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

Jou Chun Lin *

November 30, 2023

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. Leveraging 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.

*Department of Economics, University of California, Davis. joulin@ucdavis.edu. Acknowledgement: I thank Marianne Bitler, Monica Singhal, Jenna Stearns, Marianne Page, participants in the Social Mobility Tea Time and Applied Micro Student Talk at the Department of Economics, University of California, Davis. I also thank Eunju Lee, Seojung Oh, and Chang Jae Lee for helpful comments along the development of this paper.

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 states[1]. 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 data[3]. Building on the SNAP eligibility provided by TRIM3, I identify the already-eligible households by predicting the likelihood of a household satisfying the traditional

[1]The 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.

[2]Information 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.

[3]SNAP 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; that is, 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 Broad-Based Categorical Eligibility (BBCE)

The Supplemental Nutrition Assistance Program (SNAP), or the Food Stamp Program, is the second largest in-kind transfer program in the United States (following Medicaid). The eligibility criteria for SNAP, particularly the income and asset limits, have been established in federal law since 1980. Despite the scale of the program, the same set of income and asset limits have never received any evaluation on their efficacy over the past 50 years. Starting in 2000, the Broad-Based Categorical Eligibility (BBCE) serves as a rare opportunity for researchers to examine federal limits by leveraging the states' changes in rules. In this section, I first introduce the SNAP eligibility rules before and after BBCE, then discuss the outcomes likely affected by BBCE and their implications on program design.

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 is 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, shelter/housing, 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 (referred to as "assets"), which includes cash and bank accounts[4], 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.

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,

[4]The federal law also sets a vehicle limit at $4,650, but almost all states set a higher vehicle limit nowadays because the federal limit is considered outdated and too restrictive.

categorical eligibility should be given to households with all members eligible for cash assistance from other means-tested programs[5]. The purpose is to reduce the burden on 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.

One side note is that these eligibility requirements apply to U.S. citizens. Non-citizens can be eligible by satisfying additional criteria regarding their immigration circumstances. Due to the complication of these criteria and the fact that most of them are unobserved from my data, this paper focuses on households with at least one citizen member.

2.2 Changes to eligibility by BBCE

The origin of BBCE traces back to The Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) of 1996, also known as the Welfare Reform. A significant component of the reform was replacing the Aid to Families with Dependent Children (AFDC) with Temporary Assistance for Needy Families (TANF). This change affected the food stamp categorically eligible households for two reasons: 1) AFDC was an entitlement program that any qualified families are guaranteed to receive benefits, while TANF is a block grant, which is a fixed amount of federal funds to states and does not cover as many households as AFDC; 2) AFDC is primarily cash benefits, but TANF benefits are of states' discretion and can be noncash. Noncash TANF benefits were not conferred to categorical eligibility for SNAP in the federal law at the time. However, in 1996, there was no modification in the Food Stamp law except for simply substituting the term AFDC with TANF. As a result, many households were no longer automatically eligible for food stamps, so they had to go through the income and asset tests, which also created burdens for the agencies.

[5] These include 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

It was not until 2000 that the USDA amended the regulation[6] on how states can choose to extend categorical eligibility to those who are qualified for noncash TANF/MOE benefits. With such "broad-based categorical eligibility"[7] 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 as categorically eligible. In practice, states can deem a household with one member qualified to receive a brochure printed by a sufficient portion of TANF/MOE funds to be automatically eligible for SNAP. This implies that by designing the eligibility rules for TANF/MOE noncash benefits, states also define whom they would like to extend SNAP eligibility. The eligibility requirements for noncash benefits are then generalized as BBCE policies for SNAP.

BBCE policies are much less restrictive than the federal income and asset limits. Most states set higher gross income limits than the regular 130% of the FPL, and some exempt asset tests from BBCE qualification rules. On the other hand, while some states apply BBCE to all households, others only apply BBCE to specific groups, such as households with dependents (see Figure 2). If the state applies the more generous income and asset limits to all households, it is essentially a reform to the federal income and asset limits. I group the states that adopted the most generous form of BBCE, namely setting a gross income limit higher than the federal gross income limit (130% FPL), while also eliminating the net income limit and asset test, and naming them as "BBCE Max". I expect BBCE Max to have larger impacts than generally adopting any BBCE policies.

2.3 Expected effects on state administration

The most salient effect of BBCE on state administration is streamlining the application process. By adopting BBCE Max, state agencies now only conduct a single (more generous) gross income test instead of three tests for a general applicant. This requirement reduction has significantly eased the burdens on caseworkers, especially by removing the costly asset test. During site visits to 5 states and 18 local SNAP offices by the U.S. Government Accountability Office,

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

[7] The 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.

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). Therefore, a simplified application process would likely reduce states' SNAP administration expenditures, which are largely generated by the certification processes. In the studies of Geller, Zic, Isaacs, and Braga (2019), BBCE was associated with a reduction in SNAP administrative costs by 7 percent during FY1999-FY2016. This paper will distinguish the BBCE Max from general BBCE and causally identify its effect on SNAP administrative costs.

Nevertheless, the three tests were implemented to screen and combat fraud, and simplifying them may widely expand the eligible population and increase fraud. The former is less of a concern. In a report based on 2014 observations, newly eligible participants accounted for only 8 percent of SNAP participants and 1.2 percent of all benefits issued (Cunnyngham, 2016). Analyzing changes in the eligible population due to BBCE, I find that it expanded by approximately 2%, suggesting that the expansionary nature of BBCE is much less than simplifying the application processes for households already eligible under the three-test system.

Regarding fraud, while a simpler process may facilitate information falsification, it also enhances detection capabilities. If fraud is identified before certification completion, benefits will not be issued, resulting in no loss in public funds. Furthermore, it remains unclear whether the incentives for fraud have increased significantly, given that benefits are still determined by the same formula, with decreases when net income rises. As a result, the potential increase in fraud cases remains ambiguous.

In sum, state administrative costs for SNAP, the number of eligibility fraud cases, and benefits issued by fraud are the outcomes of interest at the state level.

2.4 Expected effects on households

For those who were already eligible before BBCE implementation, the change of eligibility rules per se does not affect them. However, the streamlined application process may increase their incentive to apply for the benefits. If the state eliminates asset tests, households no longer need to provide their asset information, resulting in about half to one page less of the application forms to go through. Moreover, simplified eligibility requirements make it easier for households to comprehend and assess their eligibility. This argument is corroborated by Anders and Rafkin (2022), who found that each ten percentage points of FPL higher gross income limits lead to roughly a 1 percent increase in take-up rates, and the information channel primarily drives the effects.

In general, BBCE is expected to increase the take-up rate by reducing administrative burdens and increasing information for households, and BBCE Max should have larger effects than general BBCE.

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 timing of adoption for 41 states and DC through 2015, and I cross-refer it with Laird and Trippe (2014). Figure 1 shows that 28 states adopted BBCE between 2009 and 2012 during the Great Recession. However, studying the effects of BBCE during the Great Recession could be challenging, as the economy expanded the eligible population, and the American Recovery and Reinvestment Act of 2009 raised SNAP benefits together with many other non-SNAP stimulus measures. Therefore, I focus on observation periods from 1996 to 2007, during which 13 states adopted BBCE, and 6 adopted BBCE Max. South Carolina was the first state to adopt BBCE in October 2000, followed by Oregon, Maryland, Delaware, Michigan, and North Dakota. From the geographical distribution of first adoption timing in Figure 3, there is no apparent correlation within regions or the politically "blue" or "red" states such as the East/West Coasts or the South. Another merit of focusing on this period is that the treatment is monotone within states, meaning these states never repeal or modify their BBCE policies once adopted. In contrast, many states made their BBCE policies more restrictive after the Great Recession.

As mentioned in the previous section, 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 eliminating the net income and asset test, naming them as "BBCE Max". It would be ideal to analyze the income and asset tests separately, but unfortunately, these policies were almost always implemented together. Figure 2 shows that only one state solely raised gross income limits, and only one state solely eliminated asset tests. Nevertheless, BBCE Max represents the most salient change in program rules, and grouping them also ensures the homogeneity of treatment.

3.1 Examining the exogeneity of BBCE adoption

To establish the quasi-random nature of states' BBCE adoption, I formally test if states adopted BBCE for particular reasons. For example, if states adopted BBCE because they suffered from too many administrative errors in eligibility and benefit determination, the high error rates could correlate with some inherent characteristics of the state government, such as low efficiency, which also affects my outcomes of interest. In a working paper (Lin, 2022), I tested five plausible reasons for state variations in SNAP policies: voters' preferences for welfare programs, voters' negative attitudes toward Black Americans, state economic conditions, states' fiscal reliance upon federal grants[8], and states' SNAP administrative costs and error rates[9]. I found none of these factors significantly predicted states' BBCE adoption during 1996 to 2015, only the contemporaneous unemployment rate. In this paper, I focus on the states that adopted BBCE between 2000 and 2007 and conduct three analyses as described below. Note that for analyses on BBCE Max, I dropped the states that adopted BBCE but not BBCE Max.

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:

$$adopt_s = \alpha + \mathbf{X_s}\gamma + u_s \tag{1}$$

$adopt_s$ is an indicator of whether the state adopted BBCE before 2008. X_s includes the aforementioned five main factors, some additional state demographics, the SNAP take-up rate, and the share of the SNAP-eligible population averaged between 1996 and 1999. 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

[8] Measured by share of state expenditures covered by their own sources of revenue. If the states cannot cover their expenditures, they may have more incentive to expand federally funded programs.

[9] Administrative costs majorly come from certification, benefit issuance, and fraud inspection. Error rates mean the share of recipients for whom the state falsely determined their eligibility or amount of benefits. The federal government periodically evaluates error rates through quality control checks.

the state-month level of observations:

$$bbce_{sym} = \alpha + \mathbf{X_{s,y-1,m}}\gamma + \theta_s + \sigma_y + u_{sym} \tag{2}$$

Here, $bbce_{sym}$ indicates whether the state s has BBCE in place in month m of year y. The predictors are the same variables as equation 1, but are time-varying and observed in the same month in the previous year or the previous year if observed annually. 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 some unobserved time-varying factors are still not controlled for by these factors. The likely scenario is that the states are simultaneously implementing other policies affecting state administration and household 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 aids such as online applications and waiving face-to-face interviews, vehicle limits, outreach spending, and electronic benefit issuance[10], are also controlled for in the main analyses.

[10] The federal law mandated a change of benefit issuance from paper vouchers to electronic cards by 2002. The transition was completed in 2004.

4 Data

In this section, I present the data sources pertaining to the study's outcomes and covariates. State-level observations were obtained from administrative publications. Household-level data were derived from the Transfer Income Model, Version 3 (TRIM3) sample, which simulates public program eligibility using the Current Population Survey — The Annual Social and Economic Supplement (CPS-ASEC) observations. Based on the TRIM3 sample, I construct a prediction model to identify households likely to be already eligible without BBCE and those newly eligible only through BBCE.

4.1 State-Level Observations

One of the primary outcomes of interest is the administrative costs incurred by states in administering SNAP. As per federal law, the federal government reimburses the state agencies at a rate of 50%[11]. State agencies are required to submit the standard Financial Status Report (or Form SF-269[12]) to the federal government quarterly, along with a final report for the fiscal year. Information from Form SF-269, summarized and published by the U.S. Department of Agriculture (USDA) in the State Activity Report series, reveals that over half of the total administration costs are attributed to certification-related activities[13], namely the collection and verification of income and asset information. The remainder is allocated among various activities such as automatic data processing operations, benefit issuance (paper vouchers and electronic cards), and fraud control, with each component constituting no more than 7% of total costs. I use the total administrative costs before distinguishing the federal and the state shares as the primary outcome. A minor consideration is that total administrative cost reporting commenced in 1997, with only the federal share reported before that. I conducted a robustness check using the federal share of costs from 1996 to 2007, and the results are consistent.

[11] Some special items are reimbursed at more than 50%, e.g., 100% for employment and training programs, but these account for relatively small portions of total administrative costs.

[12] After 2012, Form SF-269 is replaced by Form SF-425

[13] Only the federal share of administrative costs are reported by activities. I calculated the shares of costs of each activity for the federally paid administrative costs and assumed that they were roughly the same for the state share of administrative costs.

The second outcome of interest is the fraud cases, specifically eligibility fraud. State agencies can initiate fraud investigations if there is a suspicion of information falsification. For example, if the caseworker suspects that the applicant lied about their household composition, staff or an investigator can visit the applicant's residence for an investigation. Each investigation and the result are reported to the federal government as one of the states' reporting responsibilities and for reimbursement of administrative costs. The State Activity Report Series also publishes the total number of investigations and confirmed fraud cases. In the reports, the benefits issued to fraud cases are also available. The fraud benefits are realized only upon the fraud cases that complete the certification; therefore, it is more of a measurement of the loss of public funds than the frequency of fraud incidents. I analyze both the number of confirmed fraud cases and fraud benefits amounts.

For state adoptions of BBCE and other SNAP policies, I use the SNAP Policy Database built by the Economic Research Service (ERS), USDA, and cross-refer them with Laird and Trippe (2014), which is a USDA-commissioned report on state categorical eligibility policies. For state-level covariates, I obtained the seasonally adjusted unemployment rates from the U.S. Bureau of Labor Statistics[14], and minimum wage rates from the U.S. Department of Labor.

4.2 Household-Level Observations: Transfer Income Model, Version 3 (TRIM3)

The advantage of using samples from TRIM3 is manifold. TRIM3 is a microsimulation model the Urban Institute maintains 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 SNAP, 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, TRIM3 performs well in correcting the under-reporting issue with CPS-ASEC by matching

[14] I take the simple average over the twelve months in the calendar year.

external data sources, including administrative data. Figure B.1 compares the counts of the total number of SNAP participants between TRIM3, CPS-ASEC, and the administrative data published by USDA. TRIM3 fits the administrative counts much better than the raw CPS-ASEC and thus measures the take-up rate more accurately.

Although we cannot directly examine how well TRIM3 simulates the eligibility, we can infer its performance by comparing the participants captured by TRIM3 to the administrative data — the SNAP Quality Control Database[15]. Despite the fact that the administrative data collect precise eligibility and benefit-related information, other characteristics not directly required are somewhat non-randomly missing, for example, education and race/ethnicity. In Table B.1, I compare the sample means of some selected characteristics between TRIM3 and QC. Most characteristics differ at a very small magnitude except for gross income, which might raise concerns for TRIM3 capturing a more well-off population. Nevertheless, based on the benefit levels being so similar at the mean, the high gross income in TRIM3 may be a result of wider variation instead of an inconsistent population. This is confirmed by an exercise in which I calculate the eligible benefits using TRIM3 income and QC income, respectively[16]. Figure B.2 plots my calculated distributions of eligible benefits for SNAP recipients. TRIM3 renders an almost identical distribution of benefits with QC. The higher income at the mean for TRIM3 does not lead to more participants at the lower benefits end. This exercise reassures the quality of the TRIM3 data.

4.2.1 Sample - the always-eligible households

To distinguish those who are always eligible regardless of BBCE and those who are newly eligible only through BBCE, I construct a model to predict the likelihood of a household passing the three federal income and asset tests. Supposedly, households with income and assets below the corresponding thresholds are eligible without BBCE. However, BBCE might affect household

[15]In 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 as the SNAP Quality Control Data (QC) for public use. According to the 2016 Technical Documentation of the SNAP Quality Control Data, units determined as eligible and received benefits of at least $1 will be made into the SNAP Quality Control Data, which Mathematica then edits for public use.

[16]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 increases with household size. I input the income data of TRIM3 recipients and QC samples in the calculator and estimate the eligible benefits.

behaviors such that their observed income and assets differ from what they would have behaved without BBCE. For example, eliminating asset limits could encourage more savings, resulting in households having higher savings with BBCE than without it. To account for these potential behavioral shifts, I use the observations from the states and years in which BBCE was not adopted as the training sample to acquire fitted coefficients. The predictors include mostly fixed household characteristics and state characteristics:

$$pass^m_{ist} = \alpha + \mathbf{head_{ist}} + \mathbf{unit_{ist}} + \mathbf{economy_{st}} + \mathbf{policy_{st}} + \theta_s + \sigma_t + \epsilon_{ist} \tag{3}$$

$pass^m_{ist}$ is a binary indicator of whether household i in state s passes the income and asset tests for m months in year t, $m \in \{\geq 1, \leq 6, 12\}$. While CPS-ASEC collects annual-level observations, TRIM3 provides monthly levels of income. This is done by allocating the reported total number of weeks worked in the past year into each month and matching with the monthly employment published by the Bureau of Labor Statistics (BLS)[17]. I utilize this monthly information to distinguish households who are eligible for at least 1 month, at most 6 months, and 12 months. The first group is the most generalized eligibility definition. The 6 months group should represent those who are only temporarily eligible, and the 12 months group should represents those who are eligible in the longer term.

$\mathbf{head_{ist}}$ is a vector of household head characteristics, including age, age^2, female, race, education, employment status, marital status, and disabilities status. $\mathbf{unit_{ist}}$ 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 elderly 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 t.

[17] More 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`

$\mathbf{economy_{st}}$ is the BLS published state unemployment rate in year t, $t-1$, $t-2$, and $t-3$. $\mathbf{policy_{st}}$ include whether the state has adopted other food stamp policies that change eligibility rules in year t. Such policies include vehicle limits, non-citizen eligibility, proportions of participants in year t and $t-1$ who are only certified for 1-3 months of benefits and need to re-certify after that. In addition to food stamp policies, I include the state minimum wage rate and states' welfare expenditure per capita in year t. Some other food stamp-specific factors in year t are also included: state administrative costs, error rates in determining eligibility and benefits[18], standard deduction of income, and maximum shelter deduction[19].

