Broad-Based Categorical Eligibility Policy and SNAP Participation

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Abstract

The Broad-Based Categorical Eligibility (BBCE) policy allows states to bypass federal gross income and asset tests for Supplemental Nutrition Assistance Program (SNAP) eligibility. Policymakers often propose limiting BBCE's scope or eliminating it altogether. Yet, our understanding of BBCE's impact on SNAP participation has relied solely on static two-way fixed effects (TWFE) estimators, which have been criticized for assuming no treatment effect heterogeneity across states and over time. In this study, using a heterogeneity-robust difference-in-differences estimator, we provide new estimates of BBCE's impact that are more than twice as large as those derived from the static TWFE models. Importantly, our event-study analysis shows that BBCE's effect has increased uniformly over time across state groups defined by their adoption timing, explaining the smaller effects estimated by the static TWFE model. Additionally, we find that although BBCE extended eligibility to higher-income households, most of its impact on participation occurred among households already eligible under federal gross income limits. Our counterfactual simulations further show that between 2000 and 2016, extending eligibility to higher-income households accounted for approximately 11.5% of the increase in participation and 3.8% of the rise in program spending resulting from BBCE, with the remainder driven by already income-eligible households.

Keywords: SNAP Participation, Broad-Based Categorical Eligibility, Difference-in-Differences, Staggered Treatment Adoption, Treatment Effect Heterogeneity

JEL Classification: C13, C23, C32, C54, I38

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1 Introduction

Over the past two decades, the Supplemental Nutrition Assistance Program (SNAP) has witnessed exponential growth in both participation and spending. While the program's expansion has underscored its critical role in reducing the prevalence of food insecurity (see, e.g., Smith and Gregory 2023), it has also spurred policy debates about how best to shape its future. At the heart of these debates is the state-level Broad-Based Categorical Eligibility (BBCE) policy (Waxman and Joo 2019; Wheaton 2019; Congressional Budget Office 2012; Congressional Research Service 2022), which allows states the flexibility to expand program eligibility to households whose gross incomes and countable resources may exceed thresholds specified by federal eligibility rules.

This policy flexibility has made BBCE a focal point of legislative debate in recent years. For instance, the House-passed version of the 2014 Farm Bill (H.R.2642 2014) sought to eliminate BBCE entirely. A similar sentiment echoed in the House-passed version of the 2018 Farm Bill (H.R.2 2018), albeit with a more limited approach of restricting rather than eliminating BBCE (see Congressional Research Service 2022, for a fuller discussion of these proposals). In 2019, the Trump Administration also proposed a rule to limit BBCE, arguing that it confers eligibility without "a robust eligibility determination," thereby "[compromising] program integrity" (see USDA-FNS 2019). Although none of these proposals were enacted into law, they highlight the ongoing need for a comprehensive analysis of BBCE's impact on SNAP participation, particularly among higher-income participants to better inform such policy debates.

Our study aims to provide a comprehensive evaluation of BBCE's role in the notable rise in SNAP participation since its introduction. Rigorous evaluations of this policy are crucial for informing evidence-based policymaking and assessing its potential adjustments aimed at addressing ongoing controversies, such as the so-called BBCE "loophole" (see, e.g., Bergh and Rosenbaum 2023; Edwards 2023). We present new estimates of BBCE's effects on SNAP participation using a recently developed difference-in-differences (DD) estimator whose identifying assumptions are better suited to the policy's staggered adoption across states. We also estimate BBCE's dynamic effects and assess whether its impact on participation emerged immediately after adoption or intensified over time with prolonged policy exposure.

Moreover, we examine policy heterogeneity based on the socioeconomic characteristics of SNAP participants—namely, gross income level, household composition, and participation in other welfare programs—to identify which subpopulations are most affected by BBCE. Understanding this heterogeneity is critical, as the policy's design may have produced differential effects on program participation depending on household circumstances. For example, regarding gross income level, we might expect a smaller impact on higher-income households if they remain ineligible due to other binding eligibility criteria (e.g., the net income test) or, if eligible, perceive the lower monthly benefits associated with higher income as less appealing. Finally, we supplement our analysis with counterfactual simulations to estimate how program participation and benefit spending would have evolved had no states adopted BBCE.

Previous studies have investigated the role of various state-level SNAP policy options, including BBCE, in expanding program participation over recent decades (Kabbani and Wilde 2003; Ribar, Edelhoch, and Liu 2008; Klerman and Danielson 2011; Mulligan 2012; Ziliak 2015; Han 2016; Klerman and Danielson 2016; Ratcliffe et al. 2016; Ganong and Liebman 2018; Dickert-Conlin et al. 2021).[1] For instance, using SNAP Quality Control data, Klerman and Danielson (2011) estimated that BBCE expansion increased SNAP participation by 6%. Using data from the Current Population Survey, Ziliak (2015) estimated an 8% increase in participation. Similarly, Klerman and Danielson (2016), using administrative SNAP participation data from the U.S. Department of Agriculture's Food and Nutrition Service (USDA-FNS), found short-term effects of 4–5% and long-term effects of 8–11%, depending on the specification. Additionally, Ganong and Liebman (2018), using USDA-FNS administrative

[1] Although SNAP benefits are federally funded, the program is administered jointly with states.

data, estimated that BBCE was responsible for a 6% increase in SNAP participation.

These studies commonly exploit variations over time and across states due to the *staggered* adoption of BBCE—where states adopted the policy at different times—using a *static* two-way fixed effects (TWFE) model, invoking the so-called "parallel trends" assumption.[2] However, in such settings, even if the parallel trends assumption holds, this model provides a "causally interpretable" estimate of the policy's effect only if treatment effects are homogeneous across time and states—an assumption that is often implausible in empirical applications.[3]

In the case of BBCE, a homogeneous treatment effect assumption is difficult to justify *a priori*, as states adopted the policy at different times and differ in both observed and unobserved characteristics, which in turn could lead to treatment effect heterogeneity. This is problematic because when such heterogeneity is present, the static TWFE model recovers a weighted sum of average treatment effects across states and over time—where some weights may be negative. As a result, the model can produce misleading estimates, including negative treatment effects even if the policy increased SNAP participation in every treated state (De Chaisemartin and d'Haultfoeuille 2020; Goodman-Bacon 2021; Borusyak, Jaravel, and Spiess 2024; Baker et al. 2025), casting doubt on the relevance of such estimates for policymaking.

This study expands upon existing research in several ways. First, we highlight the lack of a credible causal interpretation in the static TWFE model's estimates of BBCE's effects on SNAP participation, due to its reliance on ad hoc homogeneity assumptions. We demonstrate this by comparing static TWFE estimates to those from a heterogeneity-robust difference-in-differences (DD) estimator developed by Callaway and Sant'Anna (2021) (CSDD). Our results reveal that when accounting for treatment effect heterogeneity, the estimated average

[2]Throughout, we use the term "static" to refer to a model that estimates BBCE's impact as a singular treatment effect that does not vary over time. In contrast, we use the term dynamic" to refer to a specification that allows for non-parametric changes in treatment effects over time (see Sun and Abraham 2021).

[3]As we point out below, static TWFE models that include covariates also require an additional assumption: treatment effects must be homogeneous across covariate strata for the estimated treatment coefficient to be causally interpretable (see, e.g., Caetano et al. 2022; Caetano and Callaway 2024).

effect of BBCE on per-capita SNAP participation more than doubles—from 5.9% under the static TWFE model to 15.3% using the CSDD estimator—suggesting that the static TWFE model significantly underestimates the policy's true effect.

Moreover, our study is the first to conduct an event-study analysis using dynamic versions of the TWFE and CSDD estimators to explore how BBCE's impact on SNAP participation has evolved over time. Although the dynamic TWFE model allows treatment effects to change over time, it requires all "groups" of BBCE-adopting states—defined by their adoption timing—to follow the same treatment effect trajectory (see Sun and Abraham 2021). As with the static TWFE model, a failure of this homogeneity assumption limits the causal interpretability of dynamic TWFE estimates. Therefore, we also compare dynamic TWFE estimates to those from the dynamic CSDD estimator, which accommodates arbitrary treatment effect heterogeneity. Interestingly, the resulting estimates are statistically indistinguishable, with both indicating that BBCE's effect on SNAP participation has increased over time, from about 3% in the implementation year to over 24% after seven years of implementation, where it reaches a plateau. This result suggests that while BBCE's effect has evolved over time, it has done so uniformly across different groups of BBCE states, which also helps explain the smaller effects estimated by the static TWFE estimator.

Furthermore, we conduct heterogeneity analyses using socioeconomic characteristics of the SNAP participants. Importantly, we explore whether BBCE's effect on SNAP participation is driven primarily by expanding eligibility to higher-income households or by increasing participation among households already eligible under federal rules. We find that, although SNAP participation among households with gross incomes slightly above federally set thresholds has been more responsive to BBCE, the absolute increase in participation from these otherwise ineligible households has been relatively small due to their low representation in the total SNAP population. As a result, BBCE's overall impact on SNAP participation appears to be primarily driven by increased take-up among households already eligible under the federal gross income test. Our heterogeneity analyses based on other socioeconomic characteristics also indicate higher responsiveness to BBCE among subpopulations more likely to be constrained by gross income test thresholds, such as households with earned income.

Finally, we conduct counterfactual simulations to project how SNAP participation and benefit spending would have evolved from 2000 to 2016 had BBCE not been adopted by any state, holding all else equal. Our findings suggest that, without BBCE, annual SNAP enrollment would have been lower by approximately 1.6 million individuals on average, and annual benefit spending would have been about $2.2 billion lower—amounting to 27.3 million fewer participant-years and $37.1 billion in foregone benefits over the 17-year period. We also show that BBCE's expansion of eligibility to higher-income households accounts for around 11.5% of the total increase in participation and approximately 3.8% of the additional benefit spending, or about $82 million per year. The remaining effect is attributable to increased take-up among households already eligible under the federal gross income threshold.

2 Institutional Background

SNAP eligibility can be determined through two main pathways. The first involves passing a gross income test, a net income test (i.e., gross income minus indispensable household expenditures such as childcare, shelter, and medical costs), and an asset test. Gross income must not exceed 130% of FPG, and net income should remain below 100% of FPG.[4] The asset test has varying thresholds based on household type. In fiscal year 2022, the liquid asset threshold was set at $3,750 for households with elderly or disabled members and $2,500 for other households.[5]

Alternatively, a household can be automatically or "categorically" eligible for SNAP, based on receipt of *cash* benefits from other means-tested assistance programs such as the

[4]Households with elderly or disabled members only need to meet the net income test.

[5]When determining a household's liquid assets, the value of their home, retirement accounts, and education savings are not considered. In contrast, if a household owns a vehicle with a market value exceeding $4,650, its value will be included in the asset evaluation. However, states have the option to exempt the first vehicle with market value lower than $15,000. Furthermore, licensed vehicles typically are not counted toward the test (USDA-FNS 2024).

Temporary Assistance for Needy Families (TANF), the Supplemental Security Income (SSI), or the state-run General Assistance (GA) programs. In such cases, households bypass the federal gross income and asset tests but must still pass the net income test. The eligibility landscape saw a considerable shift after the 1996 welfare reforms when states were authorized to introduce and implement BBCE policies. These policies allow households to become automatically eligible for SNAP even if they are beneficiaries of exclusively *non-cash* benefits from TANF, thus expanding categorical eligibility beyond its traditional form.

Under BBCE, states have the discretion to increase the gross income test threshold from the federally mandated limit of 130% of FPG to a maximum of 200% of FPG. Additionally, they can raise the asset test threshold or even choose to eliminate it.[6] The staggered implementation of BBCE across the United States (US) is graphically represented in Figure 1. The onset of the Great Recession in 2008 resulted in a substantial increase in the number of states implementing BBCE. Table 1 categorizes states by the year they first adopted BBCE, grouping them into nine adoption groups, along with a separate category for the ten states that had not implemented BBCE as of 2016.

The varying intensities of BBCE implementation by states, stemming from the gross income test, is presented in Figure 2. The gross income threshold varies substantially across BBCE states, likely due to differences in economic conditions of states such as the cost of living and wage rates. Notably, several states shown in the lightest gray, such as Alabama, Louisiana, and West Virginia, opted to maintain their existing gross income test limits of 130% of FPG. It is also important to highlight that BBCE states could adjust their eligibility criteria over time. For example, South Carolina began to relax its gross income test threshold to 200% of FPG in 2001 but then reverted to 130% of FPG in 2009 while still maintaining

[6]Other safety net programs in the United States, such as Medicaid and the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC), also use categorical eligibility to extend benefits to individuals participating in other means-tested programs. For instance, WIC grants automatic eligibility—referred to as "adjunctive eligibility"—to individuals receiving SNAP, Medicaid, or TANF, bypassing a separate income test. However, BBCE is distinct because, unlike these programs, which apply categorical eligibility within fixed federal guidelines, it grants states the flexibility to modify or eliminate SNAP's gross income and asset tests.

its BBCE status.

