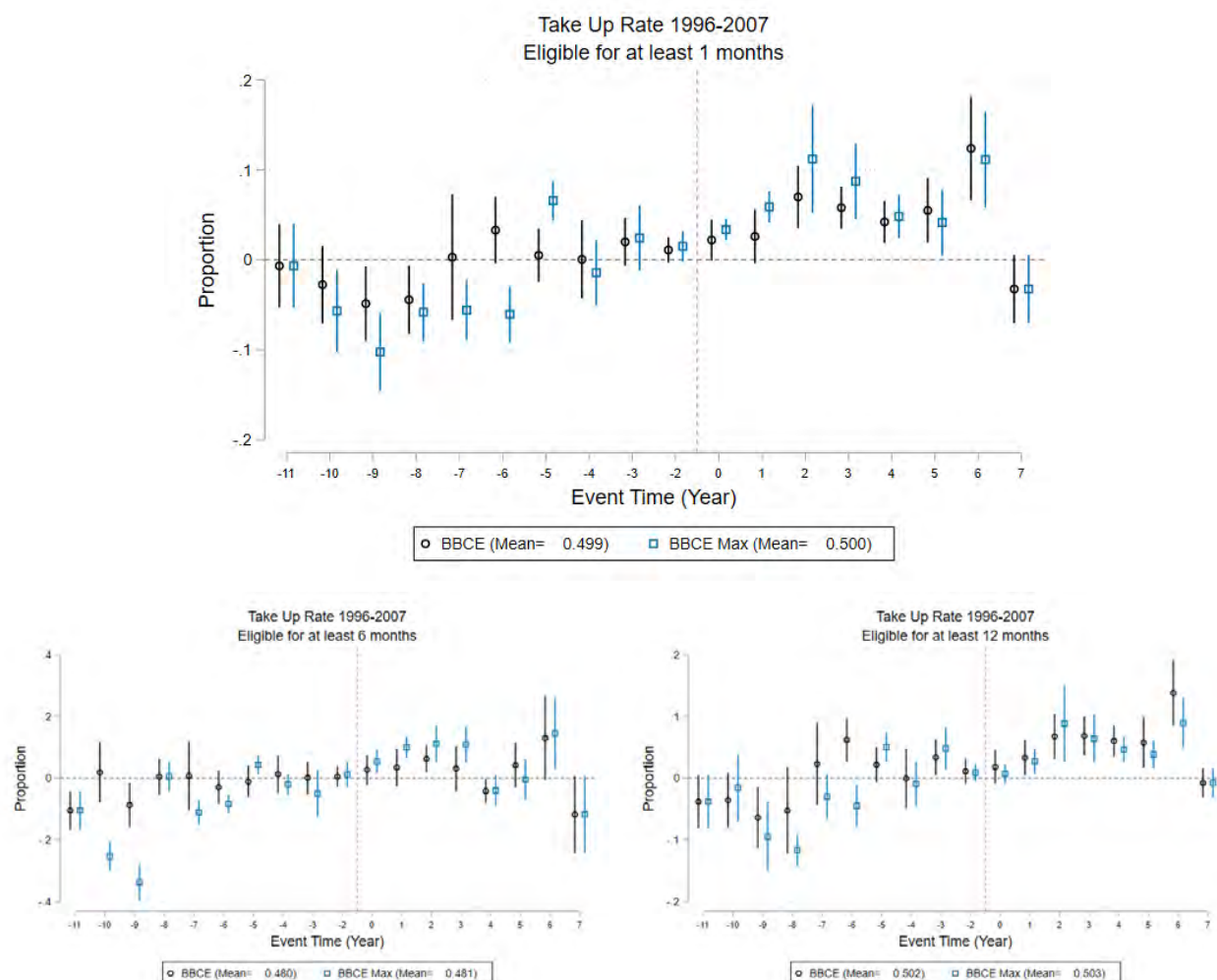
Figure C.11: Take-Up Among Always Eligible: Balanced Panel



Sun & Abraham (2021) Event Study Estimates. Weighted by household sampling weights. Clustered standard errors at the state level. All covariates as well as state and year fixed effects included.