To ensure that decision-makers for passing the federal income and asset tests are accurately represented, households exclusively comprised of children members and households exclusively comprised of noncitizen members are omitted from the analysis. This selection ensures that the included households are more likely to reflect those with decision-making authority when meeting the stipulated federal criteria.

I construct some of the above variables as they are unavailable in the public data: unit asset for all years, unit gross income before 2005, unit net income before 2005, and individual disability status[20]. 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 TIRM3 data in available years (2005-2015). I can 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).

For the disability status, I refer to the SNAP Quality Control Technical Documentation of 2015, which thoroughly explains how the QC team constructs individual disability status because this information is not always needed in eligibility determination. In Figure B.4, although my total counts of households with disabled members differ from QC in 1996-2002, they are much closer in later years. This is due to the fact that I use the 2015 version of the document, and

[18]The state error rates are evaluated by the federal quality control process each year and are published in the SNAP Quality Control Annual Report series.

[19]These deductions are used when calculating net income.

[20]Disability questions are included in CPS-ASEC since 2008.

over the years, the QC team has modified and improved the imputation methods. Despite the differences, my imputation has a much smoother increasing trend, corresponding to the overall trend of SNAP caseloads.

Equation 3 is able to identify 96.8% of those who either passed or failed the income and asset tests within the training sample of the at least 1-month always-eligible group. The model maintains strong predictive performance for different eligibility periods — 77.9% of classification accuracy for the 12-month eligible group and 83.6% for the 6-month group. To address concerns related to overfitting, I used Lasso regularization to shrink the coefficients. The Lasso sample of the always eligible households overlaps with the OLS sample at about 96-99.9%. I chose the OLS-predicted samples because they have a slightly higher adjusted R-squared (0.2597 versus 0.2438). I define the "always-eligible" households as those who are identified to likely pass the income and asset tests by equation 3 and are determined to be eligible in TRIM3. The "newly-eligible" households are defined as those who are predicted to not likely pass the income and asset tests while also observed to be eligible.

Table 2 and 3 report the mean characteristics of each type of eligible household. Generally, the always-eligible households are mostly alike between the pre- and post-adoption states and years (labeled as "Pre BBCE" and "Post BBCE"). Even though some characteristics are statistically different, the magnitude is rather small. In "Post BBCE" states and years, the share of newly eligible households is about 2% among all eligible households. This proportion is roughly consistent with other studies, and the characteristics of these newly eligible households are also consistent: larger household size, more likely to have children, higher earnings, and higher income (GAO, 2012; Laird & Trippe, 2014).

Despite the small magnitude, the differences in the always-eligible households between the pre- and post-BBCE require further examination. To interpret the policy effects as changes in decision-making instead of changes in population, the always-eligible households must not systematically shift by BBCE implementation. 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 examines 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 disability status of the household head is significantly different. However, according to the event studies conducted in later sections of this paper, the population shift likely happens after 6-7 years of BBCE/BBCE Max adoptions. Therefore, I focus on the first five years of adoption.

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 by first estimating the treatment effect in each event time for each treatment cohort and then using 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 for the already-eligible household analyses.

$$y_{ist} = \alpha + \sum_{c \in C} \sum_{k \neq -1} \pi_{c,k} 1(\tau_{st} = k) \cdot Cohort_s^c + \theta_s + \sigma_t + \mathbf{X_{ist}\Gamma} + \mathbf{W_{st}\Phi} + e_{ist} \tag{4}$$

y_{ist} represents the outcome of interest. When the outcome is take-up, it is measured by whether household i in state s is receiving food stamp benefits in year t. $1(\tau_{st} = k)$ is the event indicator, which equals 1 if state s in year t 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. The event study coefficient $\pi_{c,k}$ 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.

$\mathbf{X_{ist}}$ 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). I also control for the federally determined standard deduction for income and maximum benefit levels, both vary by household size and years.

$\mathbf{W_{st}}$ controls state varying factors, such as other SNAP policies. These policies include vehicle limits, application aids[21], duration of each certification (t and $t-1$), outreach spending (t and $t-1$), and electronic benefit issuance. Aside from SNAP policies, I also include states' minimum wage rates and unemployment rates (t and $t-1$).

For state-level analyses, the same estimators are applied except that the covariates only include other SNAP policies, state and year-fixed effects.

5.1 Comparison group: States that adopt BBCE between 2008 and 2012

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 state agencies or households anticipated BBCE to be adopted, responding before the actual implementation of the policy would render them no gain. 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 2008. This makes the rest of the states "never-treated" during the observation period from 1996 to 2007. However, 28 adopted between 2008 and 2012, i.e., during the Great Recession periods, while the rest of the 10 states either adopted later than 2015 or never adopted to date (July, 2023). Such deviation in adoption decisions may signal fundamental differences between the two types of "never-treated" groups. I chose the 2008 to 2012 adoption states as my comparison group.

[21] Application 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 simply 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 the dependent variable 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 effects[22] 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 the information channel, 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

[22]Simple 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.

References

Aizer, A. (2003). Low Take-Up in Medicaid: Does Outreach Matter and for Whom? *American Economic Review*, *93*(2), 238–241.

Aizer, A. (2007). Public Health Insurance, Program Take-Up, and Child Health. *The Review of Economics and Statistics*, *89*(3), 400–415.

Anders, J., & Rafkin, C. (2022). The Welfare Effects of Eligibility Expansions: Theory and Evidence from SNAP.

Cook, J., & East, C. N. (2023). The Effect of Means-Tested Transfers on Work: Evidence From Quasi-Randomly Assigned SNAP Caseworkers. *NBER Working Paper*. Retrieved from http://www.nber.org/papers/w31307

CRS. (2022). The Supplemental Nutrition Assistance Program (SNAP): Categorical Eligibility. *U.S. Congressional Research Service (R42054)*. Retrieved from https://crsreports.congress.gov

Cunnyngham, K. E. (2016). Estimates of State Supplemental Nutrition Assistance Program Participation Rates in 2018. *Mathematica Policy Research*, 1–8. Retrieved from http://www.fns.usda.gov/sites/default/files/ops/Reaching2013.pdf

Currie, J. (2006). The Take-Up of Social Benefits. In A. J. Auerbach, D. Card, & J. M. Quigley (Eds.), *Public policy and the income distribution* (pp. 80–148). New York: Russell Sage Foundation. doi: 10.7758/9781610440202.7

Deshpande, M., & Li, Y. (2019). Who Is Screened Out? Application Costs and the Targeting of Disability Programs. *American Economic Journal: Economic Policy*, *11*(4), 213–248. doi: 10.1257/pol.20180076

Dickert-Conlin, S., Fitzpatrick, K., Stacy, B., & Tiehen, L. (2021). The Downs and Ups of the SNAP Caseload: What Matters? *Applied Economic Perspectives and Policy*, *43*(3), 1026–1050. doi: 10.1002/AEPP.13076

Finkelstein, A., & Notowidigdo, M. J. (2019). Take-up and Targeting: Experimental Evidence From SNAP. *The Quarterly Journal of Economics*, 1505–1556. Retrieved from https://academic.oup.com/qje/article/134/3/1505/5484907 doi: 10.1093/qje/qjz013

GAO. (2012). Improved Oversight of State Eligibility Expansions Needed. *United States Government Accountability Office*.

Geller, D., Zic, B., Isaacs, J., & Braga, B. (2019, 2). *Exploring the Causes of State Variation in SNAP Administrative Costs Final Report December 21 2018* (Tech. Rep.). Prepared by Manhattan Strategy Group and the Urban Institute for the U.S. Department of Agriculture, Food and Nutrition Service. Retrieved from www.fns.usda.gov/research-and-analysis .

Golosov, M., & Tsyvinski, A. (2006). Designing Optimal Disability Insurance: A Case for Asset Testing. *Journal of Political Economy*, *114*(2).

Gray, C. (2019, 11). Leaving benefits on the table: Evidence from SNAP. *Journal of Public Economics*, *179*, 104054. doi: 10.1016/j.jpubeco.2019.104054

Herd, P., & Moynihan, D. (2018). *Administrative Burden.* New York: Russell Sage Foundation.

Homonoff, T., Rino, G., & Somerville, J. (2022). Administrative Burden and Procedural Denials: Experimental Evidence from SNAP. *NBER Working Paper*.

Homonoff, T., & Somerville, J. (2021). Program Recertification Costs: Evidence from SNAP. *American Economic Journal: Economic Policy*, *13*(4), 271–298. Retrieved from https://doi.org/10.1257/pol.20190272 doi: 10.1257/pol.20190272

Hoynes, H., & Schanzenbach, D. (2009). Consumption Responses to In-Kind Transfers: Evidence from the Introduction of the Food Stamp Program. *American Economic Journal: Applied Economics*, *1*(4), 109–139. Retrieved from http://www.aeaweb.org/articles.php?doi=10.1257/app.1.4.109http://www.aeaweb.org/articles.php?doi=10.1257/app.1.4.109. doi: 10.1257/app.1.4.109

Jones, J. W., Courtemanche, C. J., Denteh, A., Marton, J., & Tchernis, R. (2021). Do State SNAP Policies Influence Program Participation among Seniors? *NBER WORKING PAPER*. Retrieved from http://www.nber.org/papers/w29037

Klerman, J. A., & Danielson, C. (2011). The transformation of the Supplemental Nutrition Assistance Program. *Journal of Policy Analysis and Management*, *30*(4), 863–888. doi: 10.1002/PAM.20601

Kleven, H., & Kopczuk, W. (2011). Transfer Program Complexity and the Take-Up of Social Benefits. *American Economic Journal: Economic Policy*, *3*(1), 54–90. doi: 10.1257/pol.3.1.54

Ko, W., & Moffitt, R. A. (2022, 6). Take-up of Social Benefits. *NBER Working Paper 30148*. Retrieved from `https://www.nber.org/papers/w30148` doi: 10.3386/W30148

Laird, E., & Trippe, C. (2014). *Programs Conferring Categorical Eligibility for SNAP: State Policies and the Number and Characteristics of Households Affected* (Tech. Rep. No. February).

Lin, J. C. (2022). Understanding State Variation in SNAP Policies. *Working Paper*.

Meyer, B., Mok, W., & Sullivan, J. (2009). The Under-Reporting Of Transfers In Household Surveys: Its Nature And Consequences. *NBER Working Paper 15181*. Retrieved from `http://www.nber.org/papers/w15181`

Meyer, B., Mok, W., & Sullivan, J. (2015, 9). Household surveys in crisis. *Journal of Economic Perspectives*, *29*(4), 199–226. doi: 10.1257/jep.29.4.199

Nichols, A. L., & Zeckhauser, R. J. (1982). Targeting Transfers through Restrictions on Recipients. *The American Economic Review: Papers and Proceedings*, *72*(2), 372–377.

Ratcliffe, C., Mckernan, S.-M., & Finegold, K. (2008). Effects of Food Stamp and TANF Policies on Food Stamp Receipt. *Social Service Review*, *82*(2), 291–334.

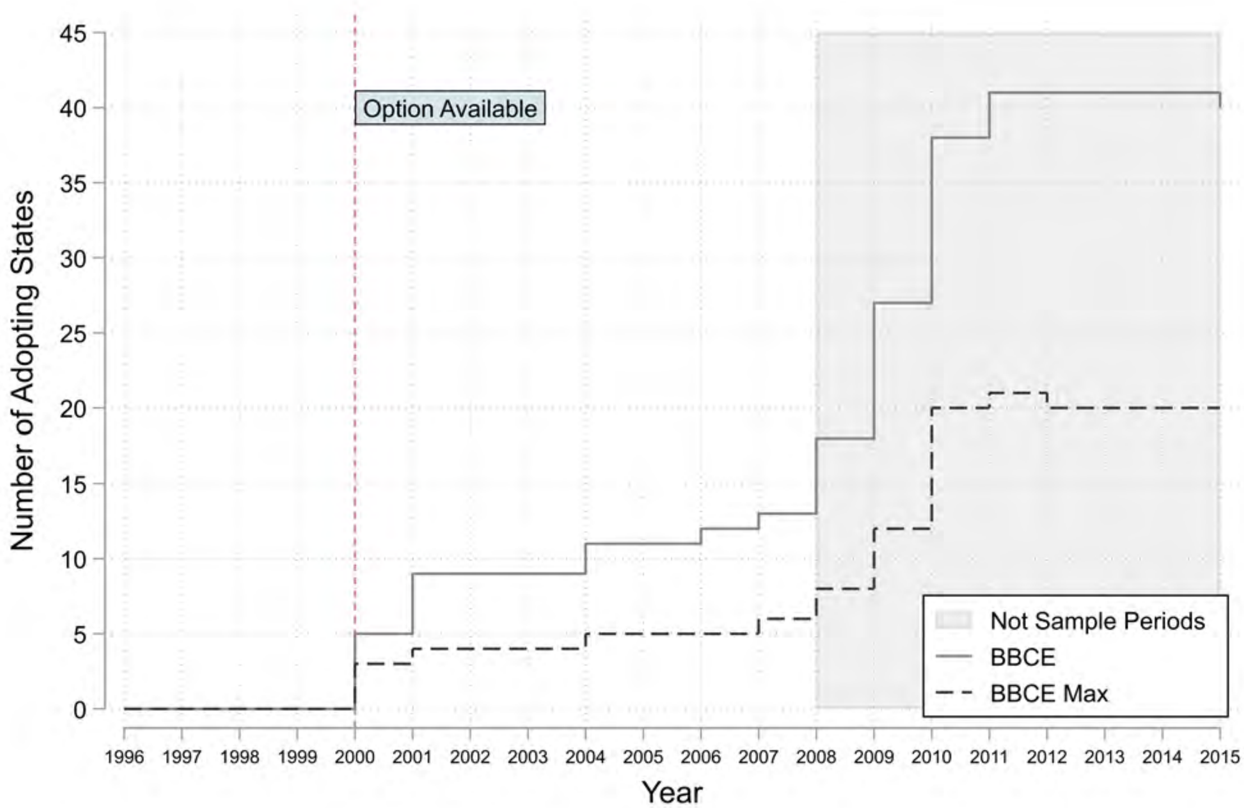
Sun, L., & Abraham, S. (2021, 12). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, *225*(2), 175–199. doi: 10.1016/j.jeconom.2020.09.006

TRIM3. (n.d.). *TRIM3 project website, trim3.urban.org, downloaded on 7/19/2023.*

Unrath, M. (2021). Targeting, Screening, and Retention: Evidence from California's Food Stamps Program. *California Policy Lab Working Paper*.

Wellschmied, F. (2021). The welfare effects of asset mean-testing income support. *Quantitative Economics*, *12*(1), 217–249. doi: 10.3982/qe1241

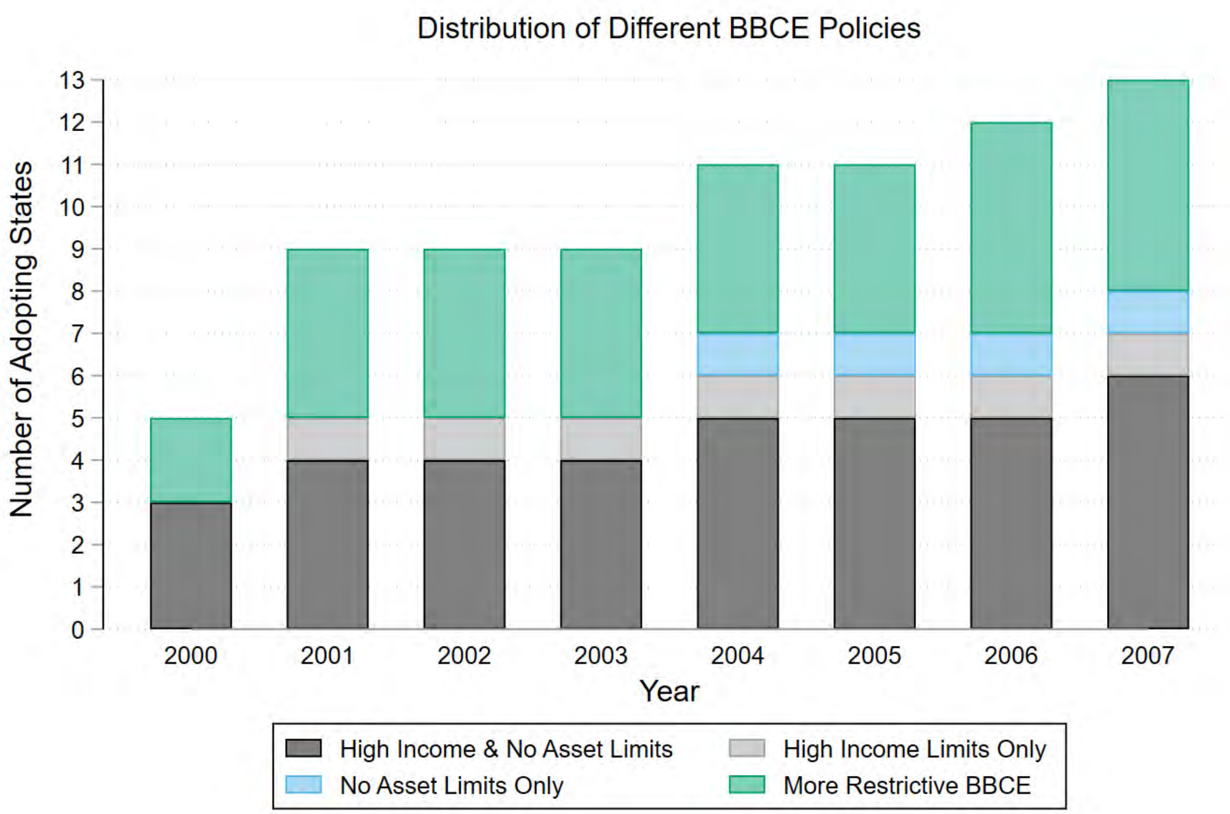
Figure 1: Number of States Adopting BBCE By Year 1996 to 2015



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.