As exhibited in Figure 3, all BBCE states have modified their asset test thresholds at the beginning or during their implementations of BBCE either by raising these thresholds or by removing them entirely. The majority of these states have chosen to eliminate the asset test throughout their BBCE implementation periods, with the exception of Idaho, Michigan, Minnesota, Nebraska, Pennsylvania, and Texas. Overall, the observed variation in BBCE adoption timing, differences in gross income and asset test adjustments across states, and other unobserved heterogeneities across adopting states may indicate that the policy's impact on SNAP participation varies across states and over time.

3 Data

3.1 Construction of SNAP Participation Measures

We examine how the adoption of the BBCE policy by states affects program participation rates for the total SNAP population and for specific subpopulations defined by gross income level, household composition, and participation in other welfare programs. Our primary dataset on SNAP participation originates from the 1996–2016 public-use SNAP Quality Control (QC) database[7] from USDA-FNS (USDA-FNS 2022). This dataset includes a stratified sample of households participating in SNAP based on administrative records, along with their economic and demographic data.

For the total population analysis, we measure monthly SNAP participation at the state level using SNAP QC data. To do this, we collapse household-level data to the state-month level, applying household sampling weights. We then normalize this measure using annual state-level population data from the US Census Bureau to derive per-capita participation.

For the analysis by household gross income level, we define eight mutually exclusive

[7]This sample period was chosen because information about state-level SNAP policy options was only available during these years.

income groups from 0% to 200% of FPG, each incremented by approximately 25%. We calculate the number of SNAP participants in each state-year income group by summing individuals within the group and applying sampling weights from the SNAP QC data. To facilitate analysis, we construct a pseudo per-capita participation measure, defined as the ratio of participants in each income group to the total state population.[8]

For the analyses by household composition and participation status in other welfare programs, we categorize participants based on several key characteristics: whether households include members who are disabled or elderly, whether there are members earning income, and whether they receive cash benefits from welfare programs including TANF, SSI, and state-funded GA programs. As with income groups, we construct the pseudo per-capita participation for each group by summing the SNAP recipients in the SNAP QC data, weighted by the population weights.

3.2 Construction of SNAP Policy Measures

We obtain monthly state-level SNAP policy data from the USDA Economic Research Service's public-use SNAP Policy Database (USDA-ERS 2022). This database includes information about adoption of BBCE by states, including their asset and gross income test thresholds. Additionally, we extract details on eight other SNAP policies identified in previous research as potentially affecting SNAP participation. These policies include adoption of online applications, establishment of statewide call centers to assist with application and re-certification, waiver of face-to-face interviews for initial certification or re-certification, allowing for simplified reporting of income changes, allowing for Combined Application Project for SSI recipients, exemptions on at least one vehicle, existence of SNAP participants' re-certification period greater than three months, and adoption of Electronic Benefit Transfer (EBT) systems (see Ganong and Liebman 2018; Melvin and Smith 2022).

[8]Our pseudo per-capita participation differs from the conventional measure by using the total state population as the denominator rather than the specific income group's population. Consequently, the sum of all pseudo per-capita participation values across income groups equals the outcome variable for the total population analysis.

Because states often adopted multiple policies simultaneously, it might be difficult to identify policies' individual effects with statistical precision. Thus, to avoid potential issues with multicollinearity, we follow other studies (Ganong and Liebman 2018; Valizadeh, Fischer, and Bryant 2024) and construct a policy index by averaging the above eight SNAP policies. This produces a score between zero and one, proxying a state's flexibility in administering SNAP. However, unlike earlier studies, we do not include the BBCE policy in our policy index as we are interested in its distinct treatment effect on SNAP enrollment.[9]

For socioeconomic factors, we extract annual state population and the percentage of the population with incomes below 185% of FPG from the US Census Bureau's Current Population Survey (CPS) maintained as the Integrated Public Use Microdata Series (IPUMS) (Flood et al. 2021). Additionally, we obtain annual state unemployment rates from the Bureau of Labor Statistics' Local Area Unemployment Statistics series (BLS-LAUS 2022).

3.3 Aggregation to State-Year Level

We aggregate state-month participation and policy data to the state-year level, in part, because some variables used in the analysis are only available at the state-year level. More importantly, as explained below, to deploy the CSDD estimator, it is recommended to assign BBCE states into a smaller number of "groups" (defined by adoption timing), each including at least a few states (see Table 1), rather than having many single-state groups (Callaway and Sant'Anna 2021).[10] We calculate annual average SNAP participation for each state by averaging the monthly data over the months of the year.

[9]In robustness checks, we included the statewide fingerprinting requirement, which has also been found to affect SNAP enrollment (see Dickert-Conlin et al. 2021), as an additional component of the policy index. We also estimated models where each policy from the index was included individually as a binary variable. Our estimates of BBCE's effect were quantitatively indistinguishable from those in our main analyses (available upon request).

[10]If we were to use monthly data, we would assign several states, such as Maine, Oregon, Washington, and Wisconsin into single-state groups. The issue persists to some extent even when using state-year data. As shown in Table 1, two of the adoption groups—those for 2006 and 2007—each include only a single state. As discussed below, we assess the robustness of our results by (1) combining these two groups—once as Group 2006 and once as Group 2007—and (2) excluding them from the analysis. Our findings remain robust to these adjustments.

To aggregate monthly policy data, in our main analysis, we consider a state an adopter of a specific policy (e.g., BBCE) in a given year if that state had implemented the policy for at least one month in that year. We refer to this as the *partial-year* aggregation scheme. To examine the sensitivity of our results to this definition, we consider two alternative definitions: the *majority-year* aggregation scheme, where a state is classified as a BBCE adopter if it maintained BBCE for more than six months, and the *full-year* aggregation scheme, where a state is classified as a BBCE adopter only if it applied BBCE for the entire year. Adoption status under these alternative schemes is presented in Appendix Figures A1 and A2.[11]

3.4 Visualization and Summary Statistics

Our final analysis sample consists of 1,071 state-year observations, covering all 50 states plus the District of Columbia over the 1996–2016 period.[12] Figure 4 shows the trajectory of average SNAP participation per capita for BBCE and non-BBCE states. BBCE states consistently demonstrate higher average per-capita participation. Following the BBCE's introduction in the early 2000s, we see a divergence in per-capita participation peaking during the Great Recession. Concurrently, an increasing number of states started to adopt BBCE (Figure 1). Notably, BBCE states often implemented additional policies that may have potentially encouraged participation, further contributing to the observed divergence in participation between the two groups.[13] Over the 2009–2016 period, the divergence continued to grow. Since most BBCE states had already long implemented BBCE by this point, it is

[11] These alternative schemes result in a larger number of single-state groups. Nonetheless, we provide estimates under these different scenarios as robustness checks.

[12] The CSDD estimator applies to "absorbing" treatments, meaning that once a treatment is adopted, it cannot be reversed. However, as shown in Figure 1, this is not the case for Louisiana, where the treatment was reversed in 2015 and 2016. To maintain the balanced structure of our panel, we replace Louisiana's treatment status with an indicator for ever having received the treatment while implementing the CSDD estimator. This new treatment variable is absorbing by construction and accounts for the effect of ever having implemented BBCE in Louisiana (see Sun and Abraham 2021). Below, we show that our results remain qualitatively unchanged with this adjustment.

[13] Appendix Figure A3 shows the trajectory of our SNAP policy index for BBCE and non-BBCE states. The divergence began in year 2003, but the differences are largely sustained thereafter.

plausible to hypothesize that the impact of BBCE on SNAP enrollment had intensified over time.

Table 2 presents summary statistics for all variables used in our empirical analyses by states BBCE adoption status. The difference in SNAP participation per capita between the two groups are statistically significant, with BBCE states typically exhibiting higher participation rates. Unemployment and income-to-poverty ratio metrics also diverge statistically significantly between the two groups. There is however no statistically significant difference in the SNAP policy index across the two groups. The summary statistics for the pseudo per-capita participation by socioeconomic characteristics are also presented in Appendix Table A1. Similarly, BBCE states register higher participation across all groups, except for participants with household income below 25%.

4 Empirical Methods

4.1 Static Two-Way Fixed Effects Model

We first estimate the effect of the staggered implementation of BBCE on per-capita SNAP participation using the static TWFE model, commonly specified as follows:

$$S_{it} = \beta BBCE_{it} + \mathbf{X}'_{it}\delta + \theta_i + \mu_t + \epsilon_{it}, \tag{1}$$

where S_{it} represents the logarithm of per-capita SNAP participation—either for the total population or for a specific socioeconomic subpopulation—in state $i = 1, ..., N$ at year $t = 1, ..., T$, for $N = 51$, and $T = 21$; $BBCE_{it}$ is a binary treatment variable indicating if state i in year t adopted BBCE; X_{it} is a vector of control variables, discussed momentarily; θ_i and μ_t are state and year fixed effects to account for unobserved confounders that only vary either across states or over time, respectively; and ϵ_{it} is an idiosyncratic error term. The coefficient of interest is β, which—under the implicit assumption of no treatment effect heterogeneity across either groups of states or over time—captures the causal impact of BBCE adoption on per-capita participation in adopting states[14] provided that a parallel trends assumption is met (De Chaisemartin and d'Haultfoeuille 2020; Goodman-Bacon 2021; Borusyak, Jaravel, and Spiess 2024).

The parallel trends assumption states that in the absence of BBCE, trends in mean per-capita SNAP participation would have followed parallel paths over time between BBCE and non-BBCE states. While the parallel trends assumption is fundamentally untestable, the unobserved selection process leading to BBCE adoption may be intertwined with specific state-level attributes, casting doubt on its plausibility. A common approach to increase the plausibility of the parallel trends assumption is to assume that it holds conditional on covariates (see, e.g., Sant'Anna and Zhao 2020; Roth et al. 2023). The specific covariates we consider include the state-level unemployment rate, poverty rate, and SNAP policy index. We include these covariates because they may plausibly influence BBCE adoption and are also identified as important state-level determinants of SNAP enrollment in prior research (see Valizadeh, Fischer, and Bryant 2024, and references therein).[15] Therefore, incorporating them in the model could mitigate concerns about the non-random adoption of BBCE across states.[16]

[14]Since our model is specified in a log-linear form, we convert β to the marginal effect using Kennedy's method (Kennedy 1981).

[15]For instance, we may expect states with higher unemployment rates to be more likely to implement BBCE to provide broader access to SNAP benefits during periods of economic downturn. Similarly, states with higher poverty rates or more lenient SNAP policies may be more likely to adopt BBCE to address food insecurity concerns or reduce administrative burden.

[16]Caetano et al. (2022) examine DD identification strategies using TWFE regressions that incorporate time-varying covariates. Briefly, it is not recommended to simply include such covariates in TWFE specifications. If the covariates are affected by treatment participation, they are considered "post-treatment" or "bad controls," and their inclusion can introduce bias (see also Sant'Anna and Zhao 2020). This issue is less likely to arise in our application because state-level variables such as the unemployment rate and poverty rate generally reflect broader macroeconomic conditions that are unlikely to be causally influenced by a state's BBCE adoption. Nevertheless, we empirically examine this by using the CSDD estimator and by treating each of the three covariates as an outcome variable. Overall, none of the covariates exhibit sustained statistically significant treatment effects, suggesting they are less likely to be affected by BBCE adoption (see Appendix Figure A4). Given this and considering that we use TWFE solely as a benchmark to replicate findings from prior research, we follow those studies in including the full time path of time-varying covariates while noting that these covariates are unlikely to be endogenous in our setting. Still, even if covariates are correctly selected, TWFE specifications require an additional assumption that treatment effects are constant across covariate strata in order to yield causally interpretable estimates—an assumption that is

Nonetheless, even under the parallel trends assumption, the static TWFE estimator may fail to yield a causally interpretable estimate of BBCE's average treatment effect on treated states (ATT) if treatment effects are heterogeneous across state groups or over time. Broadly, with the staggered treatment adoption, the BBCE effect under TWFE estimation is a weighted sum of ATTs based on three types of comparisons: (1) earlier-/later-BBCE adopting states (treatment) vs. non-BBCE states (control), (2) earlier-BBCE adopting states (treatment) vs. later-BBCE adopting states (control), and (3) later-BBCE adopting states (treatment) vs. earlier-BBCE adopting states (control). The latter type, referred to as a "forbidden comparison," can substantially distort the TWFE estimator's weights on ATTs for some group-time combinations or even make them negative when treatment effects vary across groups or over time (see De Chaisemartin and d'Haultfoeuille 2020; Goodman-Bacon 2021; Borusyak, Jaravel, and Spiess 2024).