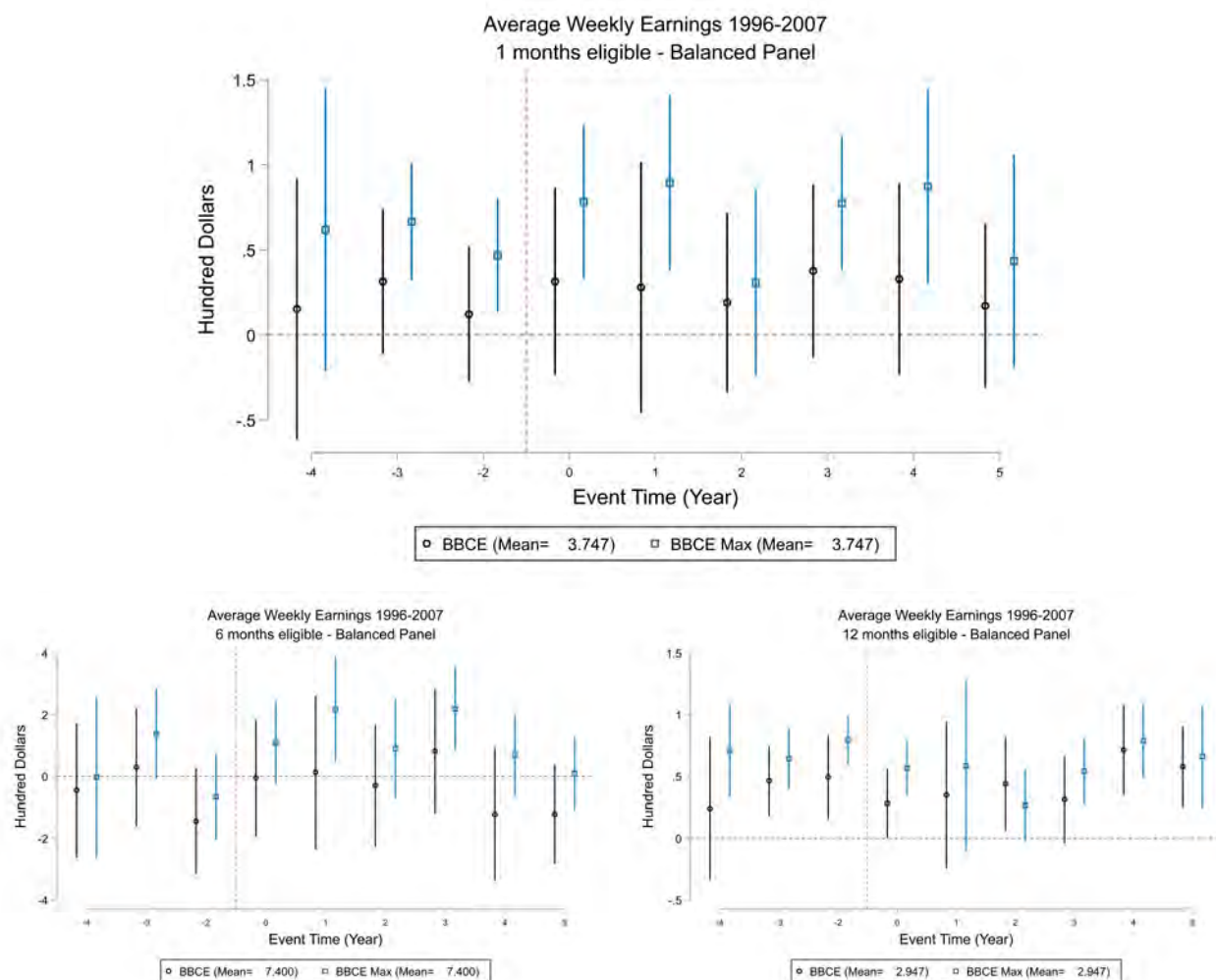
Eight out of thirteen treated states (about 85% of the sample) are included in the balanced panel of BBCE. Five out of seven treated states (about 88% of the sample) are included in the balanced panel of BBCE Max.

Figure C.12: Take-Up Among Always Eligible: Unconditional Estimates



Sun & Abraham (2021) Event Study Estimates. Weighted by household sampling weights. Clustered standard errors at the state level. No covariates included except for the state and year fixed effects.

Figure C.13: Average Weekly Earnings Among Always Eligible: Balanced Panel



Sun & Abraham (2021) Event Study Estimates. Weighted by household sampling weights. Clustered standard errors at the state level. All covariates as well as state and year fixed effects included.

Eight out of thirteen treated states (about 85% of the sample) are included in the balanced panel of BBCE. Five out of seven treated states (about 88% of the sample) are included in the balanced panel of BBCE Max.