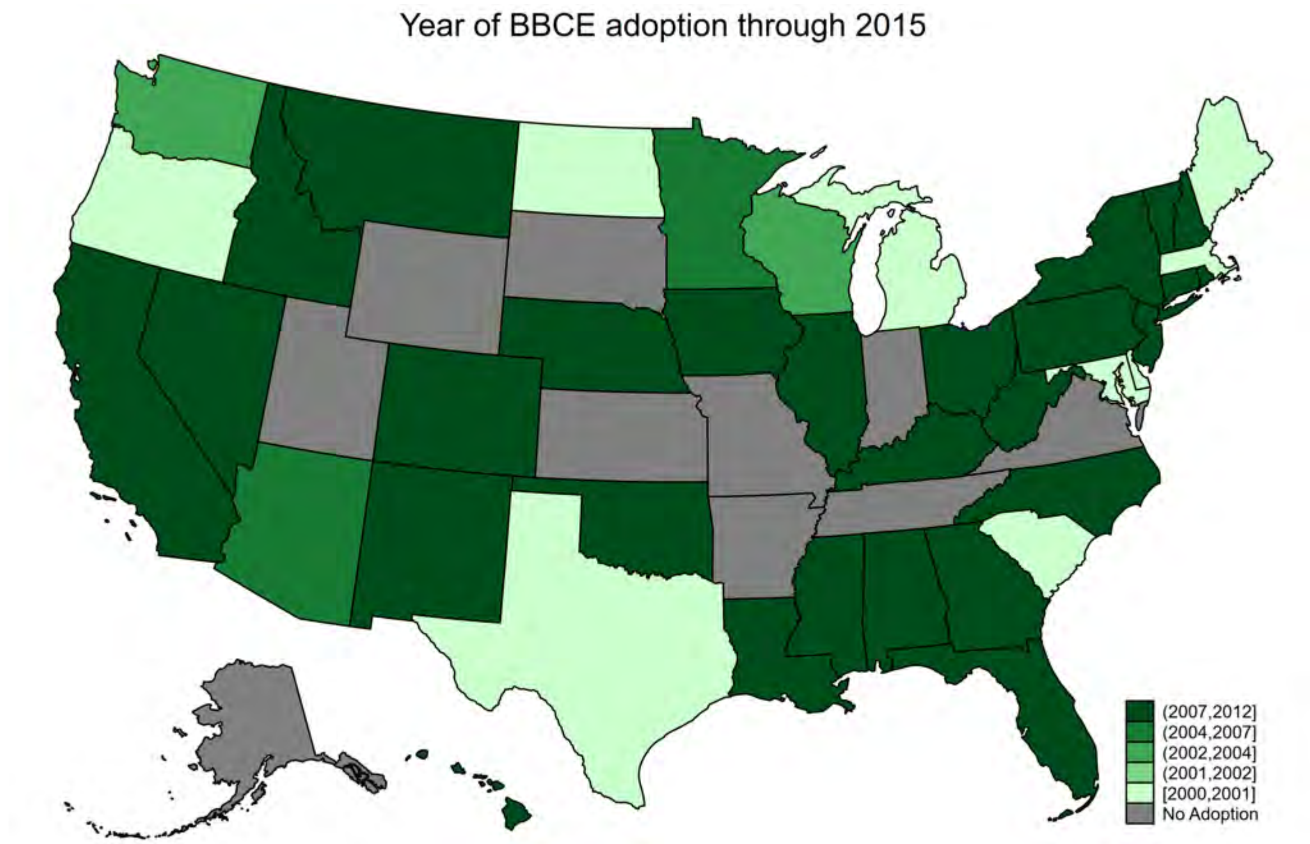
By the end of 2015, a total of 41 states had adopted BBCE. 13 of them adopted before the Great Recession (between 2000 and 2007). This paper studies the effects between 1996 and 2007 because effects during the Great Recession are likely confounded with other factors, such as other stimulus policies. 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).

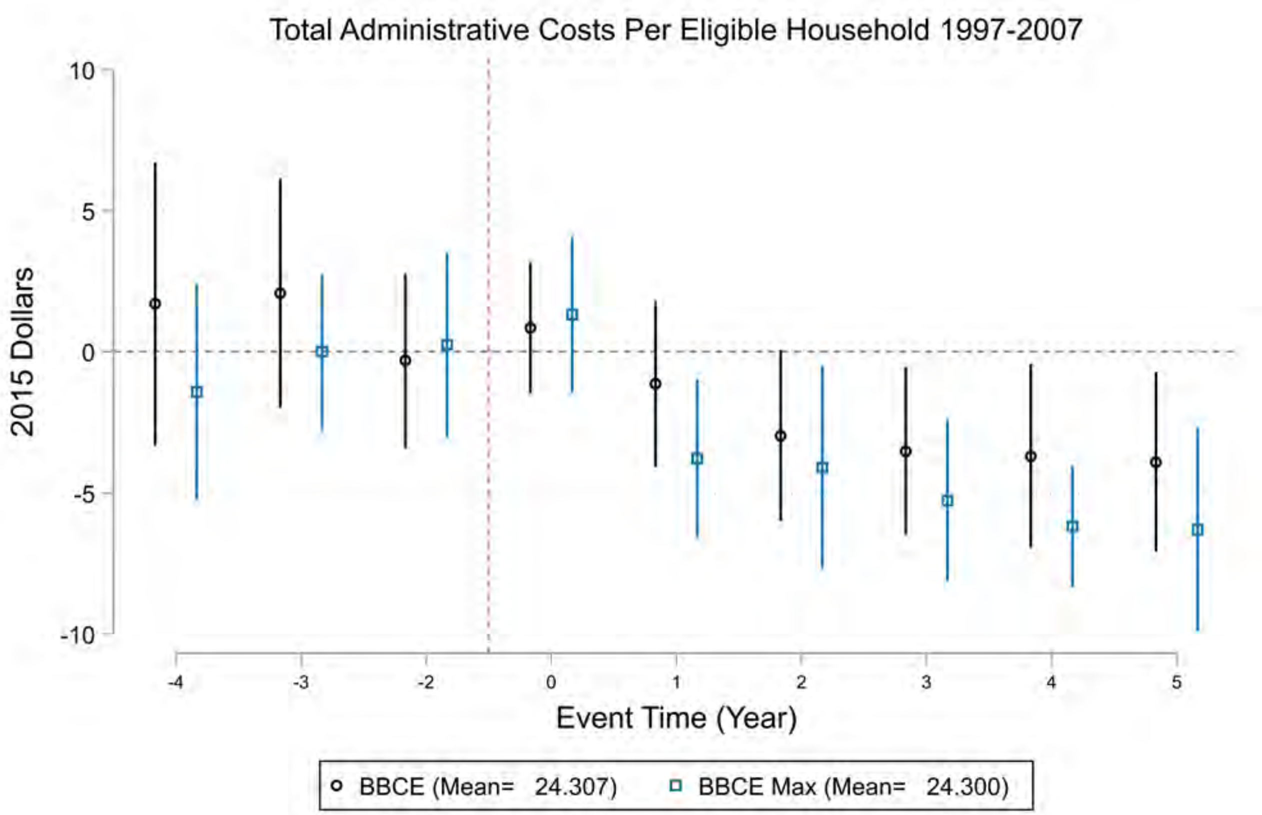
Figure 3: Geographical Distribution of BBCE Adoption Timing



Data source: SNAP Policy Database and Laird and Trippe (2014).

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.

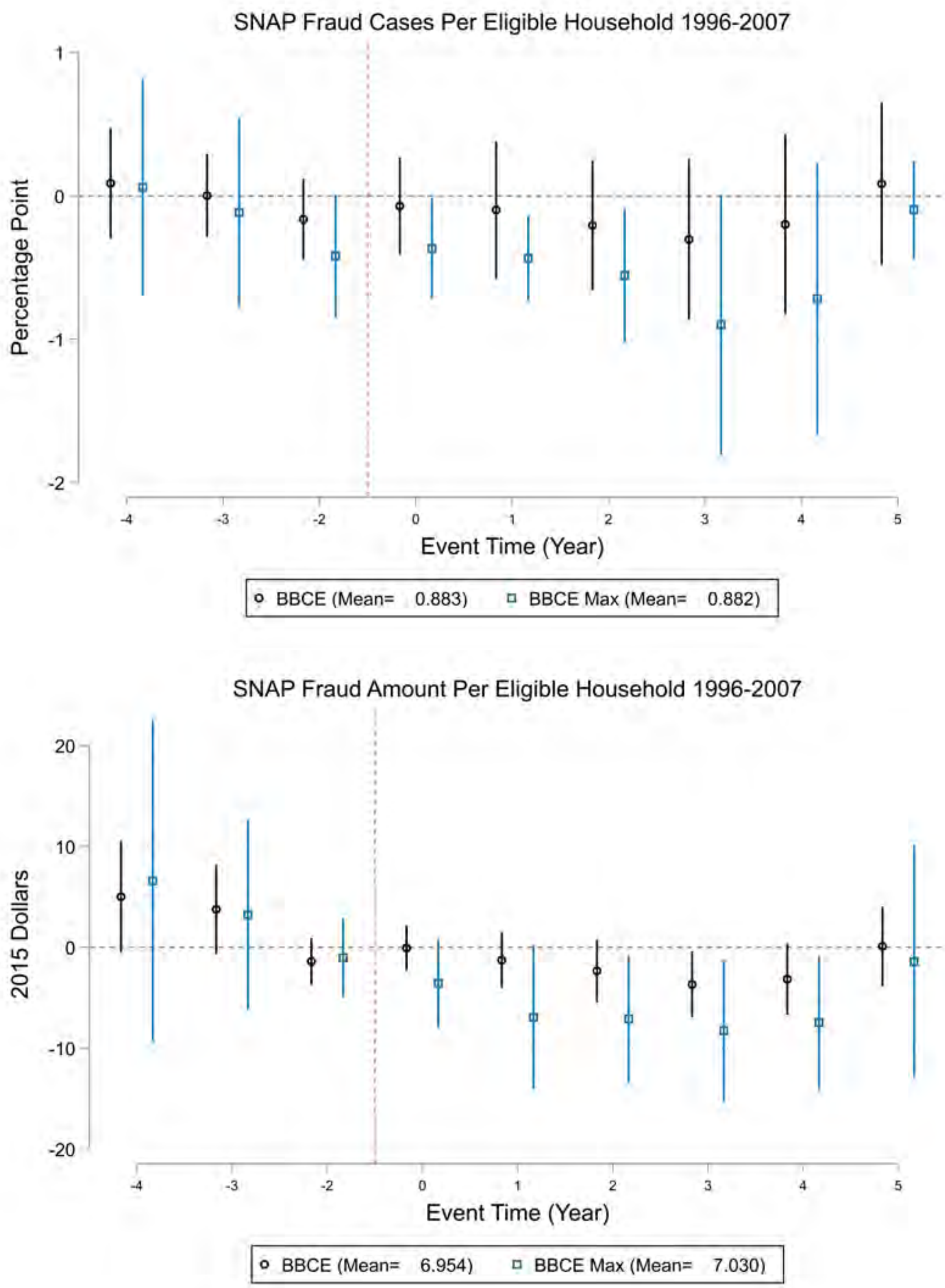
Figure 4: Event Study Estimates: State Total Administrative Costs for SNAP



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%).

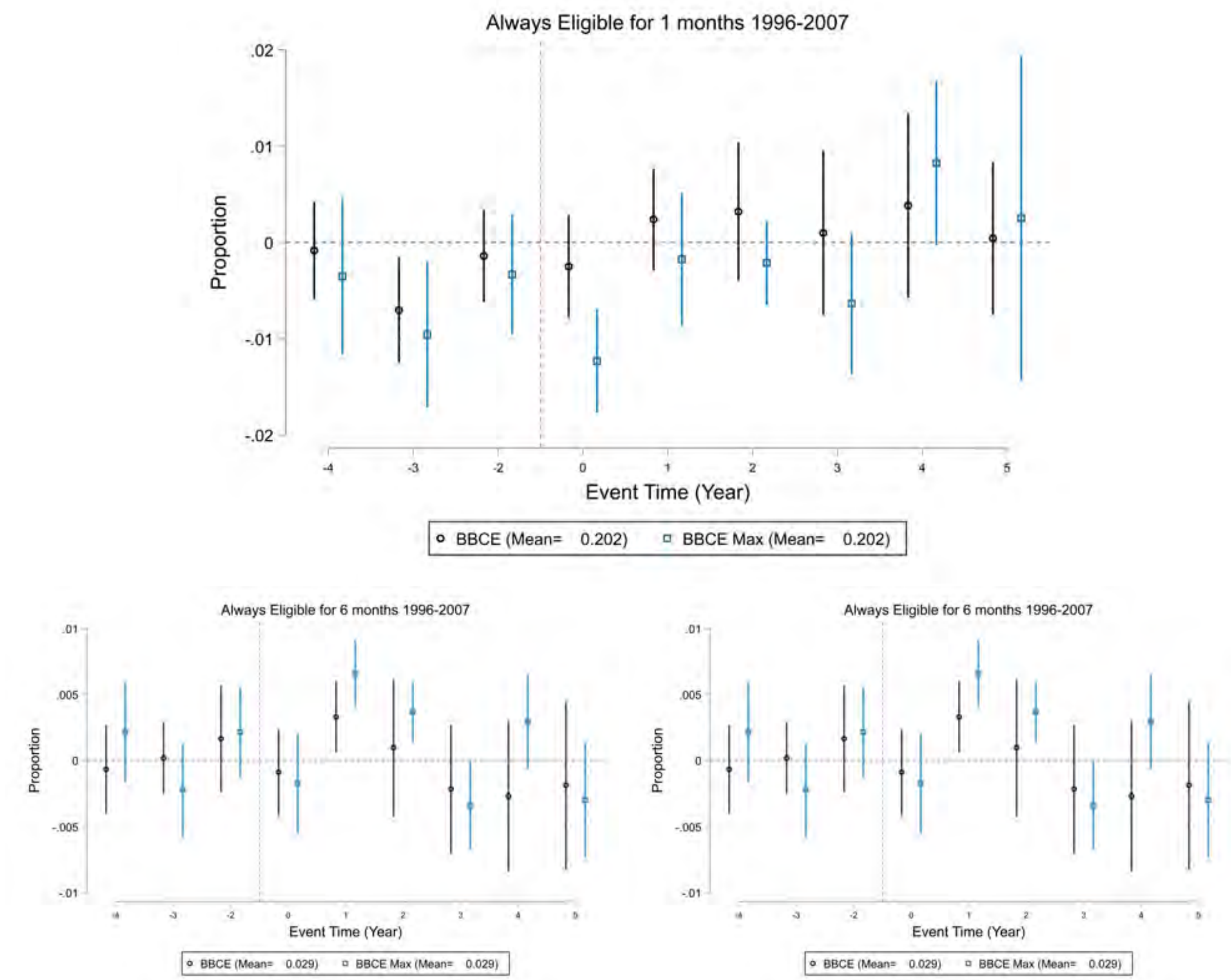
Figure 5: Event Study Estimates: SNAP Fraud Cases and Benefit Amount



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

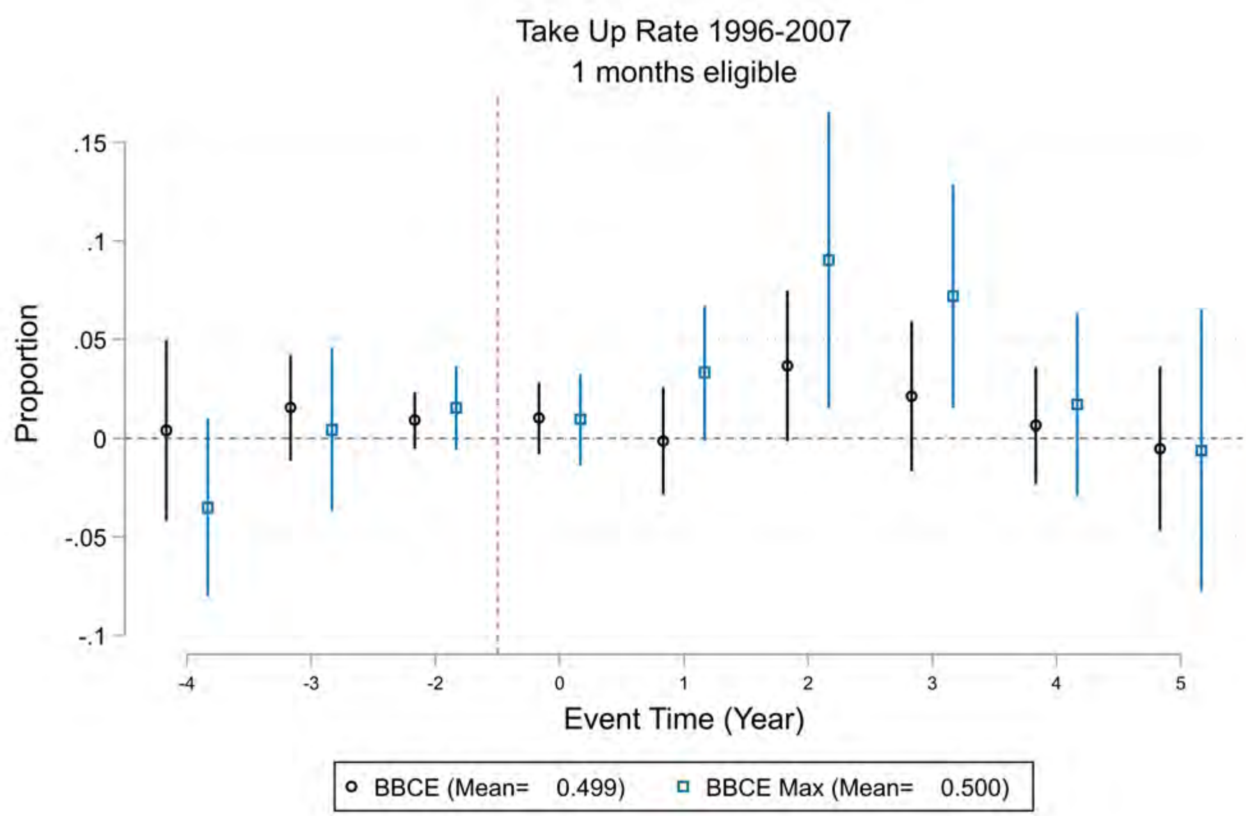


Sun & Abraham (2021) estimators using equation 4. Observations weighted by household sampling weight. Standard errors clustered at the state level.