The possibility of negative weights is particularly concerning because it is possible, for example, to get a negative TWFE estimate of the ATT even if all groups of BBCE states experience a positive effect of the policy on per-capita SNAP participation (see, e.g., De Chaisemartin and d'Haultfoeuille 2020, for a fuller discussion). Goodman-Bacon (2021) proposed a decomposition approach to evaluate whether TWFE estimators can provide meaningful causal estimates. Briefly, this method decomposes the TWFE estimator into all possible canonical two-group/two-period DD estimators. This TWFE approach however is not guaranteed to recover an interpretable causal parameter if there is a significant disparity between the estimates from "clean comparisons" (i.e., the first two types described above) and those derived from forbidden comparisons. This inconsistency becomes particularly pronounced when substantial weight is assigned to estimates from forbidden comparisons. We employ this decomposition in our analysis to better assess whether TWFE yields a reasonable causal estimate.

often implausible in practice (see Caetano and Callaway 2024). As we discuss below, our main analysis using the CSDD estimator more appropriately incorporates "pre-treatment" values for these covariates through the doubly robust estimator proposed by Sant'Anna and Zhao (2020), without restricting treatment effect heterogeneity across covariate strata.

4.2 Dynamic TWFE Estimator

One approach to allow for treatment effect heterogeneity over time in the TWFE estimator is to specify a dynamic specification, including leads and lags of the treatment, as follows (see, e.g., Sun and Abraham 2021):

$$S_{it} = \sum_{\tau=-15}^{-2} \beta_\tau BBCE_{it}^{\tau} + \sum_{\tau=0}^{16} \beta_\tau BBCE_{it}^{\tau} + \mathbf{X}_{it}^{\prime}\delta + \theta_i + \mu_t + \nu_{it} \tag{2}$$

where $BBCE_{it}^{\tau}$ are dummy variables for each year $\tau \in [-15, -2]$ before the implementation of BBCE in state i (leads), and for each year $\tau \in [0, 16]$ after the implementation (lags).[17] ν_{it} is an idiosyncratic error term, and other terms are defined as before.

In equation (2), under the implicit assumption of no treatment effect heterogeneity across groups of BBCE states, the coefficients β_τ on the lead dummies ($\tau < 0$) capture the effect of the treatment in the years leading up to the policy adoption. In the absence of anticipatory effects, omitted confounding effects, or model misspecification, these pre-policy terms should not have a significant trend in τ, providing a falsification test commonly used to examine the plausibility of the parallel trends assumption. Similarly, the coefficients β_τ on lagged dummies ($\tau \geq 0$) capture the effect of the treatment in the years following BBEC implementation.

Because this dynamic specification estimates the effects at different time distances from policy implementation year, it enables an assessment of BBCE's dynamic impact over time. However, as with the static TWFE specification, challenges arise with this dynamic model when the implicit assumption of constant treatment effects across all groups of states in a given relative year τ is violated. In this case, the coefficient on a given lead or lag can be contaminated by effects from other periods and may not have a reasonable causal interpretation

[17] We exclude the relative year $\tau = -1$ from equation (2), treating it as the reference year, to avoid perfect multicollinearity. Also, the largest lead and lag are 15 and 16, respectively, indicating that within our dataset, the states with the most prolonged lead time to BBCE adoption are Colorado, Iowa, and Nebraska (which adopted the policy in 2011), while Delaware, Maine, Michigan, North Dakota, and Oregon stand out for the longest implementation period since 2000 (see Table 1).

(Sun and Abraham 2021). Overall, while the dynamic TWFE is more flexible than its static counterpart, it still relies on restrictive homogeneity assumptions, making interpretation of its lead and lag coefficients difficult.

4.3 Callaway and Santa'Anna DD Estimator

To address concerns about negative weights and relax the treatment effect homogeneity assumptions underlying the TWFE models, we deploy the semi-parametric DD estimator introduced by Callaway and Sant'Anna (2021) (CSDD).[18] The CSDD estimator first estimates group- and time-specific average treatment effects on treated states (ATT), using two-group/two-period DD estimators. These are then aggregated using policy-relevant weighting schemes that are non-negative (discussed below) to produce interpretable summary treatment effect estimates.

Let $g \in \{2000, 2001, 2004, 2006, 2007, 2008, 2009, 2010, 2011\}$ denote the year in which a group of states first started implementing BBCE (see Table 1). The CSDD estimator provides two approaches for estimating the group-time-specific ATT, denoted by $ATT(g, t)$. The first approach relies on *never-treated* (NT) states, consisting exclusively of ten non-BBCE states, to construct a control group. This approach takes a group of states implementing BBCE in year g and compares average outcomes in any post-implementation year $t \geq g$ to average outcomes for the same group in the year immediately prior to adoption (i.e., year $g - 1$). It then subtracts the difference in outcomes for the same two periods for the single group of NT states. More formally, an unconditional estimator for $ATT(g, t)$ using the NT control

[18] Given the recent introduction of alternative estimators to address concerns about negative weights in TWFE estimators in staggered adoption settings (e.g., De Chaisemartin and d'Haultfoeuille 2020; Sun and Abraham 2021; Callaway and Sant'Anna 2021; Borusyak, Jaravel, and Spiess 2024), some studies report estimates from multiple estimators (see, e.g., Braghieri, Levy, and Makarin 2022). However, Arkhangelsky and Imbens (2024) argue that reporting results from all possible estimators "does not do justice to the fact that the estimators rely on fundamentally different assumptions, in particular about treatment effect heterogeneity," including differences in the types of parallel trends assumptions they impose and the choice of baseline periods (see Arkhangelsky and Imbens 2024, for a fuller discussion).

group can be expressed via the following double difference:

$$\widehat{ATT}^{NT}(g,t) = \left(\bar{S}_{t|g} - \bar{S}_{g-1|g}\right) - \left(\bar{S}_{t|\infty} - \bar{S}_{g-1|\infty}\right) \quad \forall t \geq g, \tag{3}$$

where $\bar{S}_{t|g}$ and $\bar{S}_{t|\infty}$ denote, respectively, the within-group average of the logarithm of per-capita SNAP participation for the treatment group g and the single NT control group in year t. Likewise, $\bar{S}_{g-1|g}$ and $\bar{S}_{g-1|\infty}$ reflect within-group averages for the pre-BBCE adoption year $g-1$.

The second approach uses an alternative control group constructed as the average of the groups that adopt the treatment but do so after period t, referred to as the *not-yet-treated* (NYT) control group. This alternative estimator can be expressed using a similar double difference as above:

$$\widehat{ATT}^{NYT}(g,t) = \left(\bar{S}_{t|g} - \bar{S}_{g-1|g}\right) - \frac{1}{n(g')}\sum_{g'>t}\left(\bar{S}_{t|g'} - \bar{S}_{g-1|g'}\right), \quad \forall t \geq g \tag{4}$$

where $g' > max\{g,t\}$ denotes groups of states that adopt BBCE after period t, when we evaluate the effect for earlier-adopting BBCE states, and $n(g')$ denotes the number of g' groups.

The identification of each $ATT(g,t)$ requires the parallel trends assumption, which as mentioned above, may not hold unconditionally due to concerns about the nonrandom adoption of BBCE across states. To address this, we incorporate pre-treatment values — measured in year $g-1$ — for our covariates into both estimators using the doubly robust (DR) estimation procedure from Sant'Anna and Zhao (2020), as recommended by Callaway and Sant'Anna (2021). In our main analysis, we focus on estimates from the DR estimator using NYT control group and report results from $\widehat{ATT}^{NT}(g,t)$ as robustness checks for two reasons. First, we are concerned about the insufficient number of non-BBCE states to serve as a valid control group. Second, non-BBCE states might inherently differ from BBCE states, making them less appropriate as a control group.

We aggregate $\widehat{ATT}(g,t)$ in two ways. First, to contrast CSDD estimates with those from the static TWFE model, we compute *group-specific* ATT estimates, denoted by $\widehat{ATT}(g)$, by taking the simple (unweighted) average of all $\widehat{ATT}(g,t)$ for all post-adoption periods $t \in$ {g, g+1, ..., 2016} for each g. We then calculate the overall $\widehat{ATT}$ as a weighted average of $\widehat{ATT}(g)$ across all g, where the weights correspond to the share of states adopting BBCE in each g. This aggregation method ensures that the resultant ATT estimates are comparable to those from the canonical DD setup "in the context of multiple time periods and variation in treatment timing" (see Callaway and Sant'Anna 2021).

Next, to estimate the dynamic treatment effects of BBCE, we first convert the time period t in each $\widehat{ATT}(g,t)$ estimate to relative year $\tau = t - g$. Then, we aggregate $\widehat{ATT}(g,\tau)$ by weighting each estimate based on the share of BBCE states in group g observed at τ to obtain the dynamic $\widehat{ATT}(\tau)$ at each τ (see Callaway and Sant'Anna 2021). This is done for all relative years before and after policy implementation, with estimates from the pre-treatment periods used to assess the plausibility of the parallel trends assumption.[19]

5 Results

5.1 Full Sample Analysis

5.1.1 Static TWFE and CSDD Estimates

The estimated impact of BBCE implementation on per-capita SNAP participation using the static TWFE and CSDD estimators for the full sample are presented in Table 3. Our unconditional (Column 1) and conditional (Column 2) static TWFE estimates indicate that BBCE implementation increased per-capita SNAP participation by 8.5% and 5.9%, respectively.

[19]It is possible to summarize $\widehat{ATT}(\tau)$ across all non-negative τ values to obtain the overall estimate of the policy's effect (see Callaway and Sant'Anna 2021, equation (3.12)). Using this alternative method, we obtained slightly larger yet qualitatively similar estimates of overall $\widehat{ATT}$. However, Callaway and Sant'Anna (2021) argue that interpreting the estimated overall effect from this alternative aggregation method may be "complicated by the issue of the changing composition of groups across different values" of τ. As such, we use the aggregation method described above, which is recommended by Callaway and Sant'Anna (2021).

These point estimates are statistically indistinguishable from each other[20] and fall within the range of estimates found in previous studies (e.g., Klerman and Danielson 2011; Ziliak 2015; Ganong and Liebman 2018). The unconditional and conditional CSDD estimators, on the other hand, suggest that BBCE's introduction increased per-capita SNAP participation by statistically similar values of 15.5% and 15.3%, respectively.[21,22] These CSDD estimates are robust to the choice of never-treated states as controls (Appendix Table A2), as well as to alternative aggregation schemes (i.e., majority- and full-year methods) for converting monthly data to annual data (Appendix Table A3).[23]

A comparison of results across TWFE and CSDD estimators in Table 3 indicates that as we account for the possibility of treatment effect heterogeneity via the CSDD estimator, we see a substantial increase in the estimated effect of BBCE implementation on SNAP participation across both specifications with and without covariates. Since previous studies exploring the state-level determinants of SNAP participation use conditional specifications, for comparison purposes, we prioritize interpretations based on conditional estimates. In this context, the findings show a statistically significant and economically meaningful increase of approximately 160% (9.4 percentage points, moving from 5.9% to 15.3%) in the magnitude of BBCE's estimated effect on per-capita SNAP participation.

Turning to results from the Goodman-Bacon decomposition analysis in Table 4, we ob-

[20]We used the statistical test developed in Clogg, Petkova, and Haritou (1995) to test the null hypothesis of equality of coefficients across models without and with covariates as well as between TWFE and CSDD estimators.

[21]Standard errors for TWFE and CSDD estimates are clustered at the state-level. For CSDD, standard errors are calculated using the multiplier-type bootstrap method proposed in Callaway and Sant'Anna (2021).

[22]The unconditional and conditional group-specific CSDD estimates ($\widehat{ATT}(g)$) are presented in Appendix Figures A5 and A6, respectively.

[23]Regarding the robustness of our results to the choice of estimation procedures, our CSDD estimates from alternative estimation procedures using a balanced panel, which assumes Louisiana as a BBCE adopter in 2015 and 2016 (see footnote 12), are similar (Appendix Table A4). For the unbalanced panel, which excludes Louisiana observations for 2015 and 2016, only the inverse probability weighting (IPW) estimation (Abadie 2005) was feasible, yielding qualitatively similar results to our main DR estimates based on the balanced panel (Appendix Table A5). We note that conditional CSDD estimate for group 2006, which comprises a single state (Minnesota), is infeasible due to insufficient observations to construct inverse probability weights. As a result, the overall conditional CSDD estimate does not reflect the effect of this group. Nevertheless, we show that our overall conditional CSDD estimate remains robust across alternative approaches for handling the single-state groups 2006 and 2007—either by excluding them from the analysis or by combining them into a single group (2006 or 2007)—as shown in Appendix Table A6.

serve that canonical two-by-two DD estimates using later treated groups as treatments and earlier treated ones as controls (i.e., forbidden comparisons) constitute approximately 28% of the total TWFE weights. This has a substantially lower ATT estimate of 2.2% compared to 11.6% and 8.5% exhibited by other two-by-two DD estimates (see also Appendix Figure A7).[24] Since these problematic comparisons account for a non-negligible portion of the overall TWFE estimate, we expect the TWFE model to underestimate BBCE's impact, consistent with the results in Table 3. Overall, our comparative analysis of static DD estimators underscore the importance of accounting for potential treatment effect heterogeneity when assessing the impact of BBCE implementation on SNAP participation.

5.1.2 Dynamic TWFE and CSDD Estimates

Figure 5 illustrates results from the event-study analysis by exploring the dynamic effects of BBCE. The solid circles and triangles represent point estimates of the percentage change in SNAP participation per capita from dynamic CSDD and TWFE specifications with covariates, respectively, at various lead and lag years relative to the baseline year immediately preceding BBCE implementation. All point estimates are accompanied by 95% confidence bands. The dashed and dashed-dotted lines show the corresponding static estimates reported in Table 3.

First, the estimated lead coefficients are statistically insignificant from zero, providing evidence for the parallel trends assumption conditional on covariates.[25] More importantly, the trajectory of point estimates from both the dynamic CSDD and TWFE estimators in Figure 5 illustrates the evolution of BBCE's impact post-implementation. Both estimators suggest that the impact of BBCE has increased with time since implementation, from 3%

[24] The estimate of 7.5% from the Goodman-Bacon decomposition remains unadjusted by the bias-correction method of Kennedy (1981) to calculate the marginal effect. This adjustment method is constrained because it necessitates both the point estimate and its corresponding standard error. Conventionally, the Goodman-Bacon decomposition sidesteps covariates as their inclusion alters the intrinsic nature of the treatment variable (see Goodman-Bacon 2021).

[25] Similar patterns are observed in estimates from dynamic specifications without incorporating covariates (Appendix Figure A8), providing evidence for parallel trends assumption even without conditioning on covariates. These patterns also hold for each group g (available upon request).

upon implementation (i.e., in year 0) to 25% seven years post-implementation under CSDD estimates, and likewise from 2% to 24% under TWFE estimates. In both cases, the effects appear to reach a plateau after seven years of implementation. Although dynamic CSDD point estimates tend to be slightly larger than their TWFE counterparts, particularly at earlier lags, these differences are not statistically significant.

One possible explanation is that unlike the static TWFE model, the dynamic TWFE specification allows for time-varying but homogeneous treatment effects across adoption groups. As such, the lack of significant differences between estimates from dynamic CSDD and TWFE estimators suggests that treatment effect heterogeneity indicated by results in Table 3, is primarily driven by the dynamic nature of BBCE's impact—gradually increasing over time—rather than by its differential effects across adoption groups.[26] Taken together, these findings suggest BBCE's treatment effects evolved over time but uniformly across all adoption groups.

5.2 Effects by Participants' Socioeconomic Characteristics

In previous subsections, we established that the static TWFE model yields substantially smaller estimates of BBCE's effects on SNAP participation, primarily due to its increasing impact over time. Therefore, below, we focus on estimates from the CSDD estimator to examine how these effects vary across participants' socioeconomic characteristics and direct readers to the appendix for the corresponding TWFE estimates.

Figure 6 demonstrates the estimated impact of BBCE on program participation across eight mutually exclusive groups based on household gross income level, spanning from 0% to 200% of FPG, in increments of approximately 25%. The right vertical axis, corresponding to the bar graph, denotes the proportional contribution of each group to total SNAP participation. Meanwhile, solid circles on the left vertical axis represent point estimates for the

[26] Yet, the dynamic TWFE model uses earlier treated states as controls for later treated states. Therefore, in the case of increasing treatment effects, we expect a relatively flatter pattern in the post-period for dynamic TWFE estimates as observed in Figure 5.

percentage change in per-capita participation, accompanied by 95% confidence bands.

The results indicate that BBCE increased SNAP participation across almost all income groups, including those already eligible under federal gross income limits (i.e., gross income $\leq$ 130% of FPG, hereafter referred to as "already income-eligible"). Among households with gross income above this threshold (i.e., $>$ 130% of FPG), those in the 130%–150% range exhibit the highest responsiveness, showing larger percentage increases in participation than any other higher-income group. However, because higher-income households represent a small share of the total SNAP population (right axis), their contribution to total participation growth remains limited. Thus, most of BBCE's impact on SNAP participation stems from increased take-up among already income-eligible households rather than those that would otherwise be ineligible.

Figure 7 presents results for the heterogeneity analysis by household composition and participation status in other welfare programs. We observe larger estimated effects on SNAP participation among households without disability compared to those with disability ($p < 0.01$). This might be explained by the positive association between poverty and disability status (Moffitt 2015; Coleman-Jensen 2020) or the exemption of disabled households from SNAP gross income tests. Similarly, the estimated impact is significantly larger ($p < 0.01$) among households with earned income than those without earned income, which aligns with expectations since the federal gross income limit is more likely to be binding for those with earned income. Lastly, we find higher estimated effects among households not receiving cash benefits from other welfare programs compared to those receiving cash benefits ($p = 0.03$). One explanation might be that BBCE extends eligibility to those receiving non-cash benefits from other welfare programs, and those receiving cash benefits were already categorically eligible by the traditional categorical eligibility rules.[27,28]

[27]For most socioeconomic groups, TWFE estimates were significantly smaller than CSDD estimates (see Appendix Figures A9 and A10).

[28]Dynamic estimates by participants' socioeconomic characteristics are shown in Appendix Figures A11 and A12. The estimated coefficients on lead variables provide evidence for parallel trends assumption for each socioeconomic group. Similar results were obtained from specifications without covariates (available upon request).

5.3 Counterfactual Simulation

In this section, we simulate how SNAP participation would have evolved from 2000 to 2016 under the counterfactual scenario where BBCE was never introduced, keeping all other factors (e.g., macroeconomic conditions and the policy index) unchanged. To better inform policy discussions, we perform this exercise by household gross income level, relying on our CSDD estimates, denoted by $\hat{\beta}_m$, where m indexes income groups defined above.

We first calculate simulated changes in annual per-capita SNAP participation for each income group for each BBCE state by dividing the observed per-capita SNAP participation by $(1 + \widehat{\beta}_m)$. We then recover the simulated number of SNAP participants for each income group by multiplying the simulated per-capita SNAP participation with the actual number of SNAP participants for each state and year. Finally, we obtain the simulated total number of SNAP participants at the national level by aggregating the simulated participation across all income groups and states for each year. To translate participation reductions into changes in SNAP benefit spending, we multiply the simulated participation decline for each income group by its corresponding average monthly per-capita SNAP benefit for each year, drawn from SNAP QC data.

Simulation results are shown in Figure 8. Panels A and B illustrate the simulated year-by-year reductions in SNAP participation and benefit spending, respectively, from 2000 to 2016 under a no-BBCE counterfactual scenario. The results suggest that, absent BBCE, SNAP participation and benefit spending would have been lower each year, with the largest simulated declines occurring after 2009, when most states adopted BBCE. In 2012, for example, the simulated reduction in participation would have been approximately 3.2 million participants (6.9% of total participation), and SNAP spending would have been about $4.7 billion lower (10.1% of total benefit spending) relative to observed annual levels.[29] Notably, these

[29] In comparison, Congressional Budget Office (2012) estimated that restricting Categorical Eligibility to only households receiving cash assistance would result in an average annual reduction in SNAP participation and expenditure of 1.8 million people and $1.2 billion, respectively, between 2012 and 2022. The difference in simulated impacts can be partly attributed to differences in the simulated scenarios considered and methodological differences. First, while our simulated reductions are a result of the total impact of BBCE—including

simulated reductions are primarily concentrated among already income-eligible households, who make up the majority of SNAP participants.[30]

These patterns across income groups become clearer when examining the cumulative simulated reductions in participation and spending. Over the 17-year period from 2000 to 2016, the cumulative simulated decline in participation stands at 27.3 million. Of this total, 24.2 million (88.5%) participants are from already income-eligible households, while about 3.1 million (11.5%) participants are from newly eligible households with gross incomes above 130% of FPG. Similarly, the cumulative decline in benefit spending totals nearly $37.1 billion over this 17-year period. Of this amount, $35.7 billion (96.2%) is attributable to already income-eligible households, while less than $1.4 billion (3.8%)—or about $82.4 million per year, on average—is associated with expanding eligibility to higher-income households that would otherwise be ineligible.[31]

6 Conclusion

Recent policy discussions surrounding BBCE have highlighted the need to re-evaluate its causal impact on SNAP participation and to assess the robustness of previous findings. This motivation is compounded by recent advancements in causal modeling and critiques against the static TWFE model, which has been employed exclusively by the past literature studying state-level determinants of SNAP participation, including the BBCE policy. More specifically, the static TWFE model's identifying assumption of homogeneous treatment

both its effect on the otherwise-eligible population and its role in expanding eligibility—CBO's estimates only excluded households not receiving cash benefits from SNAP and overlooked BBCE's impact on the otherwise-eligible population. Moreover, our simulation assumes a historical counterfactual where BBCE was never implemented, holding other factors (e.g., macroeconomic conditions) constant, whereas CBO's estimates are conditional forecasts that may incorporate additional assumptions about evolving macroeconomic conditions.

[30] See Appendix Figure A13 for simulation results using TWFE estimates.

[31] The larger effects of BBCE in driving program spending than participation (96.2% versus 88.5%) for already income-eligible households might be explained by the inverse relationship between SNAP benefit amount and household income—in the absence of BBCE, a reduction in SNAP participation within low-income households would translate into a larger decrease in SNAP benefits as lower-income households typically receive higher benefits from SNAP.

effects across states and over time has been questioned in the context of staggered policy adoption. This suggests that existing estimates of BBEC's effect on SNAP participation may not have a valid causal interpretation, given its staggered implementation across states. Our study addresses these concerns and advances our understanding of BBCE's impact on SNAP participation in several ways.

First, we employ the DD estimator developed by Callaway and Sant'Anna (2021) to accommodate BBCE's potential heterogeneous treatment effects and contrast its results with those from the static TWFE estimator. This comparison indicates a stark difference in the estimated impact of BBCE on per-capita SNAP participation—5.9% using the static TWFE model versus 15.3% using the CSDD estimator—highlighting substantial underestimation of BBCE's impact when its treatment effect heterogeneity is overlooked.

Next, we examine the evolution of BBCE's effect over time on SNAP participation using event-study analyses based on dynamic versions of the TWFE and CSDD estimators. Both estimators reveal statistically indistinguishable temporal patterns, with BBCE's impact increasing from about 3% in the first year after implementation to approximately 25% after seven years, after which it plateaus. These findings indicate that the static TWFE model's underestimation of BBCE's effect is primarily due to dynamic treatment effects which have increased uniformly over time across groups of states with the same BBCE adoption year.

The increase in BBCE's impact over time may be explained by several potential practical and behavioral factors. From a program administration standpoint, state administrations may have required time to fully introduce and promote BBCE. In addition, it may have taken time to train staff to understand how BBCE should be implemented. From a participant perspective, households may have needed time to learn how BBCE affects their eligibility or the application process. Overall, the gradual increase in BBCE's impact underscores the importance of accounting for both implementation and behavioral lags in budgeting and program planning.

We also conduct heterogeneity analysis based on several socioeconomic characteristics of

SNAP participants to identify which subpopulations are most affected by BBCE. In particular, our heterogeneity analysis across the household gross income distribution reveals that BBCE's effect on SNAP participation is largely driven by increasing take-up rates among already income-eligible households—that is, those with gross incomes not exceeding 130% of FPG. This finding aligns with that of Anders and Rafkin (2024), despite deploying different empirical strategies.

Several factors may explain the increase in take-up rates among already income-eligible households following BBCE implementation. First, by relaxing the gross income threshold, BBCE may have reduced informational and psychological barriers to applying for SNAP. Its adoption could have signaled that states were actively encouraging participation, helping to reduce stigma and raise awareness among already income-eligible households. Second, BBCE likely reduced administrative burdens and the associated "bandwidth tax"—the cognitive strain imposed by complex enrollment processes (see Mullainathan and Shafir 2013)—by eliminating paperwork through categorical eligibility and simplifying the application process. Third, some households may have reassessed their eligibility under BBCE, believing they were now eligible for a longer period because small income increases would no longer immediately disqualify them from benefits. Finally, some other already income-eligible households may have incorrectly assumed they were previously ineligible, but were prompted to apply once eligibility criteria appeared more generous or better communicated. These mechanisms align with prior research showing that simplified communication, reduced complexity, and lower administrative burdens can substantially increase program participation by alleviating key frictions (Bhargava and Manoli 2015; Herd and Moynihan 2019; Finkelstein and Notowidigdo 2019; Hemmeter et al. 2025).