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.

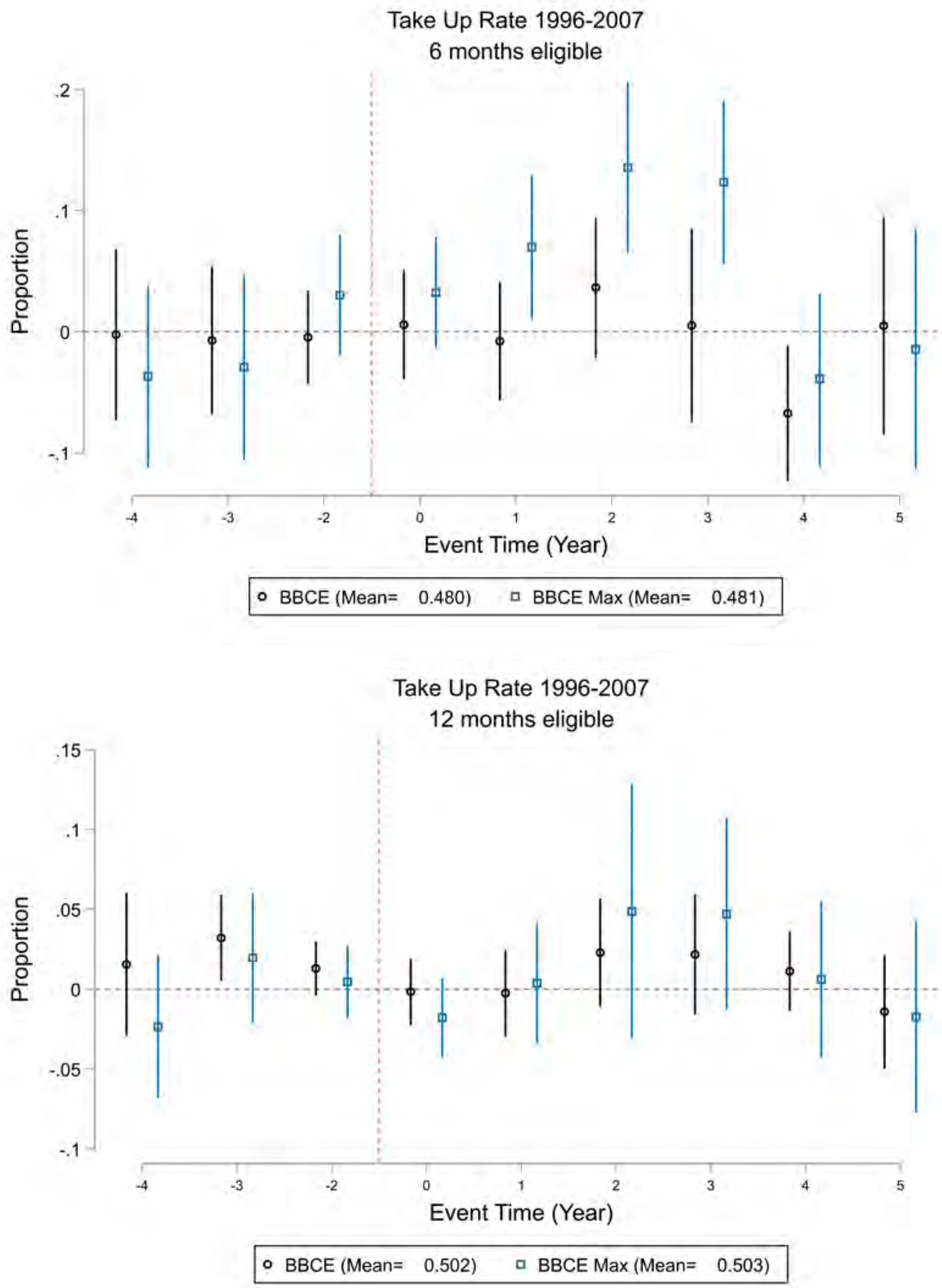
Figure 7: Event Study Estimates: Take-Up Among Always Eligible



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.

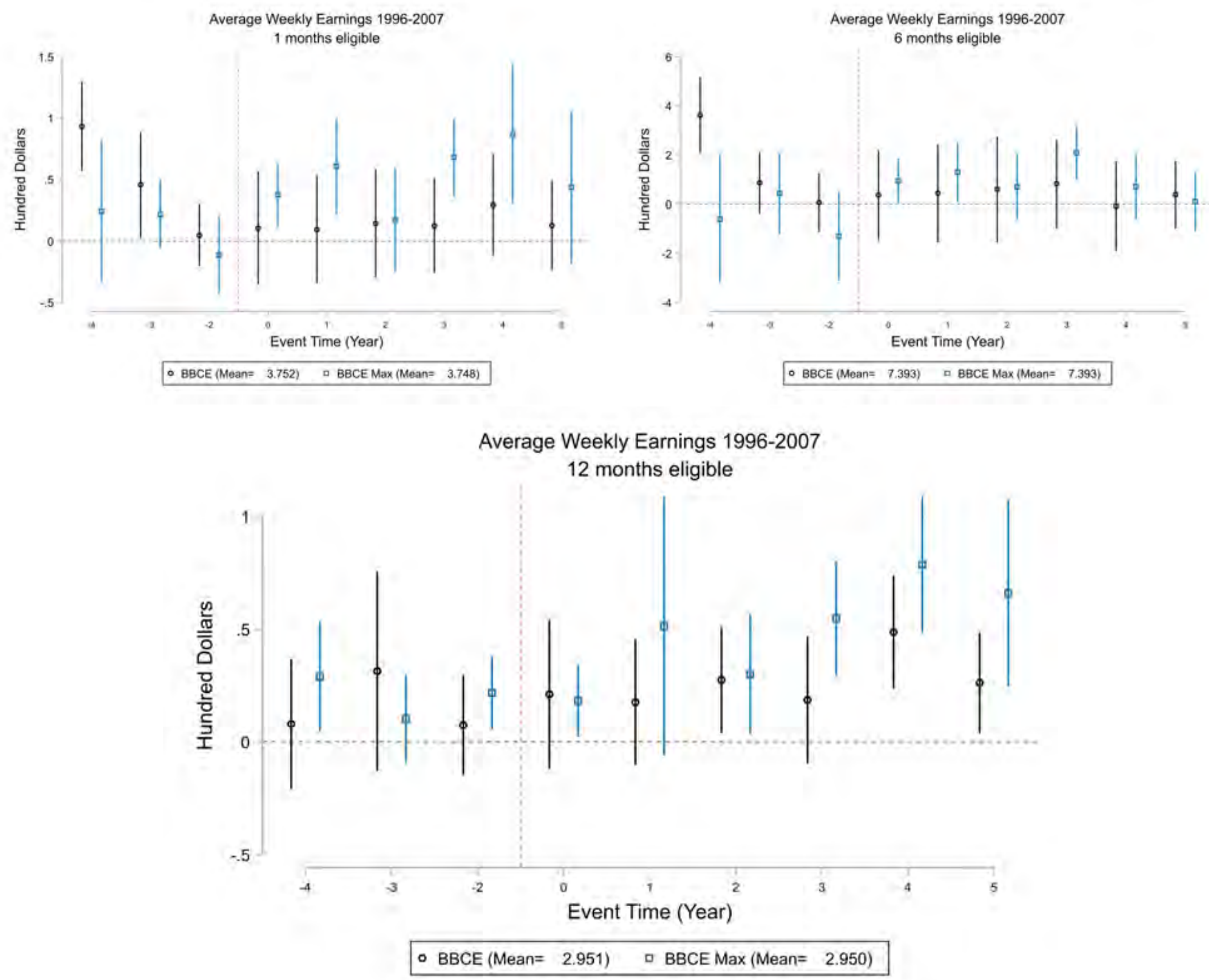
Event time ranges from -11 to 7. The complete vector of estimates are plotted in Appendix **??**. This figure includes 94% of the sample.

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.

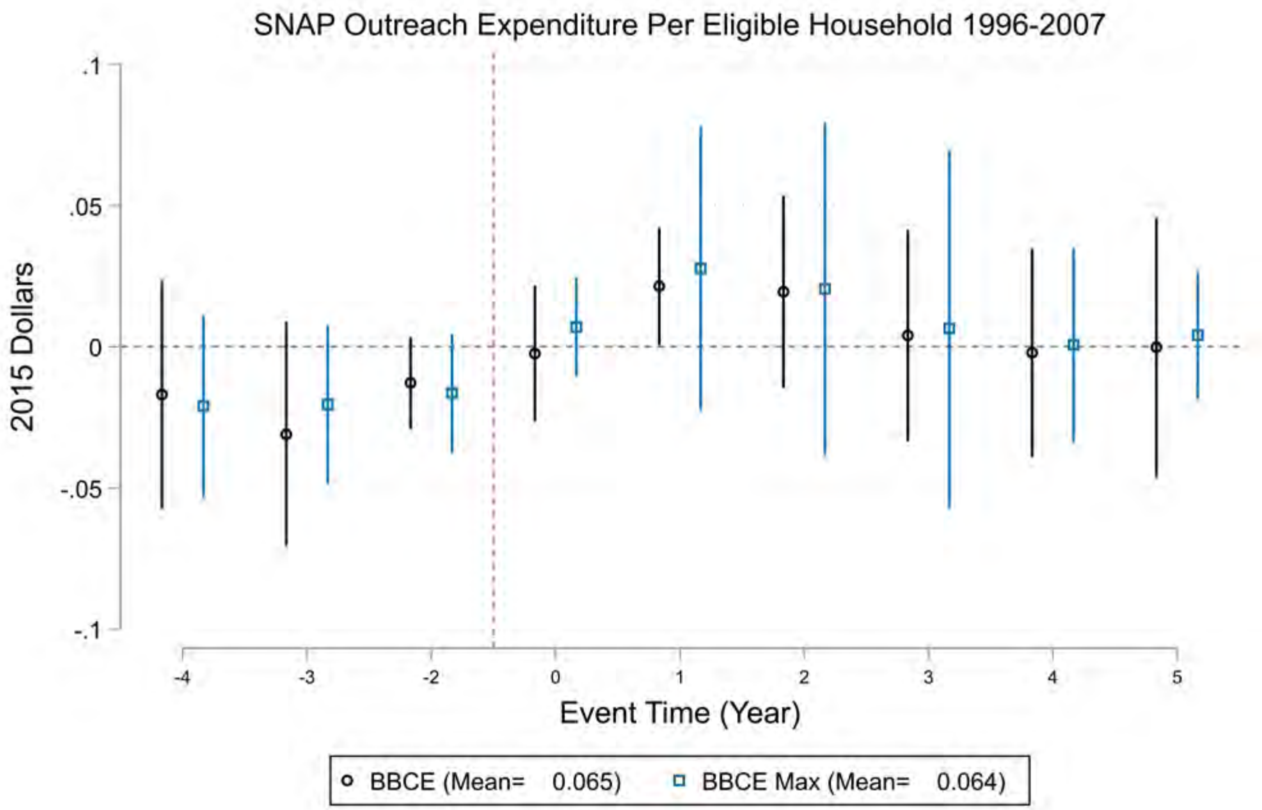
Figure 9: Event Study Estimates: Average Weekly Earnings