Lastly, BBCE-induced relaxations of the asset test may have also played an important role in qualifying some already income-eligible households with countable assets exceeding the federally set thresholds for SNAP participation—that is, households that met the gross income test threshold but were previously disqualified due to assets became eligible under

BBCE (see Ratcliffe et al. 2016). However, given the limited variation in how the asset test is implemented across BBCE states—since all BBCE states either relaxed or eliminated the asset test—it is not feasible to reliably identify how much of BBCE's participation effect among already income-eligible households is attributable to the relaxation of the gross income limit versus the asset test. As such, our estimated effects capture the combined influence of both mechanisms, reflecting a mix of increased take-up among already-eligible households and an expanded reach due to the relaxation of the asset test.

Regarding the impacts among higher-income households who would otherwise be ineligible under federal gross income limits, we find that responsiveness to BBCE is greatest among those with incomes between 130% and 150% of FPG. Above this range, the effect steadily declines as we move up the income distribution toward 200% of FPG—the highest gross income threshold for eligibility under BBCE. This tapering pattern may reflect two dynamics. First, the net income test may continue to disqualify a portion of households in the 130% to 200% of FPG range, restricting their eligibility despite gross income relaxations. Second, even if eligible, some higher-income households may be discouraged from participating due to the relatively smaller monthly benefits they would receive under the benefit formula, which is decreasing in net income.

To further explore BBCE's effect on SNAP participation and benefit spending, we conducted a counterfactual simulation to project how SNAP enrollment and benefit spending might have evolved from 2000 to 2016 had BBCE not been adopted by any states. Our findings indicate that, without BBCE, annual SNAP enrollment would have been lower by approximately 1.6 million individuals on average, and SNAP benefits would have been about $2.2 billion lower annually—totaling 27.3 million participants and $37.1 billion over the entire 17-year period, respectively. Breaking down these cumulative reductions in participation and benefit spending by gross income level—distinguishing between already income-eligible households and those otherwise ineligible—we find that BBCE's expansion of eligibility to higher-income households accounted for around 11.5% of the cumulative increase in participation and about 3.8% of the additional benefits spending. Specifically, less than $1.4 billion over the 17-year period—or approximately $82.4 million per year, on average—was attributable to expanded eligibility for higher-income households.

While this counterfactual simulation provides policy-relevant insights into BBCE's impact on SNAP participation and benefit spending, several limitations should be noted. First, the simulation holds all other factors constant. For instance, it assumes that the SNAP policy index and other state-level SNAP policies and administrative practices would have remained unchanged in the absence of BBCE. This simplifying assumption may overlook potential interdependencies, such as how BBCE could have influenced other administrative decisions (e.g., outreach efforts) that may, in turn, have affected SNAP enrollment. Second, the simulation does not account for equilibrium effects—broader systemic feedback and behavioral adjustments in response to policy changes. For example, eliminating BBCE might have led households to increase labor market participation or adopt alternative strategies to maintain food security, while states could have implemented compensatory policies. As a result, our simulation adopts a partial equilibrium framework, focusing solely on the direct impacts of BBCE while holding all other factors constant.

Nevertheless, our counterfactual simulation results, combined with our heterogeneity analysis by household gross income, suggest that while BBCE facilitated SNAP enrollment among higher-income households exceeding the federal gross income threshold, its primary effect was concentrated on increasing participation among households already income-eligible under federal eligibility rules. In addition to its effects on participation and benefit spending, BBCE may also generate meaningful administrative efficiencies. For example, evidence suggests that BBCE implementation has been associated with a 7% reduction in state-level administrative expenses (USDA-FNS 2019), likely due to streamlined eligibility determination through categorical eligibility. As such, policymakers considering potential modifications to BBCE should also weigh its role in reducing administrative costs.

In summary, assessments of BBCE's impact on SNAP participation based on estimates lacking a valid causal interpretation can lead to suboptimal policy and budgeting decisions. This study addresses previous empirical limitations and provides new estimates of the causal impact of BBCE on SNAP participation through both eligibility expansion to higher-income households and increased take-up rates among already income-eligible households under federal rules. Our findings underscore the necessity of rigorous policy evaluations to ensure that policy decision-making is informed by reliable evidence. More importantly, by identifying the channels through which BBCE has largely influenced SNAP enrollment, this study can inform current and future policymaking efforts to refine the design and implementation of the policy.

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7 Figures

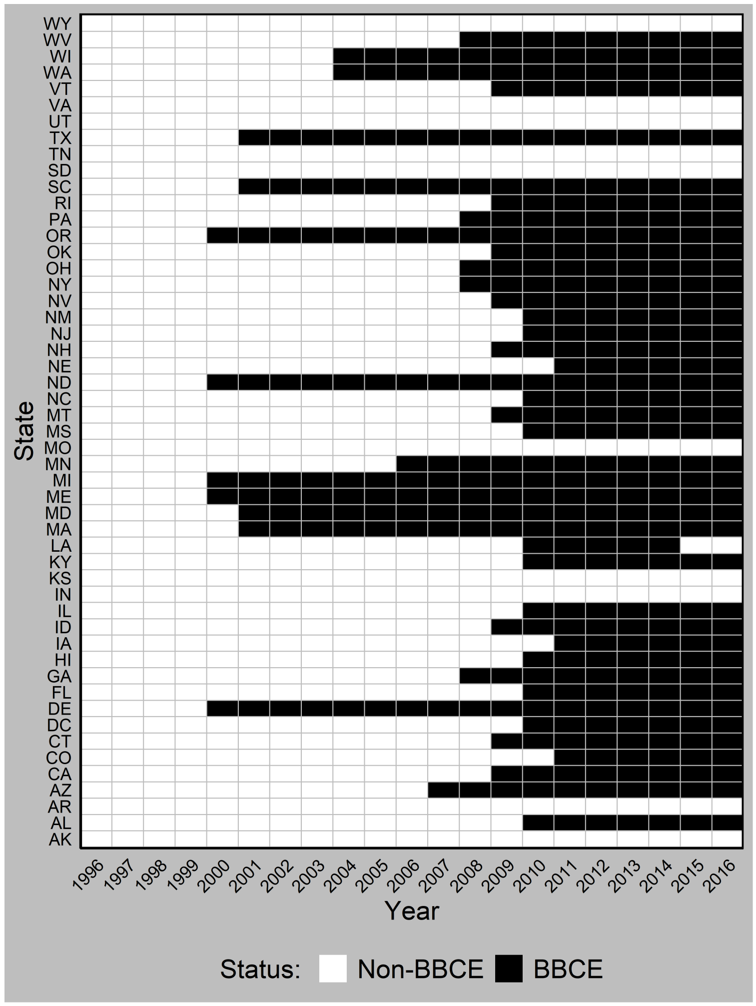

Figure 1. Staggered adoption of BBCE across states, 1996–2016

Notes: BBCE: Broad-Based Categorical Eligibility. A black grid indicates BBCE adoption by a state in a specific year. A state is classified as a BBCE adopter in any given year if it implements BBCE for at least one month within that year.

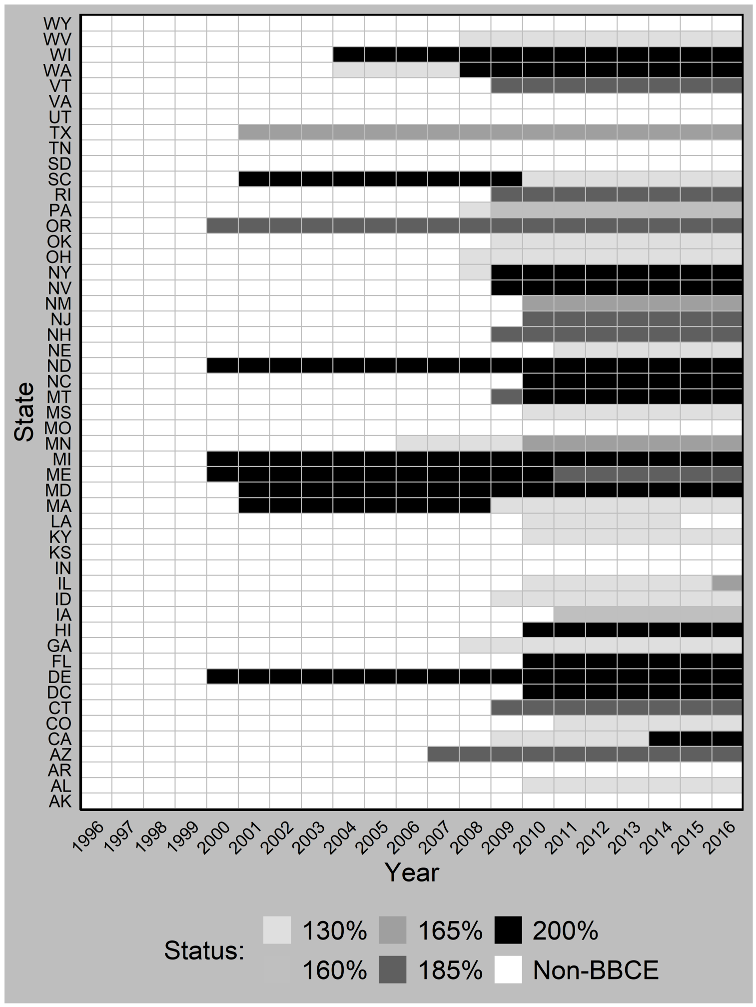

Figure 2. Gross income test threshold across BBCE states, 1996–2016

Notes: Grids are color-coded from white to black to indicate the the extent to which a state has relaxed the gross income test threshold due to BBCE in a specific year. A darker grid represents a more relaxed threshold, with the maximum threshold being set at 200% of FPG. The income test threshold level for a state is assigned to a specific percentage of FPG (130%, 160%, 165%, 185%, and 200%) in a given year only if it keeps this income threshold for at least one month within that year. BBCE states that did not raise the gross income test threshold beyond 130% are colored in the lightest gray.

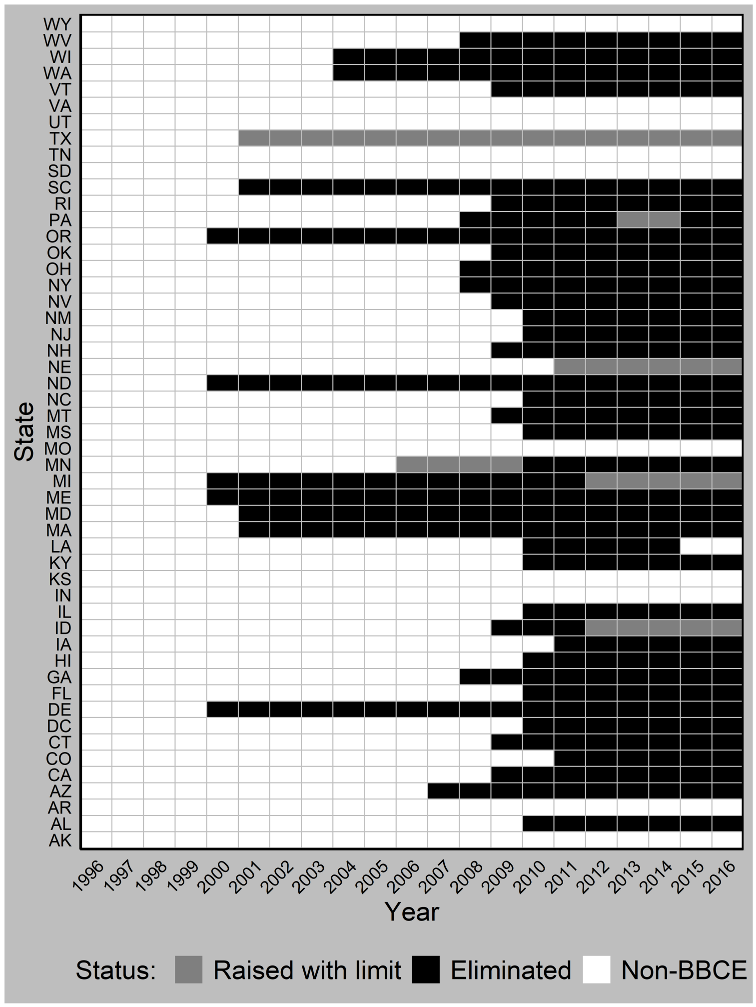

Figure 3. Adoption status of asset testing across BBCE states, 1996–2016

Notes: Grids colored in gray and black, respectively, indicate the asset test is "raised with limit" and "eliminated" due to BBCE by a state in a specific year. The adoption status for a state is defined as raised with limit or eliminated in a given year only if it raises or eliminates the asset test threshold for at one six month within that year.

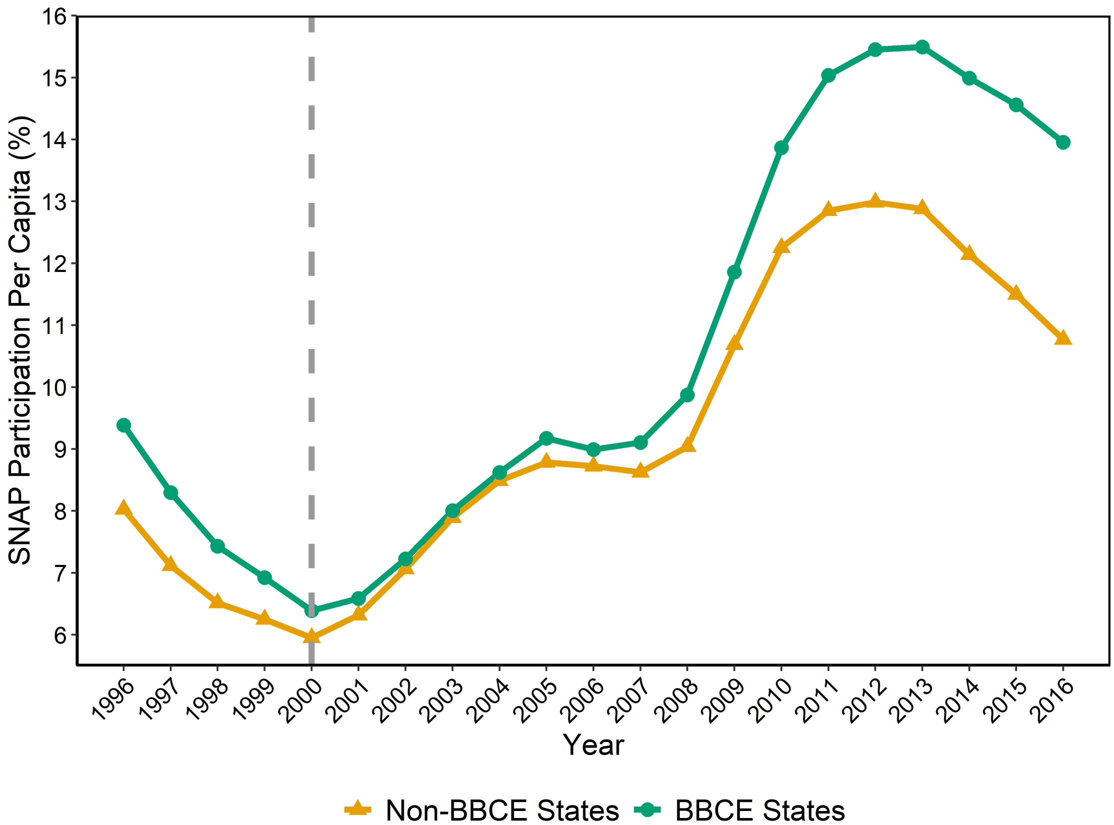

Figure 4. Trends in SNAP participation by states' adoption status of BBCE, 1996–2016

Notes: BBCE: Broad-Based Categorical Eligibility. The horizontal axis represents the year, and the vertical axis represents the average participation per capita for BBCE and non-BBCE states. The gray dashed vertical line indicates the year when the first group of states adopted the BBCE policy in 2000. A state is considered as a BBCE adopter in any given year only if it adopts BBCE for at least one month in that year.

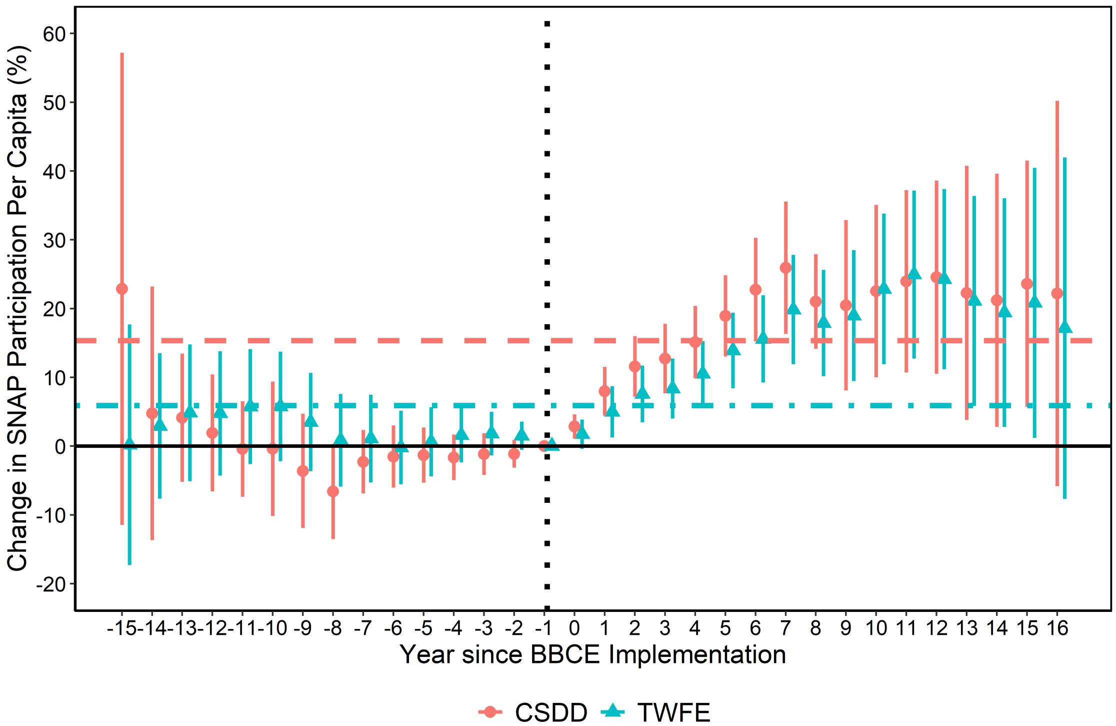

Figure 5. Event-study analysis: Estimated dynamic impacts of BBCE policy on SNAP participation, TWFE and CSDD with covariates

Notes: Outcome variable: Logarithm of SNAP participation per capita; Binary treatment variable: Implementation of Broad-Based Categorical Eligibility (BBCE). Other covariates used in the estimation process: SNAP policy index, unemployment rate, and percentage of population with income below 185% of the federal poverty guideline. TWFE: two-way fixed effects; CSDD: Callaway and Sant'Anna (2021) difference-in-differences estimator. The horizontal axis indicates the length of exposure to BBCE (i.e., the number of years since BBCE was implemented first in a state or group of states), whereas the vertical axis represents the estimated impact at each year relative to the baseline year immediately preceding the introduction of BBCE. The solid circles and triangles represent point estimates using dynamic CSDD and TWFE respectively for various lead and lag years, accompanied by 95% confidence intervals. Dashed and dashed-dotted lines represent the average estimates using static CSDD and TWFE estimators with covariates. CSDD incorporates pre-treatment covariates via the doubly robust (DR) estimation procedure, and uses not-yet-treated states as controls (Sant'Anna and Zhao 2020). The standard errors are clustered at the state level, and CSDD's standard errors are calculated using the multiplier-type bootstrap method proposed in Callaway and Sant'Anna (2021). Bias-corrected estimates in percentage terms and standard errors are calculated following Kennedy (1981).

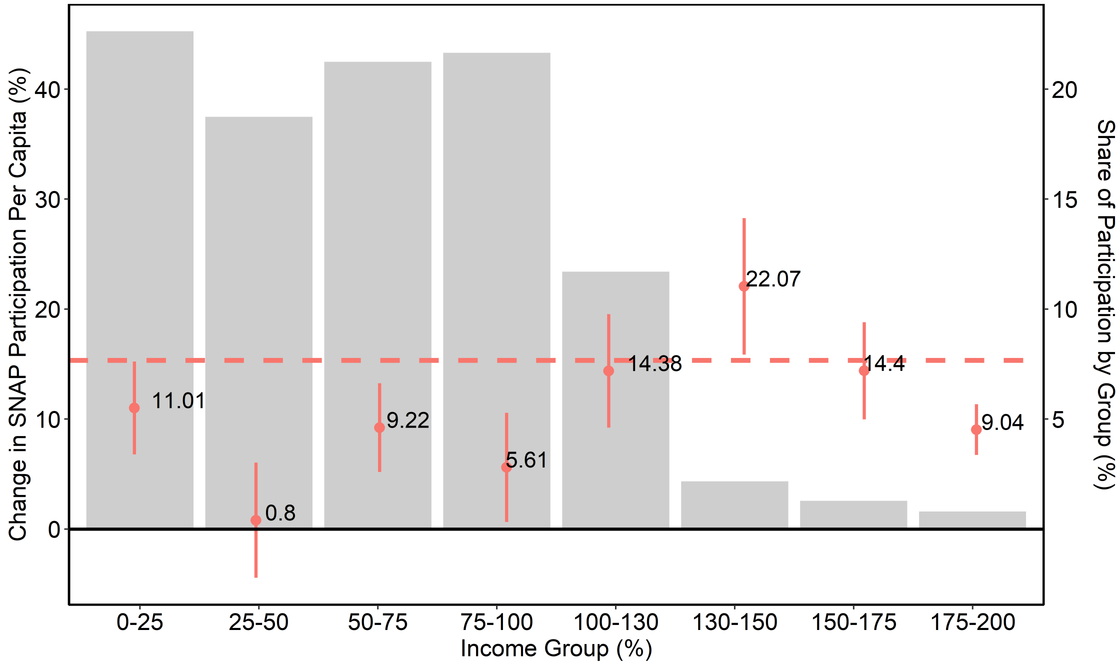

Figure 6. Estimated impacts of BBCE policy on SNAP participation by household gross income level, CSDD with covariates

Notes: Outcome variable: Logarithm of SNAP participation per capita; Binary treatment variable: Implementation of Broad-Based Categorical Eligibility (BBCE). Other covariates used in the estimation process: SNAP policy index, unemployment rate, and percentage of population with income below 185% of the federal poverty guideline. CSDD: Callaway and Sant'Anna (2021) difference-in-differences estimator. The horizontal axis represents different subgroups of SNAP participation across different gross income levels, ranging from 0 to 200% with roughly 25% increments. The right vertical axis displays gray bars indicating the percentage share of total SNAP participation for each subgroup. On the left vertical axis, solid circles represent point estimates of the percentage change in SNAP participation per capita under CSDD, accompanied by 95% confidence bands. The dashed line represents the average estimates using the static CSDD estimator. CSDD incorporates pre-treatment covariates via the doubly robust (DR) estimation procedure, and uses not-yet-treated states as controls (Sant'Anna and Zhao 2020). The standard errors are calculated by the multiplier-type bootstrap method proposed in Callaway and Sant'Anna (2021). Bias-corrected estimates in percentage terms and standard errors are calculated following Kennedy (1981).

Figure 7. Estimated impacts of BBCE policy on SNAP participation by household socioeconomic characteristics, CSDD with covariates

Notes: Outcome variable: Logarithm of SNAP participation per capita; Binary treatment variable: Implementation of Broad-Based Categorical Eligibility (BBCE). Other covariates used in the estimation process: SNAP policy index, unemployment rate, and percentage of population with income below 185% of the federal poverty guideline. CSDD: Callaway and Sant'Anna (2021) difference-in-differences estimator. The horizontal axis represents different subgroups of SNAP participation based on household socioeconomic characteristics, including the presence of disabled members, earning status, the presence of elderly members, and receipt of cash assistance from other welfare programs (i.e.,TANF/AFDC, SSI, or state-funded General Assistance). The right vertical axis displays gray bars indicating the percentage share of total SNAP participation for each subgroup. On the left vertical axis, solid circles represent point estimates of the percentage change in SNAP participation per capita under CSDD, accompanied by 95% confidence bands. The dashed line represents the average estimates using the static CSDD estimator. CSDD incorporates pre-treatment covariates via the doubly robust (DR) estimation procedure, and uses not-yet-treated states as controls (Sant'Anna and Zhao 2020). The standard errors are calculated by the multiplier-type bootstrap method proposed in Callaway and Sant'Anna (2021). Bias-corrected estimates in percentage terms and standard errors are calculated following Kennedy (1981).