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	0.0143
	(0.0235)	(0.0177)
Share of Eligible Population	0.0579	-0.0905
	(0.222)	(0.168)
Population Age < 18	-0.394	-0.363
	(0.290)	(0.219)
Population Age ≥ 65	-0.275	-0.194
	(0.176)	(0.133)
Share of Hispanic	0.0233	0.0255
	(0.0282)	(0.0213)
Share of Black	-0.0163	0.0111
	(0.0201)	(0.0152)
Share of Other Race/Ethnicity	-0.0101	0.0120
	(0.0185)	(0.0140)
Education HS or Below	-0.0434	-0.00150
	(0.0454)	(0.0342)
Share of Population with Disability	-0.343	0.0224
	(0.294)	(0.222)
Non-disabled Adults without Dependent	-0.258	-0.237
	(0.207)	(0.157)
Share of Married Persons	-0.141	-0.102
	(0.0966)	(0.0729)
Share of Citizens	0.0500	0.0593
	(0.0571)	(0.0431)
Unemployment Rate	-0.273	-0.235
	(0.253)	(0.191)
Median Household Income (Dec. 2015$)	-0.00457	-0.0441
	(0.0364)	(0.0275)
Share of Voters Support Welfare	-0.0304	-0.105
	(0.0680)	(0.0513)
Share of Voters Have Racism	0.0190	-0.0216
	(0.0387)	(0.0292)
Share of Expenditure Covered by Own Revenue	-0.00312	-0.0142
	(0.0202)	(0.0153)
Total SNAP Admin Costs Per Case	0.00559	0.0109
	(0.0120)	(0.00908)
SNAP Error Rate	-0.0343	0.0403
	(0.0469)	(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	Always-Eligible	Newly-Eligible
	(1)	(2)	(3)
Take-up rate	0.510	0.569***	0.642***
	(0.492)	(0.486)	(0.475)
Gross Income	1414.8	1387.4*	3435.3***
	(1533.8)	(1511.4)	(2670.3)
Net Income	833.0	810.3**	2044.3***
	(1138.5)	(1073.3)	(2213.5)
Eligible Benefit	147.9	149.8	148.3
	(161.0)	(164.7)	(181.3)
Age of Head	46.41	46.88***	42.90***
	(19.27)	(19.07)	(15.00)
Head Female	0.616	0.620	0.739***
	(0.486)	(0.485)	(0.440)
Head White	0.710	0.741***	0.800**
	(0.454)	(0.438)	(0.400)
Head Black	0.238	0.213***	0.152***
	(0.426)	(0.410)	(0.359)
Head Hispanic	0.187	0.222***	0.0948***
	(0.390)	(0.416)	(0.293)
Head HS or below	0.708	0.681***	0.488***
	(0.455)	(0.466)	(0.500)
Head unemployed	0.804	0.824***	0.841
	(0.397)	(0.381)	(0.366)
Head married	0.363	0.350***	0.286**
	(0.481)	(0.477)	(0.452)
Head Disabled	0.0936	0.105***	0.0864
	(0.291)	(0.307)	(0.281)
Unit Size	2.293	2.218***	3.026***
	(1.539)	(1.499)	(1.662)
Have Earnings	0.582	0.580	0.631*
	(0.493)	(0.494)	(0.483)
Has Disabled Member	0.152	0.154	0.124
	(0.359)	(0.361)	(0.330)
Has Elderly Member	0.293	0.300	0.161***
	(0.455)	(0.458)	(0.368)
Has Children 0-4	0.224	0.217*	0.206
	(0.417)	(0.412)	(0.405)
Has Children 5-17	0.339	0.324***	0.579***
	(0.474)	(0.468)	(0.494)
Has Noncitizen Member	0.116	0.114	0.0109***
	(0.321)	(0.317)	(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	Post BBCE	Pre BBCE	Post BBCE
	(1)	(2)	(3)	(4)
Take-up rate	0.525	0.550***	0.464	0.598***
	(0.494)	(0.492)	(0.485)	(0.470)
Gross Income	1160.0	1144.6	2462.5	2215.8***
	(1341.2)	(1148.6)	(3245.5)	(2337.1)
Net Income	634.0	634.0	1587.4	1430.1***
	(800.6)	(721.8)	(2409.8)	(1805.6)
Eligible Benefit	157.4	159.2	103.3	106.6
	(166.6)	(172.2)	(125.3)	(126.5)
Age of Head	50.43	50.68	37.07	36.91
	(20.48)	(19.96)	(11.51)	(11.80)
Head Female	0.680	0.677	0.401	0.410
	(0.467)	(0.468)	(0.490)	(0.492)
Head White	0.680	0.716***	0.824	0.838*
	(0.467)	(0.451)	(0.381)	(0.369)
Head Black	0.267	0.237***	0.130	0.121
	(0.442)	(0.426)	(0.336)	(0.327)
Head Hispanic	0.226	0.269***	0.0677	0.0770*
	(0.418)	(0.444)	(0.251)	(0.267)
Head HS or below	0.793	0.772***	0.424	0.406*
	(0.405)	(0.419)	(0.494)	(0.491)
Head unemployed	0.794	0.801*	0.951	0.966***
	(0.405)	(0.399)	(0.215)	(0.180)
Head married	0.344	0.344	0.408	0.361***
	(0.475)	(0.475)	(0.492)	(0.480)
Head Disabled	0.130	0.144***	0.00475	0.00444
	(0.337)	(0.351)	(0.0688)	(0.0665)
Unit Size	2.252	2.208***	2.199	2.118**
	(1.516)	(1.511)	(1.518)	(1.437)
Have Earnings	0.470	0.479*	0.860	0.848
	(0.499)	(0.500)	(0.347)	(0.359)
Has Disabled Member	0.211	0.209	0.0111	0.0110
	(0.408)	(0.406)	(0.105)	(0.104)
Has Elderly Member	0.413	0.410	0.00987	0.00882
	(0.492)	(0.492)	(0.0989)	(0.0935)
Has Children 0-4	0.242	0.233*	0.127	0.132
	(0.429)	(0.423)	(0.333)	(0.338)
Has Children 5-17	0.352	0.334***	0.234	0.234
	(0.478)	(0.472)	(0.424)	(0.424)
Has Noncitizen Member	0.157	0.153	0.0119	0.00918
	(0.364)	(0.360)	(0.109)	(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	-0.0000153	-0.000475*	-0.0000862	0.00000583	-0.0000182
	(0.0000606)	(0.0000445)	(0.000193)	(0.000147)	(0.0000587)	(0.0000446)
Head Female	0.000876	-0.000793	-0.00574*	-0.00412	0.00196	0.000423
	(0.00145)	(0.00142)	(0.00230)	(0.00248)	(0.00143)	(0.00154)
Head Black	0.00319	0.00148	0.00136	0.00182	0.00294	0.00160
	(0.00195)	(0.00157)	(0.00564)	(0.00409)	(0.00208)	(0.00195)
Head Hispanic	0.00153	0.000129	0.00130	-0.000910	0.00171	0.0000615
	(0.00182)	(0.00143)	(0.00389)	(0.00385)	(0.00210)	(0.00169)
Head Others	-0.00274	-0.00166	-0.00838	-0.0144*	-0.00265	0.000951
	(0.00309)	(0.00257)	(0.00591)	(0.00691)	(0.00366)	(0.00309)
Head HS or below	-0.000319	-0.0000229	-0.00502	-0.00340	0.00111	0.00123
	(0.00101)	(0.000678)	(0.00269)	(0.00225)	(0.00139)	(0.00106)
Head married	-0.00167	-0.000400	-0.00124	-0.00333	-0.00153	0.0000751
	(0.00107)	(0.000914)	(0.00271)	(0.00188)	(0.00131)	(0.00107)
Head Disabled	0.0106***	0.00693*	0.0175	0.0376	0.0101**	0.00568*
	(0.00290)	(0.00259)	(0.0290)	(0.0208)	(0.00313)	(0.00226)
Head unemployed	0.00234	0.000723	0.00482	0.00781	0.00337	0.000634
	(0.00125)	(0.000921)	(0.00564)	(0.00555)	(0.00205)	(0.00109)
Unit Size	0.000528	-0.000434	-0.000159	-0.0000546	0.000969	-0.000278
	(0.000622)	(0.000374)	(0.00171)	(0.00115)	(0.000720)	(0.000507)
Has Disabled Member	-0.00172	-0.00128	-0.0231	-0.0304	-0.00225	-0.000728
	(0.00220)	(0.00149)	(0.0181)	(0.0197)	(0.00247)	(0.00104)
Has ABAWD Member	0.000417	0.00124	0.00177	0.00560	-0.00119	0.000157
	(0.00189)	(0.00120)	(0.00497)	(0.00389)	(0.00215)	(0.00114)
Has Elderly Member	0.00443	0.00336	0.0168	-0.00625	-0.000269	0.00197
	(0.00219)	(0.00207)	(0.0110)	(0.00785)	(0.00279)	(0.00157)
Has Children 0-4	-0.000332	0.000423	-0.00444	0.00461	-0.00171	-0.00216
	(0.00169)	(0.00123)	(0.00474)	(0.00336)	(0.00185)	(0.00122)
Has Children 5-17	-0.000566	0.00295	0.00416	0.00632	-0.000763	0.00184
	(0.00209)	(0.00154)	(0.00545)	(0.00467)	(0.00216)	(0.00175)
Has Noncitizen Member	-0.000718	-0.00428	0.0165	0.00542	-0.00240	-0.00452
	(0.00307)	(0.00335)	(0.0141)	(0.0120)	(0.00343)	(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	-0.392	-3.702*	-4.432***	-2.395*	-4.047***
	(1.859)	(1.357)	(1.443)	(0.807)	(1.152)	(0.986)
SNAP Fraud Cases	-0.0237	-0.158	-0.139	-0.428	-0.131	-0.511*
	(0.124)	(0.220)	(0.215)	(0.239)	(0.160)	(0.217)
SNAP Fraud Amount	2.459	2.934	-2.249	-4.293	-1.736	-5.795*
	(1.736)	(3.906)	(1.535)	(2.305)	(1.276)	(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	-0.274	-3.552*	-5.138***	-1.726	-3.091**
	(1.981)	(1.689)	(1.532)	(1.406)	(1.206)	(1.160)
SNAP Fraud Cases	-0.0213	-0.233	-0.351	-0.912*	-0.177	-0.575**
	(0.130)	(0.260)	(0.268)	(0.456)	(0.175)	(0.207)
SNAP Fraud Amount	2.898	4.049	-4.450*	-8.746*	-2.024	-7.066**
	(1.793)	(4.672)	(2.010)	(3.488)	(1.384)	(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
Panel A - At least 1 month						
All Observations						
Take up	0.00938	-0.00524	0.0166	0.0512*	0.0112	0.0359
	(0.0131)	(0.0149)	(0.0129)	(0.0217)	(0.0130)	(0.0232)
Average Weekly Earnings	0.479***	0.117	0.117	0.458**	0.148	0.522**
	(0.132)	(0.179)	(0.201)	(0.161)	(0.184)	(0.199)
Balanced Panel						
Take up	0.0177	-0.0305	0.0347	0.0637*	0.0267	0.0442
	(0.0323)	(0.0210)	(0.0194)	(0.0279)	(0.0178)	(0.0268)
Average Weekly Earnings	0.197	0.584*	0.291	0.689**	0.277	0.677**
	(0.251)	(0.241)	(0.267)	(0.225)	(0.246)	(0.239)
Panel B - At most 6 months						
All Observations						
Take up	-0.00470	-0.0120	0.00982	0.0903***	-0.00389	0.0513
	(0.0247)	(0.0255)	(0.0252)	(0.0236)	(0.0222)	(0.0280)
Average Weekly Earnings	1.512**	-0.492	0.551	1.252**	0.417	0.967*
	(0.545)	(0.957)	(0.941)	(0.481)	(0.849)	(0.452)
Balanced Panel						
Take up	-0.0239	-0.0720*	0.0409	0.102***	0.0232	0.0591
	(0.0607)	(0.0320)	(0.0429)	(0.0294)	(0.0291)	(0.0309)
Average Weekly Earnings	-0.532	0.230	0.148	1.584*	-0.309	1.187*
	(0.855)	(0.764)	(0.946)	(0.632)	(0.849)	(0.533)
Panel C - 12 months						
All Observations						
Take up	0.0202	0.000306	0.0101	0.0204	0.00627	0.0117
	(0.0138)	(0.0166)	(0.0128)	(0.0242)	(0.0126)	(0.0241)
Average Weekly Earnings	0.155	0.203*	0.212*	0.385**	0.266**	0.498***
	(0.114)	(0.0910)	(0.106)	(0.135)	(0.102)	(0.144)
Balanced Panel						
Take up	0.0452	-0.0185	0.0355	0.0319	0.0304	0.0194
	(0.0335)	(0.0242)	(0.0216)	(0.0316)	(0.0208)	(0.0285)
Average Weekly Earnings	0.400*	0.716***	0.345*	0.490**	0.445**	0.568***
	(0.185)	(0.129)	(0.160)	(0.162)	(0.154)	(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	-0.000473
	(0.00192)	(0.000577)
Share of Eligible Population	-0.00970	-0.00159
	(0.0106)	(0.00765)
Population Age < 18	-0.0179	-0.0192
	(0.0137)	(0.0100)
Population Age ≥ 65	0.00657	-0.00173
	(0.0108)	(0.00593)
Share of Hispanic	0.0186	0.00231
	(0.0135)	(0.00478)
Share of Black	0.000908	-0.00252
	(0.00993)	(0.00433)
Share of Other Race/Ethnicity	-0.00354	-0.00349
	(0.0101)	(0.00319)
Education HS or Below	0.00768	0.00499
	(0.00894)	(0.00274)
Population with Disability	-0.0147	-0.00313
	(0.0223)	(0.0117)
Non-disabled Adults without Dependent	0.00129	0.000548
	(0.000746)	(0.000432)
Share of Married Persons	0.0130	0.00698
	(0.00985)	(0.00488)
Citizens	-0.00424	0.00818
	(0.00945)	(0.00555)
Unemployment Rate	0.0186	0.0188
	(0.0207)	(0.0171)
Median Household Income (Dec. 2015$)	-0.00103	0.0000279
	(0.00360)	(0.00124)
Share of Voters Support Welfare	0.0246	0.00239
	(0.0175)	(0.00691)
Share of Voters Have Racism	0.0114	0.0171
	(0.0264)	(0.0207)
Share of Expenditure Covered by Own Revenue	-0.000827	-0.000263
	(0.00151)	(0.000912)
Total SNAP Admin Costs Per Case	-0.00212*	-0.000702
	(0.000877)	(0.000379)
SNAP Error Rate	0.00583	0.000320
	(0.00391)	(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

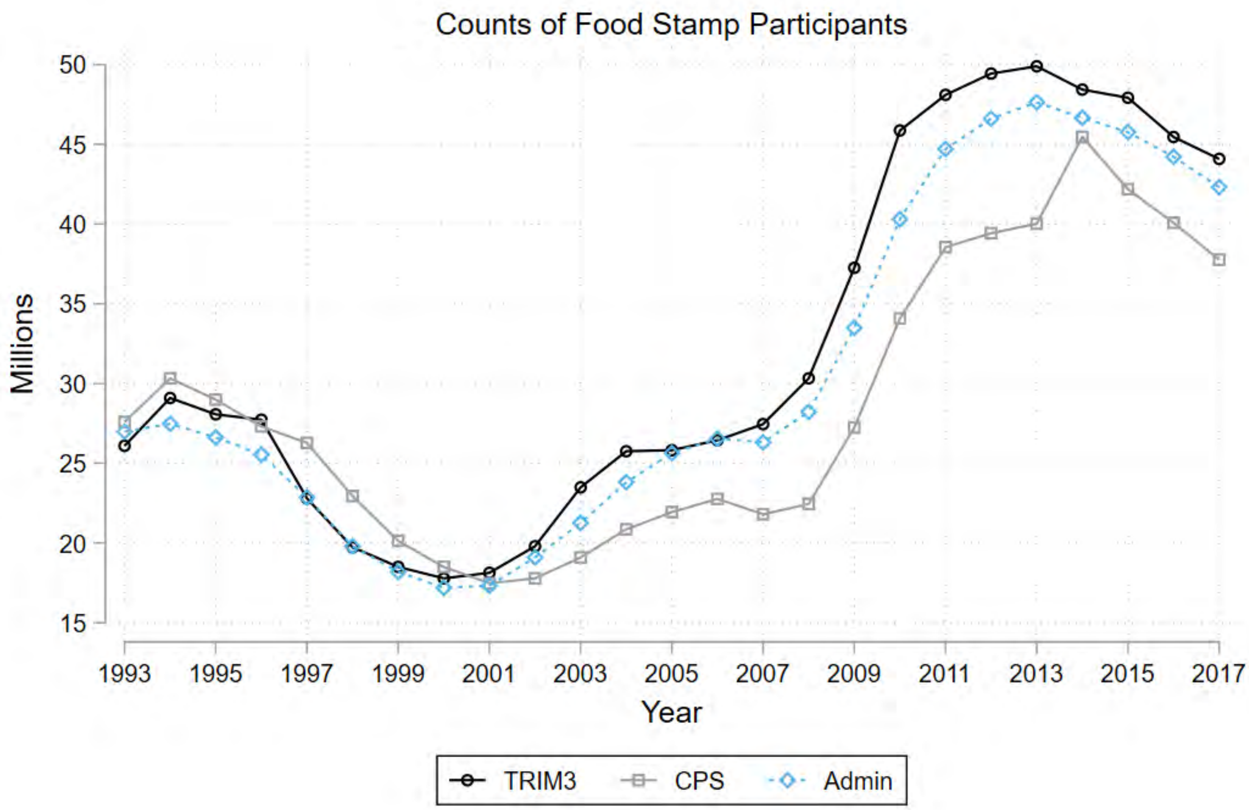
B.1 Sources of factors explaining state policy variation

- **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



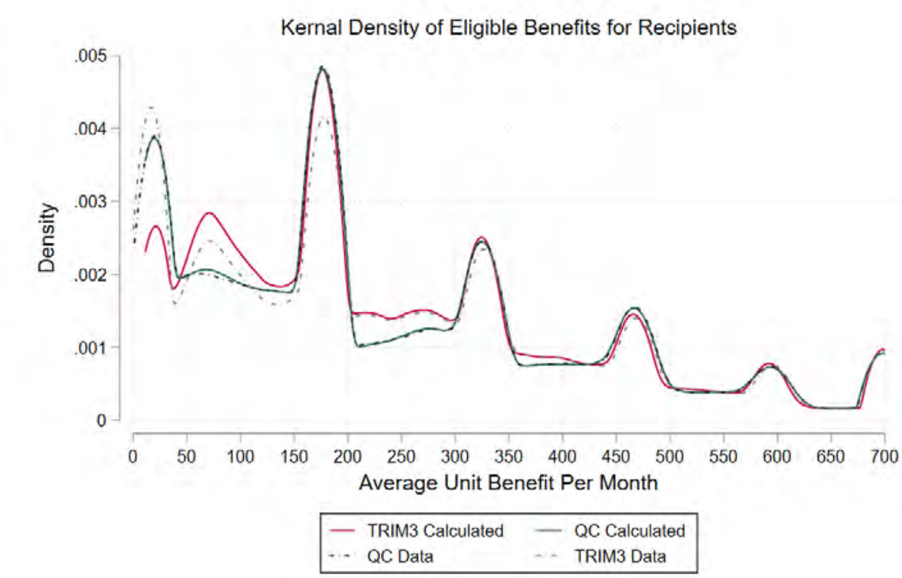
The figure plots the time series of SNAP total number of participants estimated using TRIM3 and CPS ASEC data. Official counts published by the Food and Nutrition Service, USDA is also plotted as a benchmark of the true values. It is apparent that TRIM3 counts are closer to the administrative counts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

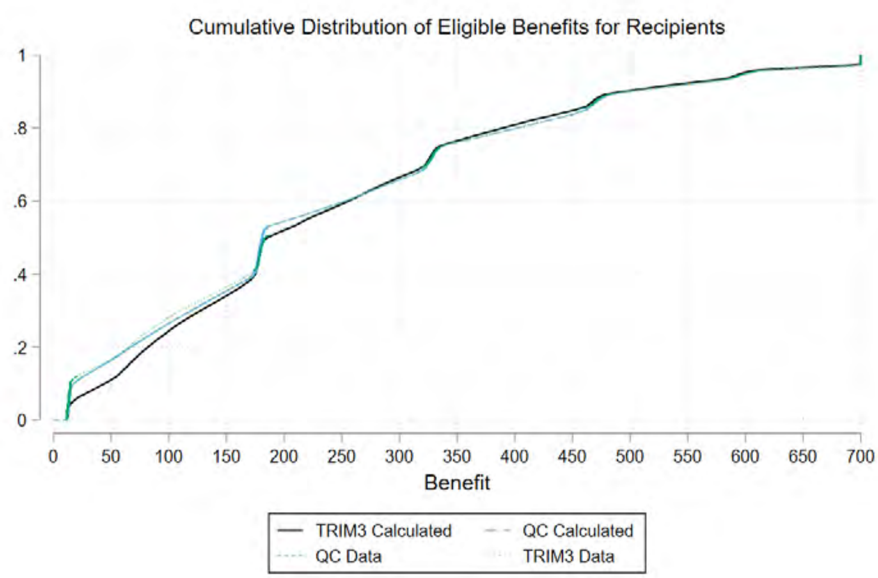
Table B.1: Characteristics of SNAP Participating Households: TRIM3 versus QC (Admin Data)