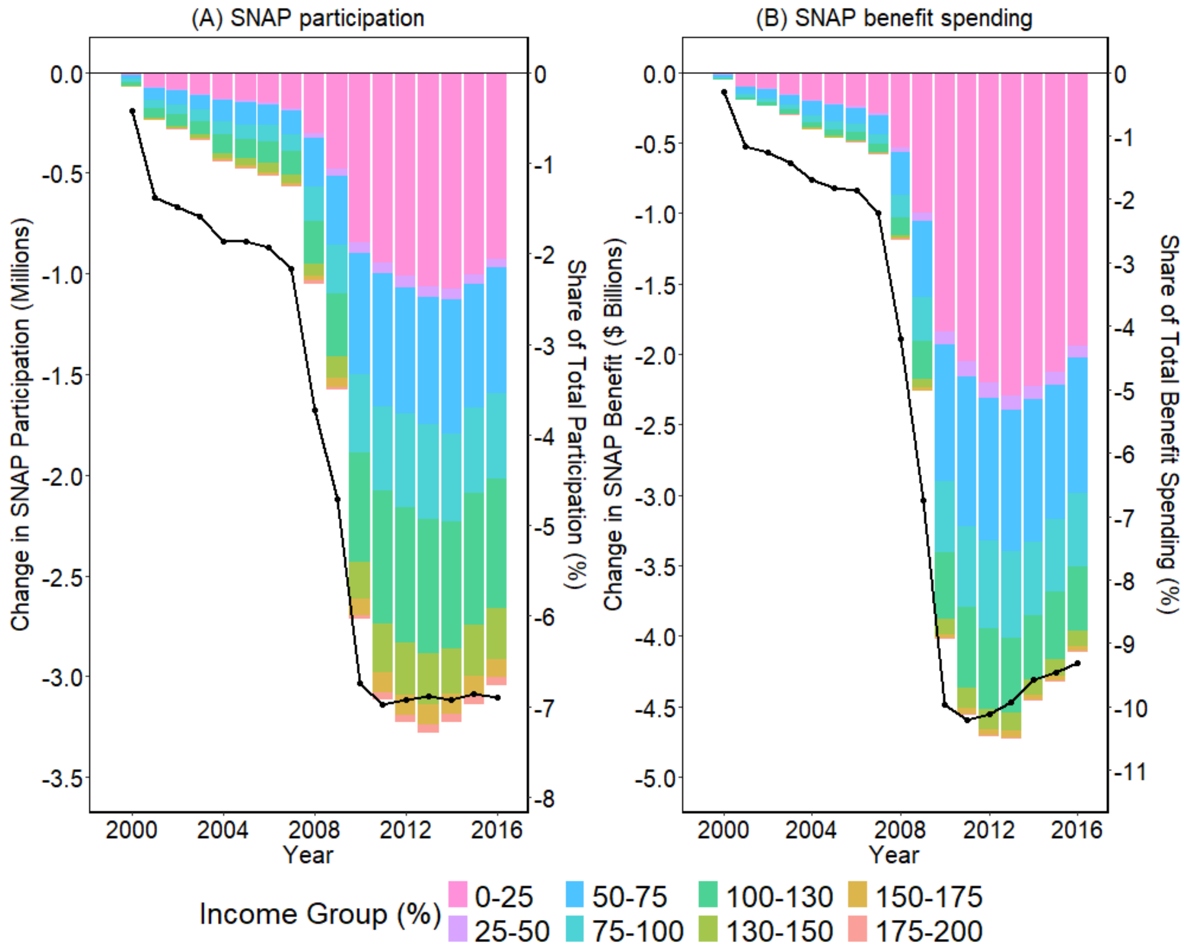

Figure 8. Simulated annual reductions in SNAP participation and total benefit spending in the absence of BBCE, 2000-2016, based on CSDD estimates with covariates

Notes: Panels A and B show the simulated annual reductions in SNAP participation and benefit spending under the counterfactual scenario that BBCE was never implemented using the income-group-specific CSDD estimates. CSDD: Callaway and Sant'Anna (2021) difference-in-differences estimator. The horizontal axis represents the year. The vertical axis represent the simulated annual reductions in SNAP participation measured in millions of participants and benefit spending measured in billion dollars. The right vertical axis displays solid lines indicating the share of SNAP participants. Different colors indicate the change incurred by different income groups.

8 Tables

Table 1. BBCE adoption timeline across states, 1996–2016

Implementation year	**States**	**State count**
2000	DE, ME, MI, ND, OR	5
2001	MA, MD, SC, TX	4
2004	WA, WI	2
2006	MN	1
2007	AZ	1
2008	GA, NY, OH, PA, WV	5
2009	CA, CT, ID, MT, NH, NV, OK, RI, VT	9
2010	AL, DC, FL, HI, IL, KY, LA, MS, NC, NJ, NM	11
2011	CO, IA, NE	3
Never adopted BBCE	AK, AR, IN, KS, MO, SD, TN, UT, VA, WY	10

Notes: BBCE: Broad-Based Categorical Eligibility. This table reports the first year each state adopted BBCE. A state is classified as an adopter if it implemented BBCE for at least one month in that year. States that never adopted BBCE are listed separately. Source: Created by authors based on information in Figure 1.

Table 2. Summary statistics by states' BBCE adoption status, 1996–2016

	Non-BBCE states	BBCE states	Difference	p-value
SNAP participation per capita (%)	9.28	10.53	1.25	<0.01
Unemployment rate (%)	5.18	5.68	0.50	<0.01
Income-to-poverty ratio $\leq$ 1.85 (%)	26.95	25.97	-0.98	0.04
SNAP policy index	0.34	0.36	0.02	0.23
Observations (state-year)	210	861		

Notes: BBCE: Broad-Based Categorical Eligibility. A state is considered as a BBCE adopter in any given year if it adopts BBCE for at least one month in that year. Income-to-poverty ratio $\leq$ 1.85 reflects the share of the state's population with incomes below 185% of the Federal Poverty Guideline. P-values represent a statistical two-sample t-test for equality of means between BBCE and non-BBCE states.

Table 3. Estimated impacts of BBCE policy on SNAP participation, TWFE and CSDD without and with covariates

Log(SNAP participation per capita)	(1)	(2)	Difference† ((1) − (2))
TWFE	8.50***	5.89**	2.61
	(3.23)	(2.64)	(4.17)
CSDD	15.52***	15.34***	0.18
	(2.97)	(2.07)	(3.62)
Difference (CSDD − TWFE)‡	7.02	9.45***	
	(4.39)	(3.35)	
Covariates	No	Yes	
Observations (state-by-year)	1071	1071	

Notes: Outcome variable: Logarithm of SNAP participation per capita; Binary treatment variable: Implementation of Broad-Based Categorical Eligibility (BBCE). Other covariates used in the estimation process: SNAP policy index, unemployment rate, and percentage of population with income below 185% of the federal poverty guideline. TWFE: two-way fixed effects. CSDD: Callaway and Sant'Anna (2021) difference-in-differences estimator. CSDD incorporates pre-treatment covariates via the doubly robust (DR) estimation procedure (column (2)), and uses not-yet-treated states as controls (Sant'Anna and Zhao 2020). The standard errors are clustered at the state level, and CSDD's standard errors are calculated using the multiplier-type bootstrap method proposed in Callaway and Sant'Anna (2021). Bias-corrected estimates in percentage terms and standard errors are calculated following Kennedy (1981). † indicates differences of the estimates between models without and with covariates. ‡ indicates differences between coefficient estimates from CSDD and TWFE estimators. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 4. Goodman-Bacon decomposition of the TWFE specification without covariates, full sample

DD Comparison	Weight	Estimated ATT (%)
Later treated as treatment vs. earlier treated as control	0.28	2.20
Earlier treated as treatment vs. later treated as control	0.26	11.60
Earlier/later treated vs. never treated	0.46	8.50
Overall (weighted average)		7.5

Notes: Outcome variable: Logarithm of SNAP participation per capita; Binary treatment variable: Implementation of Broad-Based Categorical Eligibility (BBCE). Covariates are not used. Estimates are not adjusted by Kennedy (1981). TWFE: two-way fixed effects.

A Appendix

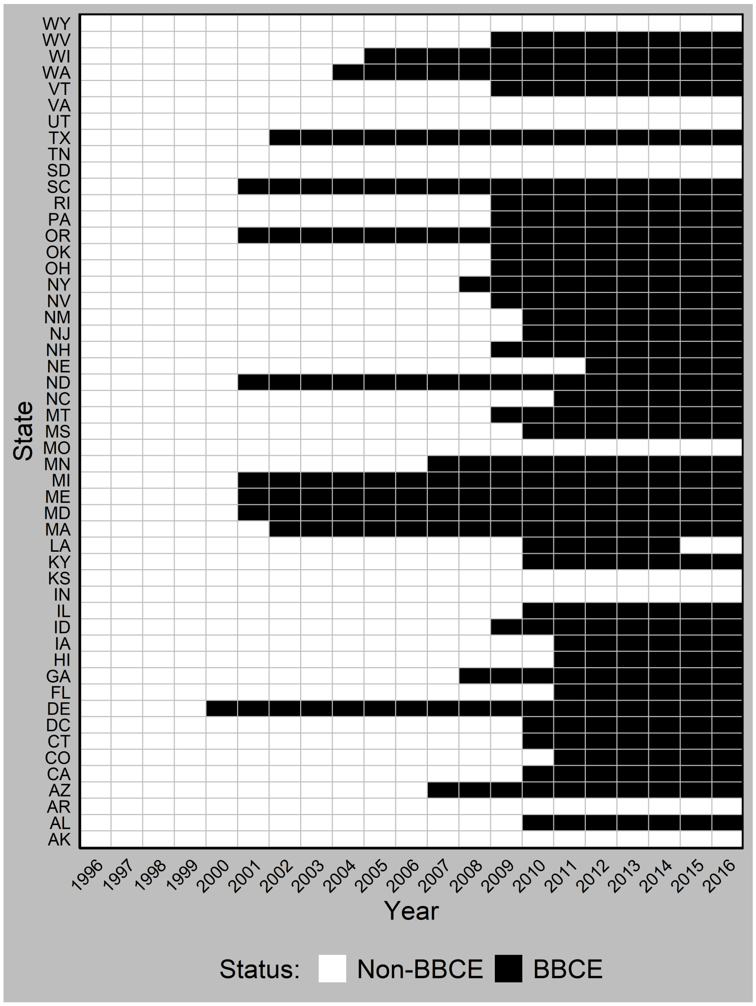

Figure A1. Staggered adoption of BBCE across states under the "majority-year" aggregation scheme of monthly to annual policy data, 1996–2016

Notes: The horizontal axis represents the year, and the vertical axis represents states. A black grid indicates BBCE adoption by a state in a specific year. Under the majority-year aggregation scheme, a state is classified as a BBCE adopter in a given year if it maintained BBCE for more than six months within that year.

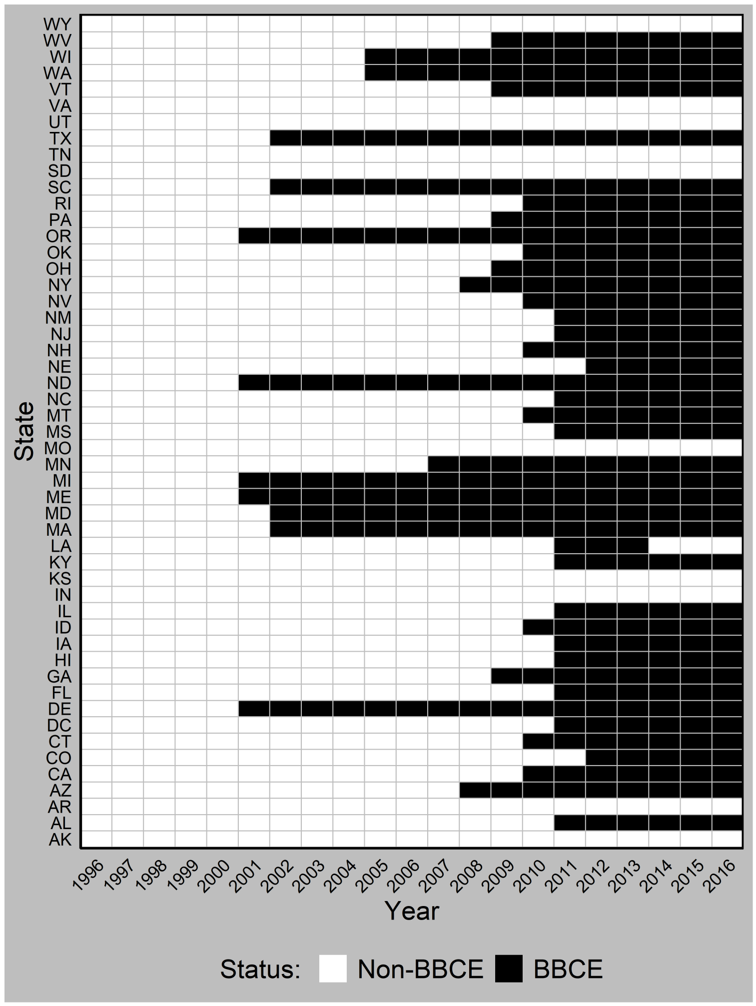

Figure A2. Staggered adoption of BBCE across states under the "full-year" aggregation scheme of monthly to annual BBCE data, 1996–2016

Notes: The horizontal axis represents the year, and the vertical axis represents states. A black grid indicates BBCE adoption by a state in a specific year. Under the full-year aggregation scheme, a state is classified as a BBCE adopter in a given year only if it maintained BBCE for the entire year.