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

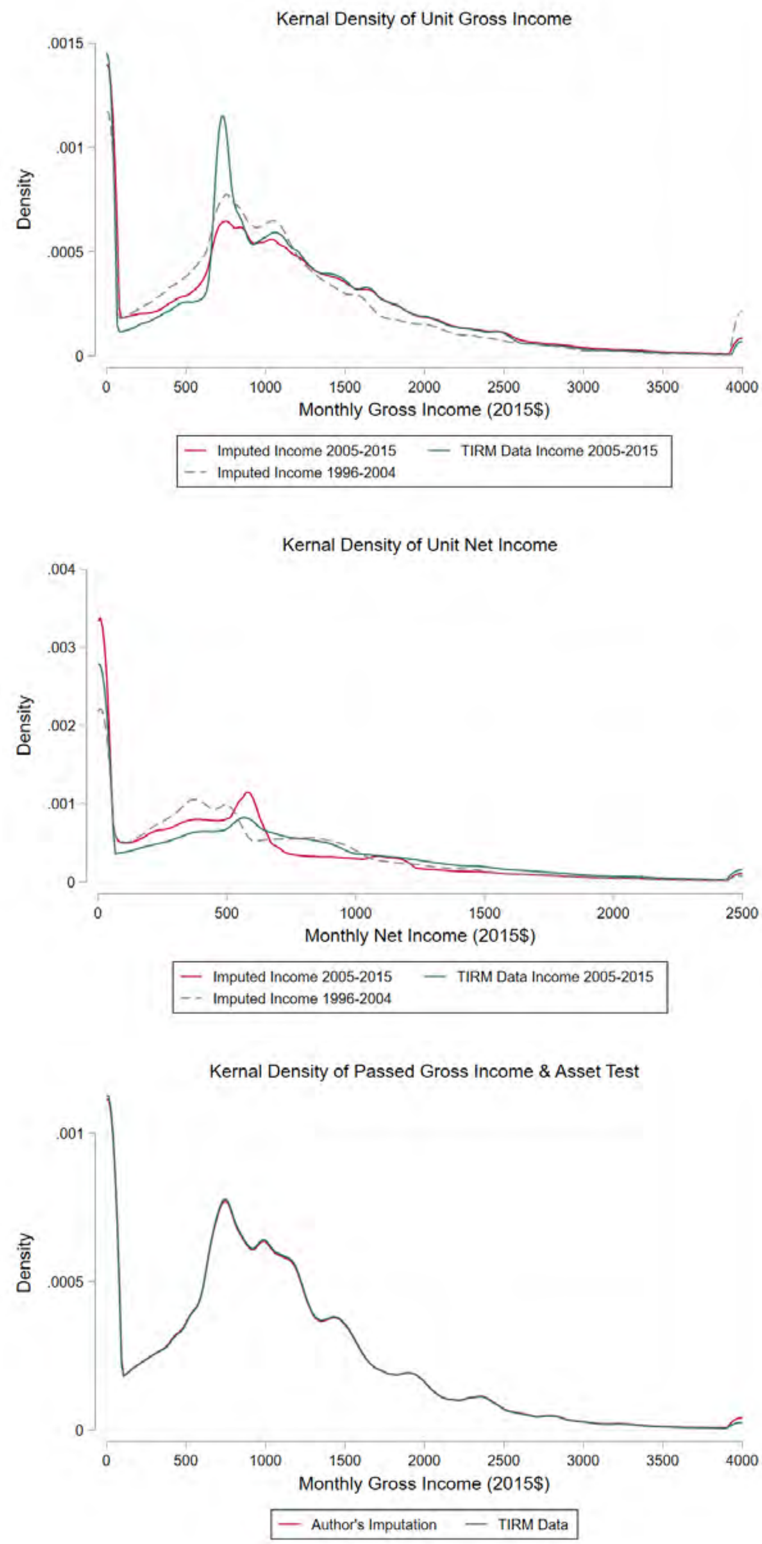
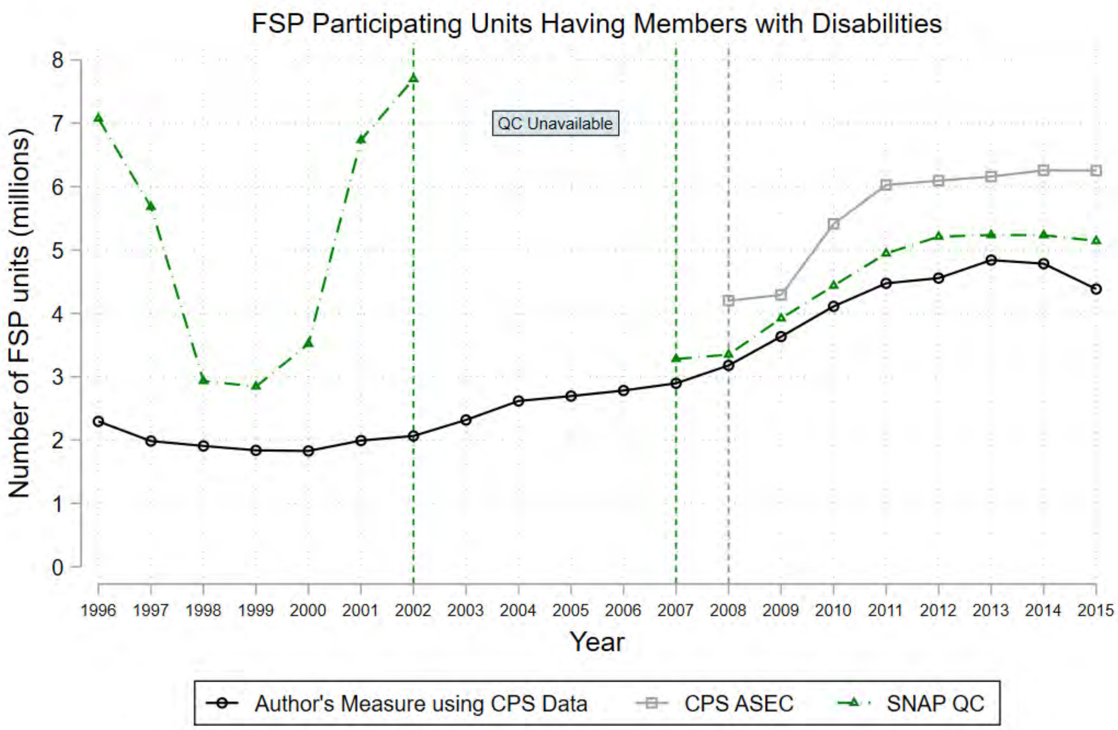
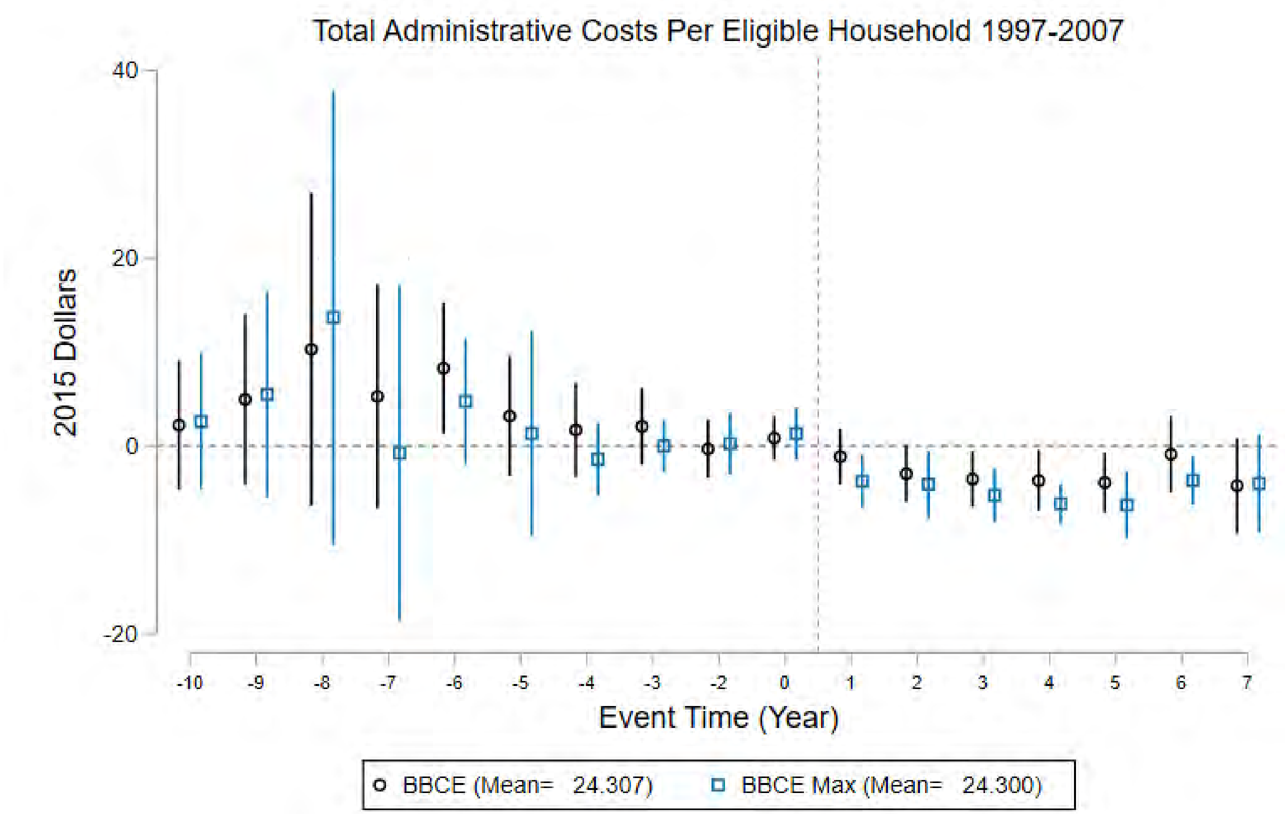


Figure B.4: Disability Measures



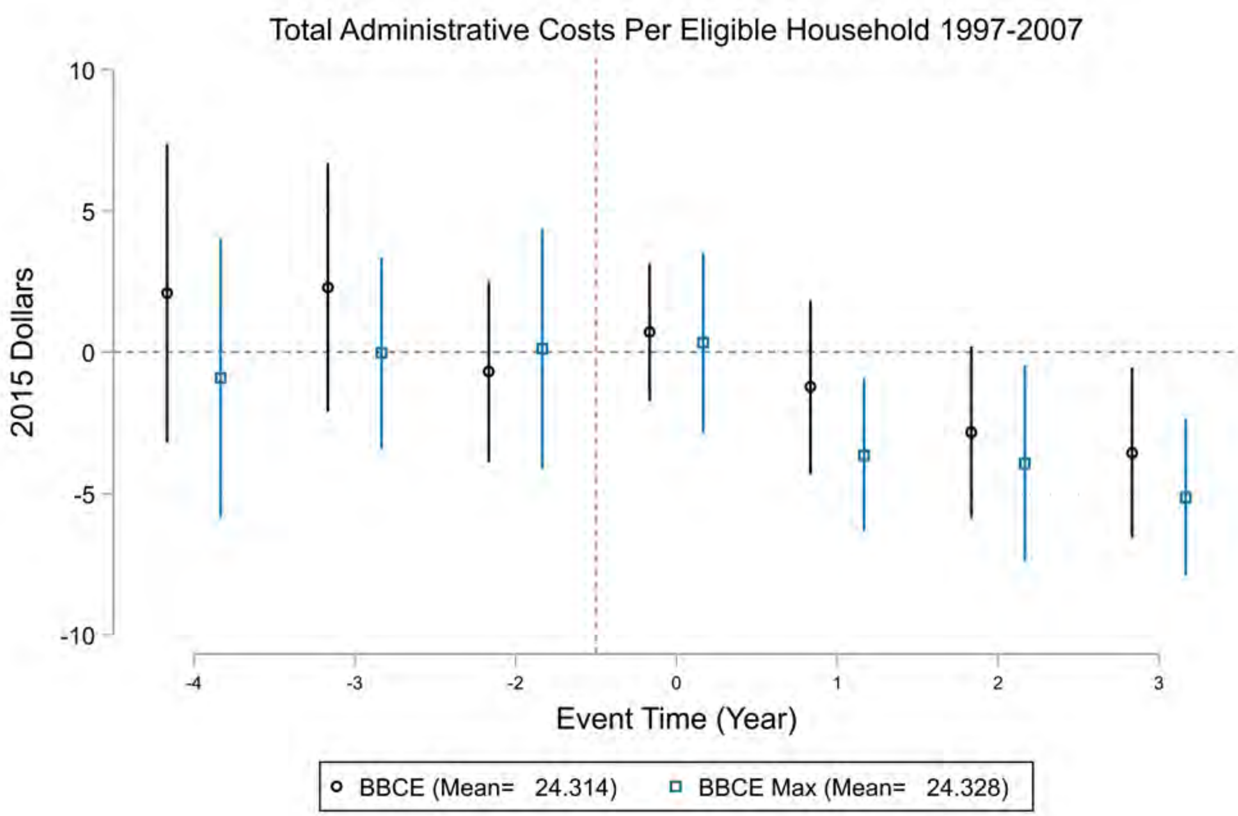
C Result Appendix

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.

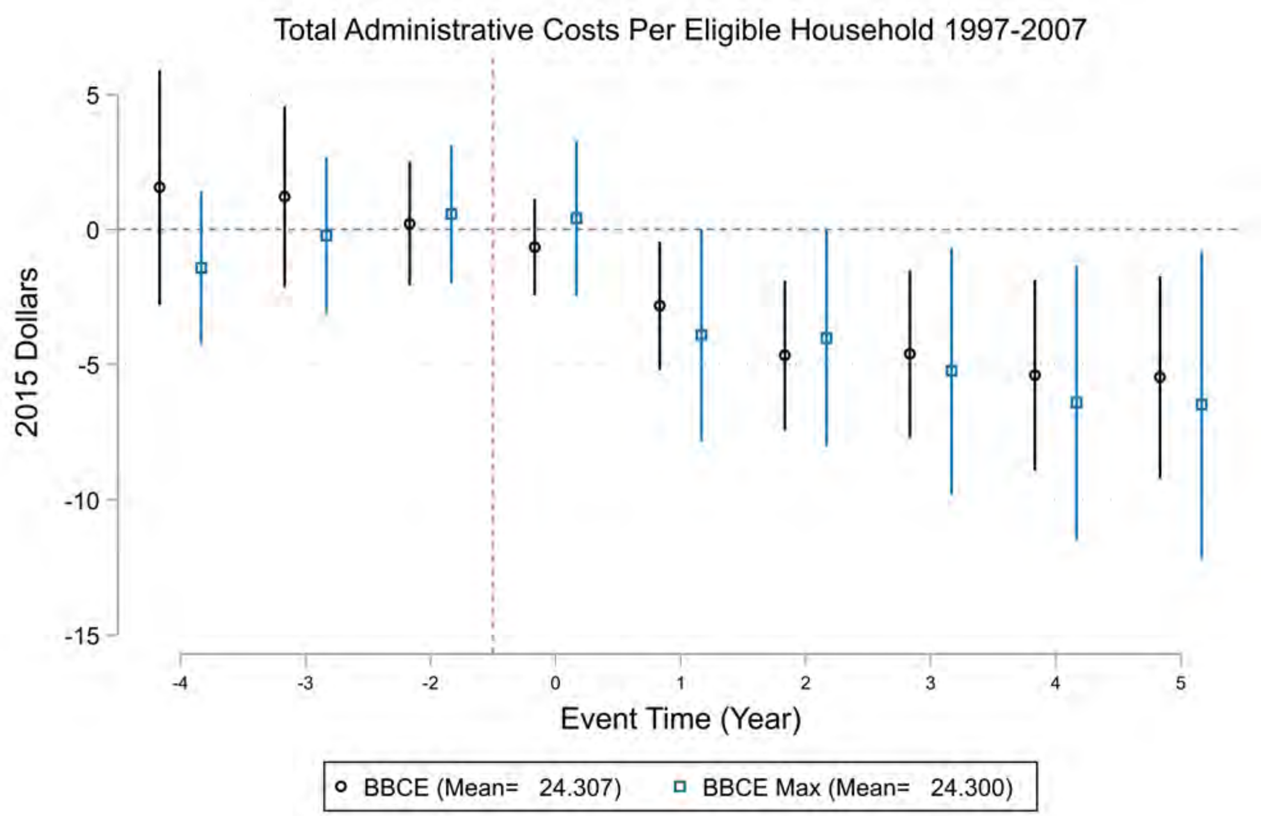
Figure C.2: Total SNAP Administrative Costs: Balanced Panel



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

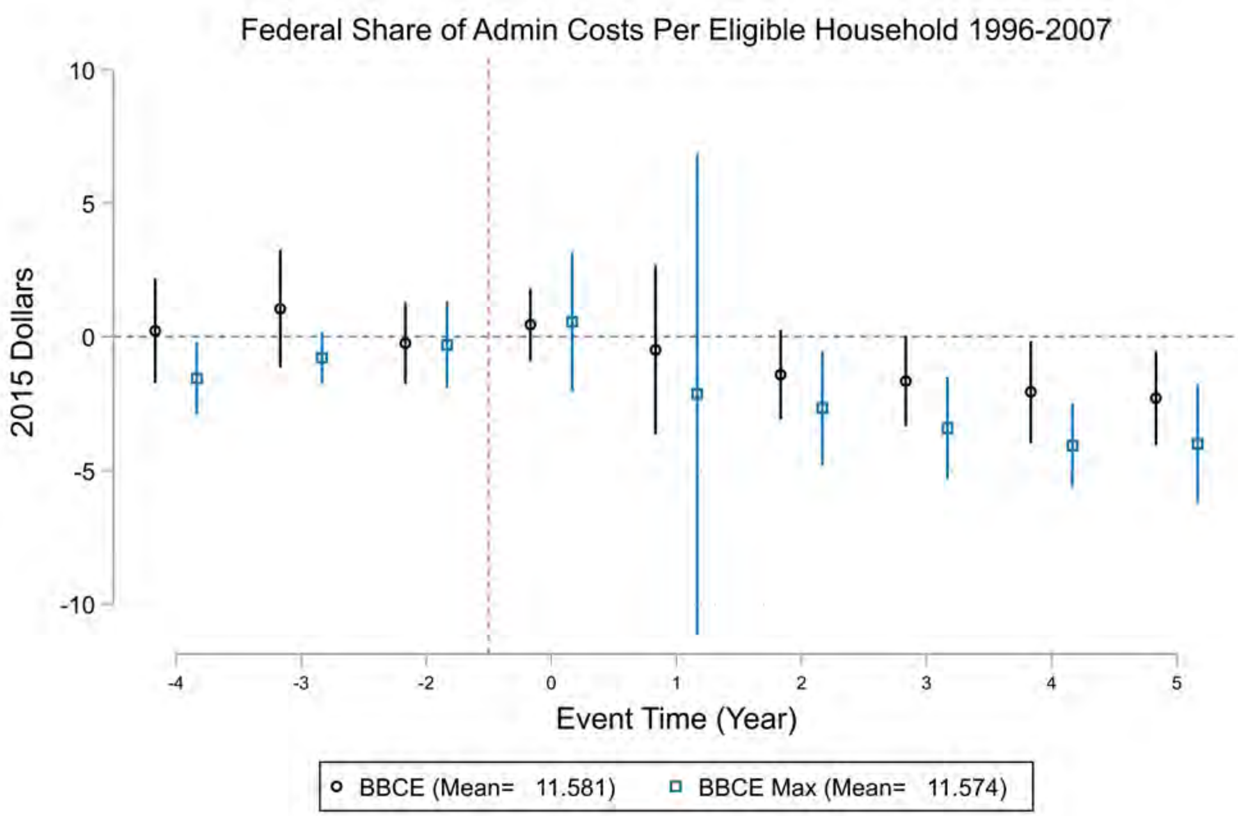
Eleven out of thirteen treated states (about 87% of the sample) are included in the balanced panel of BBCE. Six out of seven treated states (about 93% if the sample) are included in the balanced panel of BBCE Max.

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



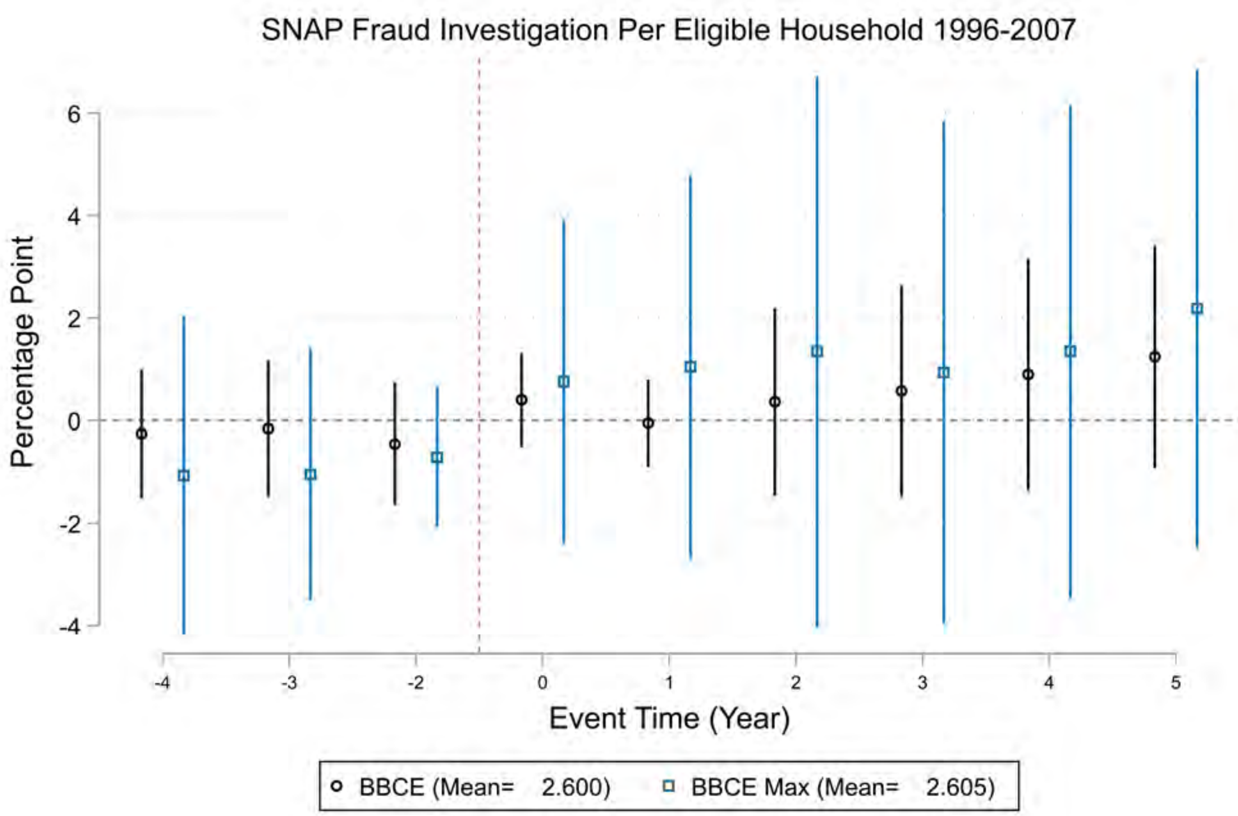
Sun & Abraham (2021) Event Study Estimates. Weighted by the size of always eligible (for any month) households. Clustered standard errors at state level.

Figure C.4: Federal Share of SNAP Administrative Costs



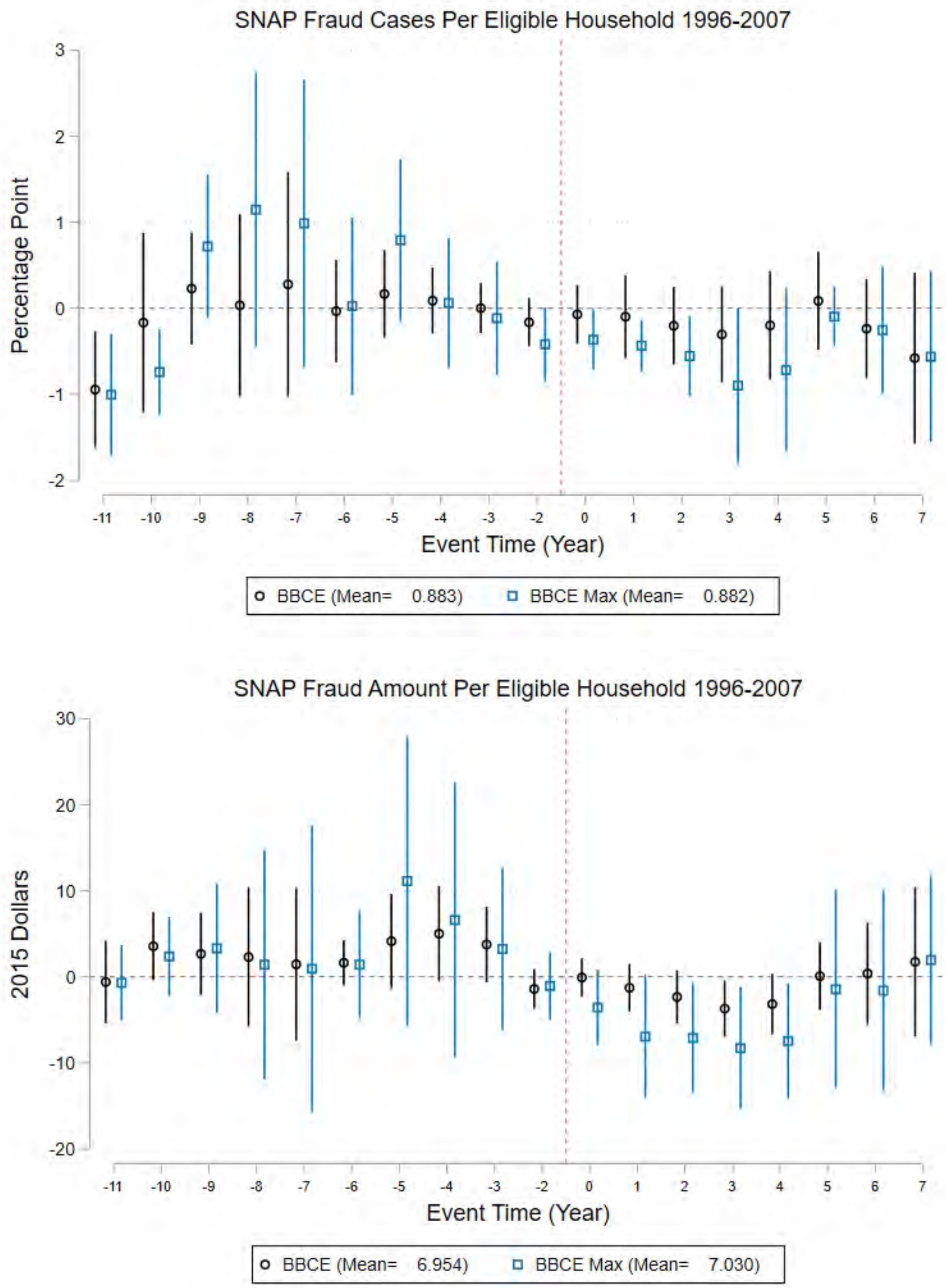
Sun & Abraham (2021) Event Study Estimates. Weighted by the size of always eligible (for any month) households. Clustered standard errors at state level.

Figure C.5: SNAP Total Fraud Investigation



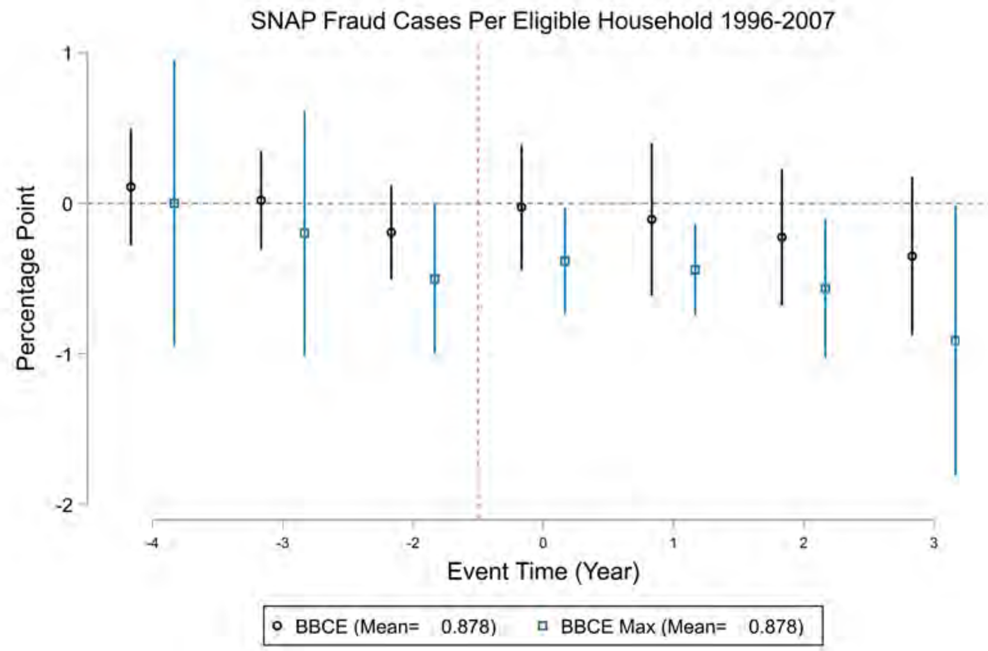
Sun & Abraham (2021) Event Study Estimates. Weighted by the size of always eligible (for any month) households. Clustered standard errors at state level.

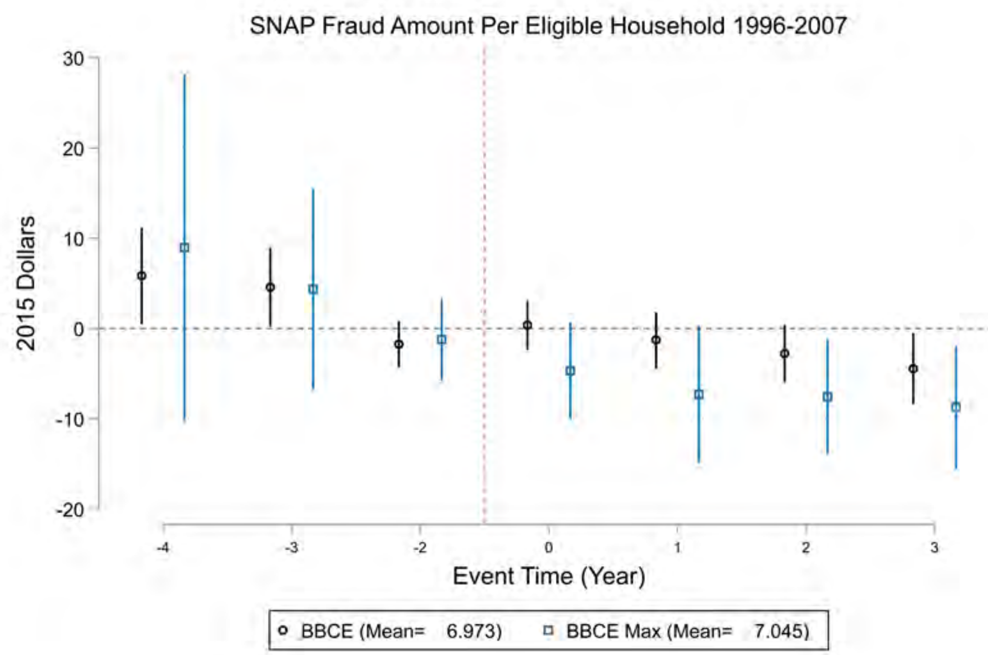
Figure C.6: SNAP Fraud Cases and Benefit Amount: All Event Estimates



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

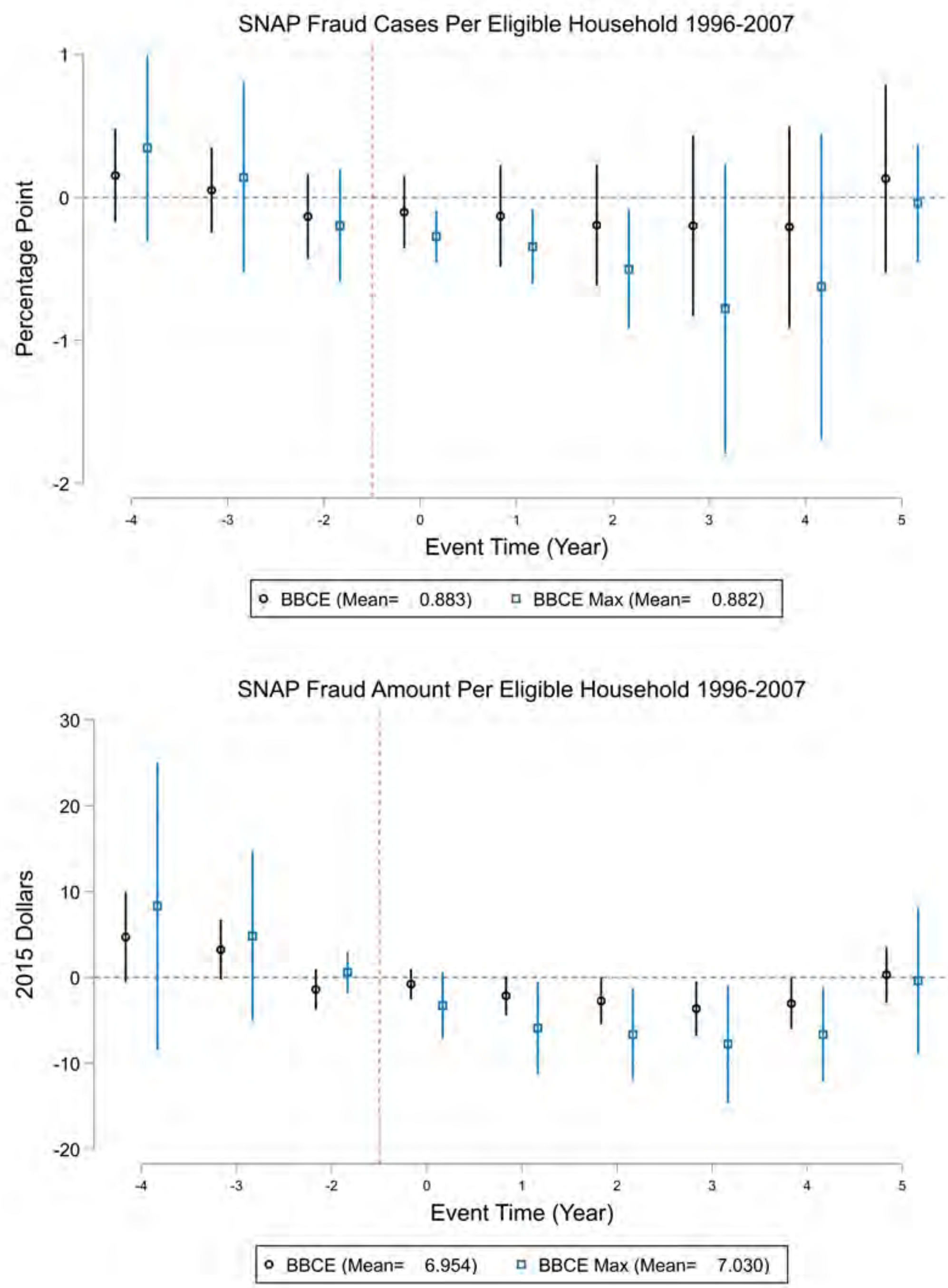




Sun & Abraham (2021) Event Study Estimates. Weighted by the size of always eligible (for any month) households. Clustered standard errors at state level.

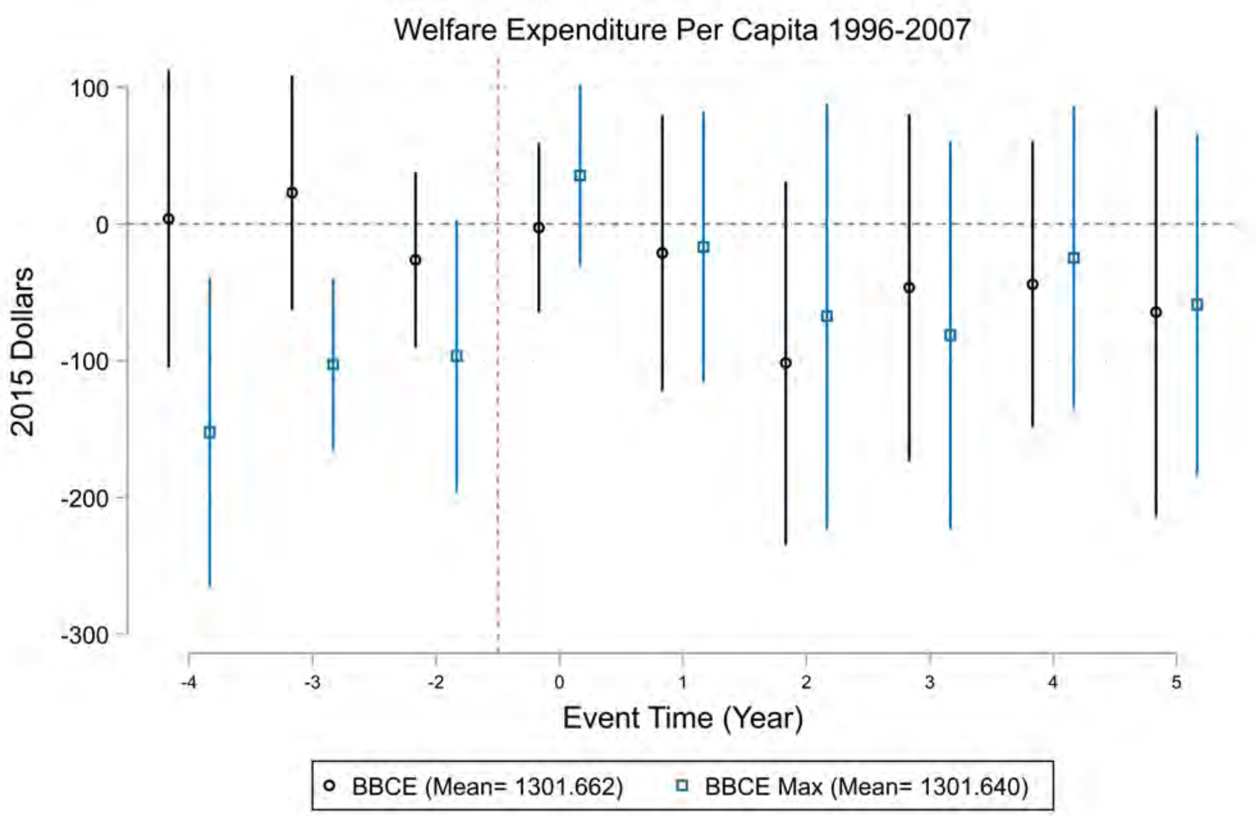
Eleven out of thirteen treated states (about 87% of the sample) are included in the balanced panel of BBCE. Six out of seven treated states (about 93% if the sample) are included in the balanced panel of BBCE Max.

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



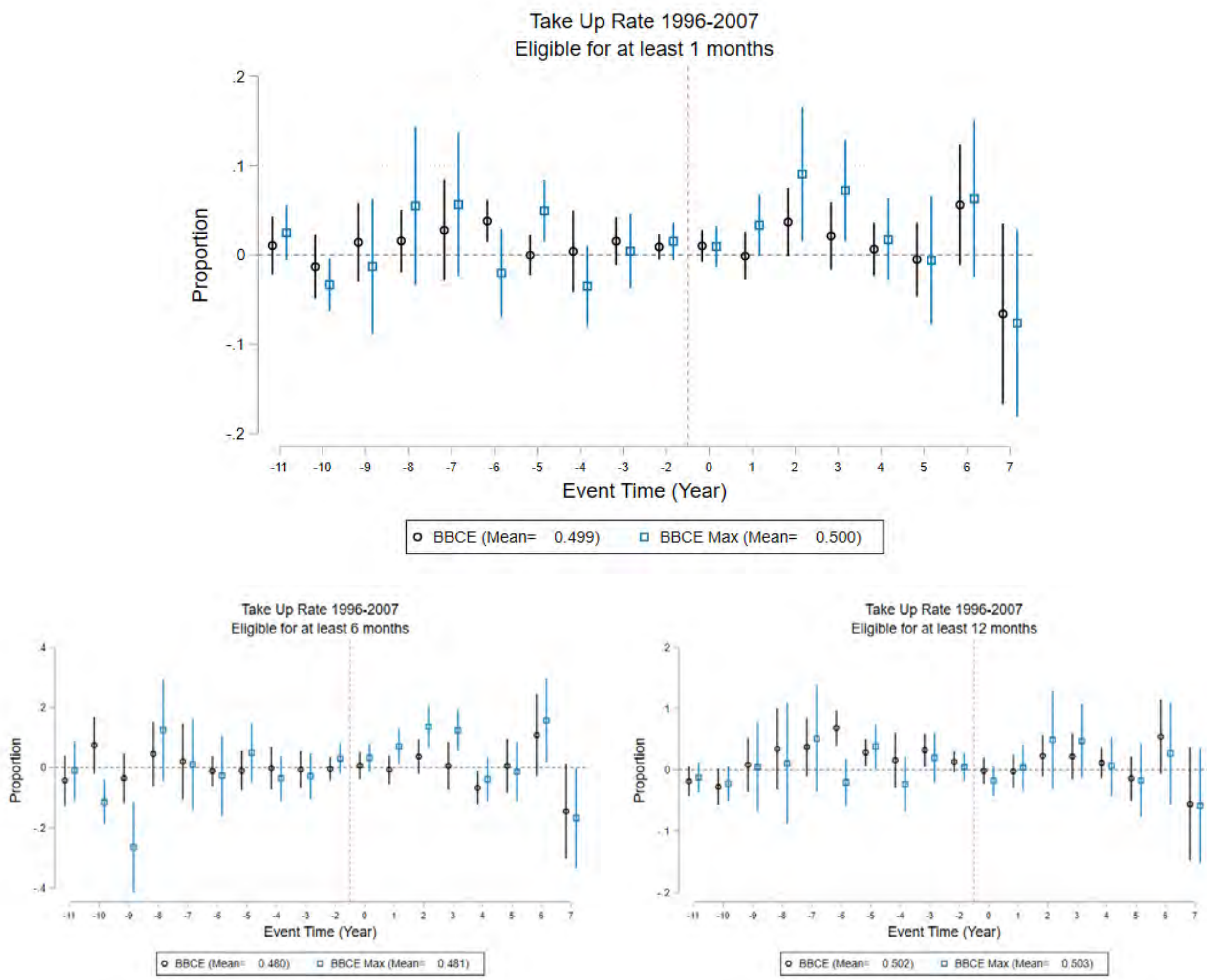
Sun & Abraham (2021) Event Study Estimates. Weighted by the size of always eligible (for any month) households. Clustered standard errors at state level.

Figure C.9: State Welfare Expenditures



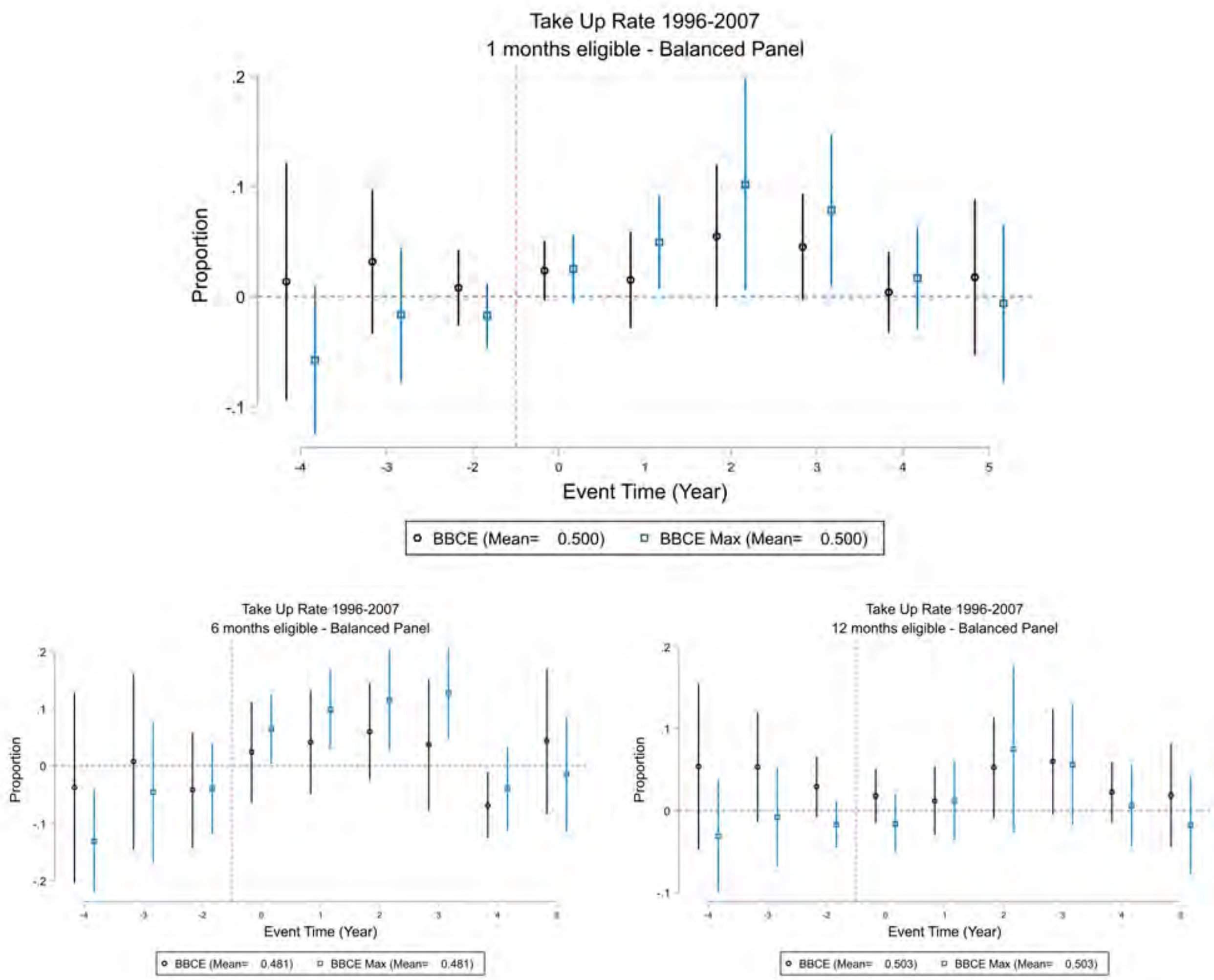
Sun & Abraham (2021) Event Study Estimates. Weighted by the size of always eligible (for any month) households. Clustered standard errors at state level.

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 convariates as well as state and year fixed effects included.

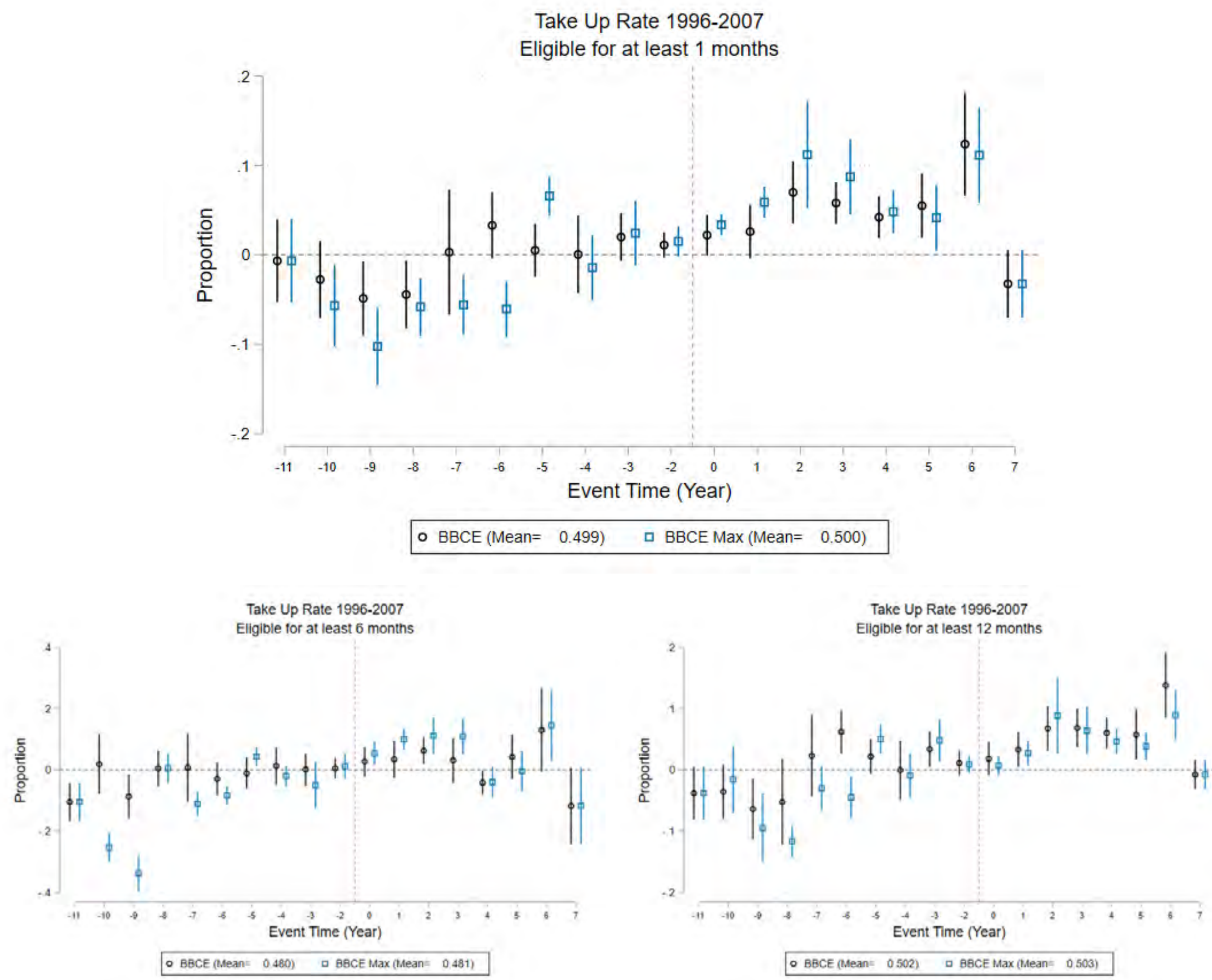
Figure C.11: Take-Up Among Always Eligible: Balanced Panel



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

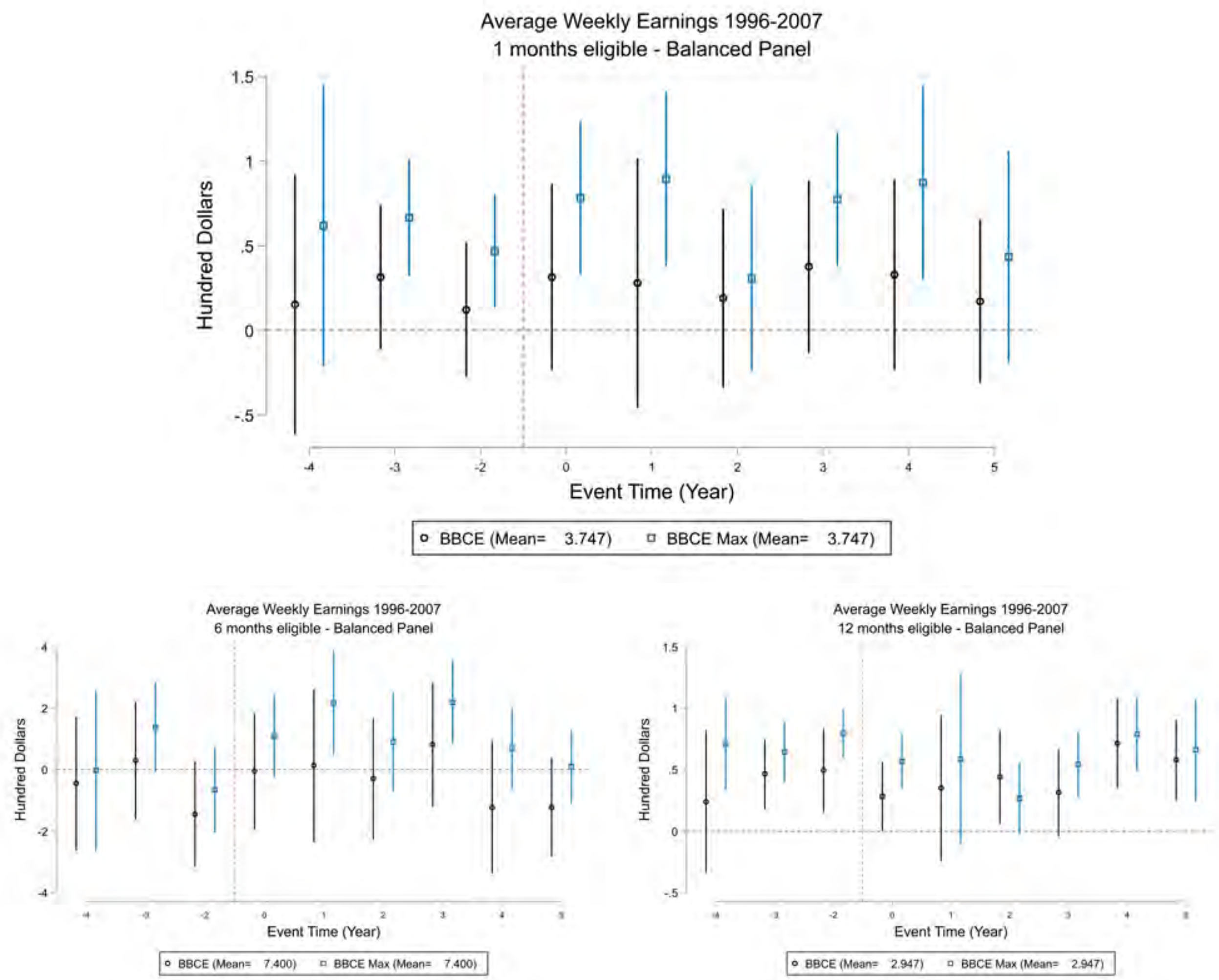
Eight out of thirteen treated states (about 85% of the sample) are included in the balanced panel of BBCE. Five out of seven treated states (about 88% if the sample) are included in the balanced panel of BBCE Max.

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 convariates 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% if the sample) are included in the balanced panel of BBCE Max.