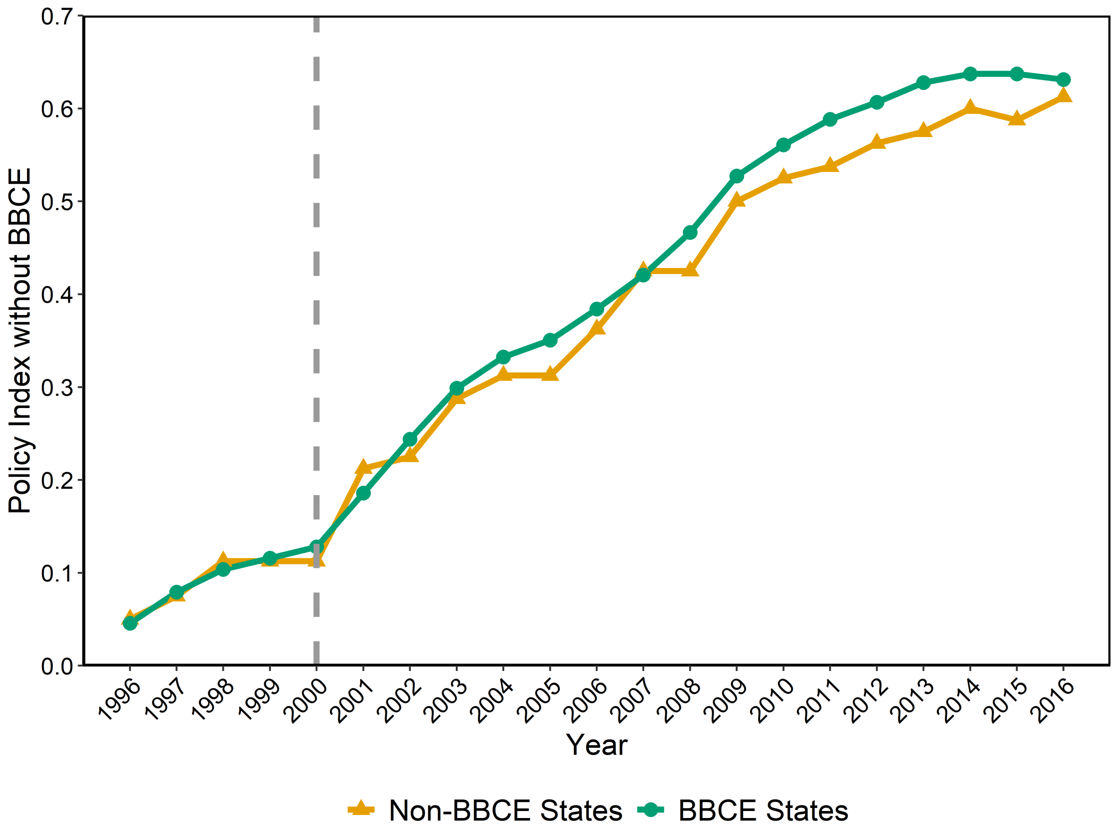

Figure A3. Trends in SNAP policy index by states' adoption status of BBCE, 1996–2016

Notes: BBCE: Broad-Based Categorical Eligibility. The horizontal axis represents the year, and the vertical axis represents the average value of the SNAP policy index for BBCE and non-BBCE states, constructed as the average of eight SNAP-related policies including: adoption of online applications, establishment of statewide call centers to assist with application and re-certification, waiver of face-to-face interviews for initial certification or re-certification, allowing for simplified reporting of income changes, allowing for Combined Application Project for Supplemental Security Income recipients, exemptions on at least one vehicle, existence of SNAP participants' re-certification period greater than three months, and adoption of Electronic Benefit Transfer (EBT) systems. The gray dashed vertical line indicates the year when the first state (Delaware) adopted the BBCE policy. A state is considered as a BBCE adopter in any given year only if it adopts BBCE for at least one month in that year.

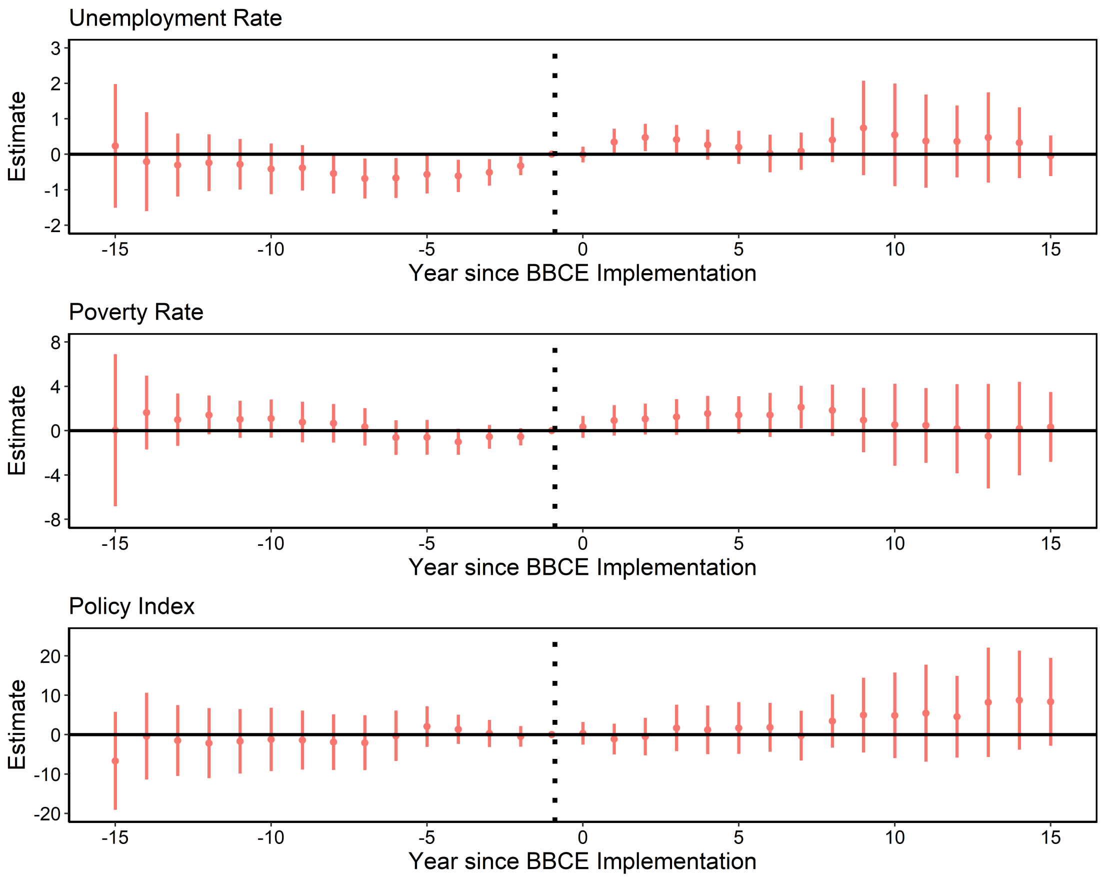

Figure A4. Diagnostic event study estimates for covariates—unemployment rate, income-poverty ratio, and policy index—using the CSDD estimator

Notes: Outcome variables: Unemployment rate, percentage of population with income below 185% of the federal poverty guideline, and policy index; Binary treatment variable: Implementation of Broad-Based Categorical Eligibility (BBCE). CSDD: Callaway and Sant'Anna (2021) difference-in-differences estimator. Each panel illustrates the dynamic estimates of BBCE for each covariates used in the analysis. The horizontal axis indicates the length of exposure to BBCE (i.e., the number of years since BBCE was implemented first in a state or group of states), whereas the vertical axis represents the estimate at each year relative to the baseline year immediately preceding the introduction of BBCE. The solid circles represent point estimates using dynamic CSDD for various lead and lag years, accompanied by 95% confidence intervals. CSDD uses not-yet-treated states as controls. The standard errors are clustered at the state level and calculated using the multiplier-type bootstrap method proposed in Callaway and Sant'Anna (2021).

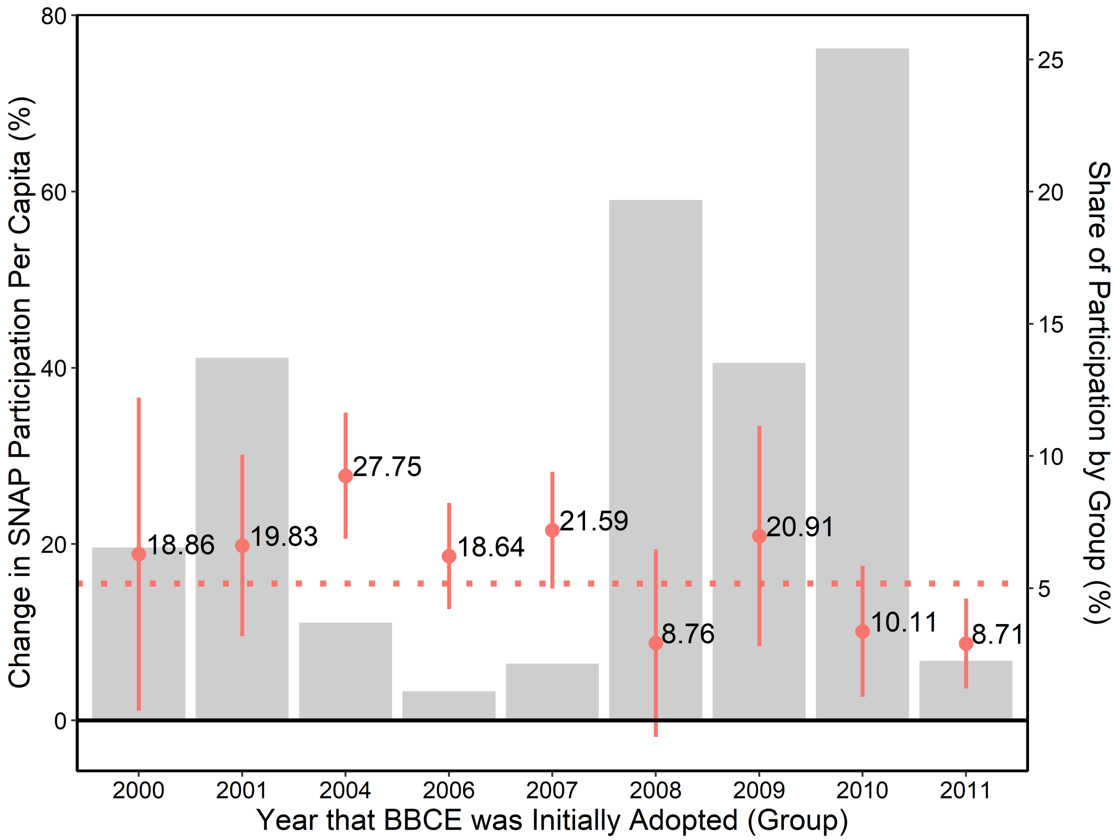

Figure A5. Estimated impacts of BBCE policy on SNAP participation across groups, CSDD without covariates

Notes: Outcome variable: Logarithm of SNAP participation per capita; Binary treatment variable: Implementation of Broad-Based Categorical Eligibility (BBCE). CSDD: Callaway and Sant'Anna (2021) difference-in-differences estimator. The horizontal axis represents mutually exclusive groups of states adopting the BBCE policy in the same year (e.g., Massachusetts and Texas belong to group 2002), whereas the vertical axes on the left and right represent the estimated percentage change in participation per capita and the percentage share of total SNAP participation. The solid circles show the estimated impacts, accompanied by 95% confidence bands, whereas the bars show the percentage share of total SNAP participation for these eleven respective groups, calculated as the ratio of the total number of SNAP participants in each group and the total number of SNAP participants across all observed years. Results are estimated using not-yet-treated as controls. The standard errors are clustered at the state level and calculated using the multiplier-type bootstrap method proposed in Callaway and Sant'Anna (2021). Bias-corrected estimates in percentage terms and standard errors are calculated following Kennedy (1981). The dashed line represents the average treatment effect from using the static CSDD estimator without covariates.

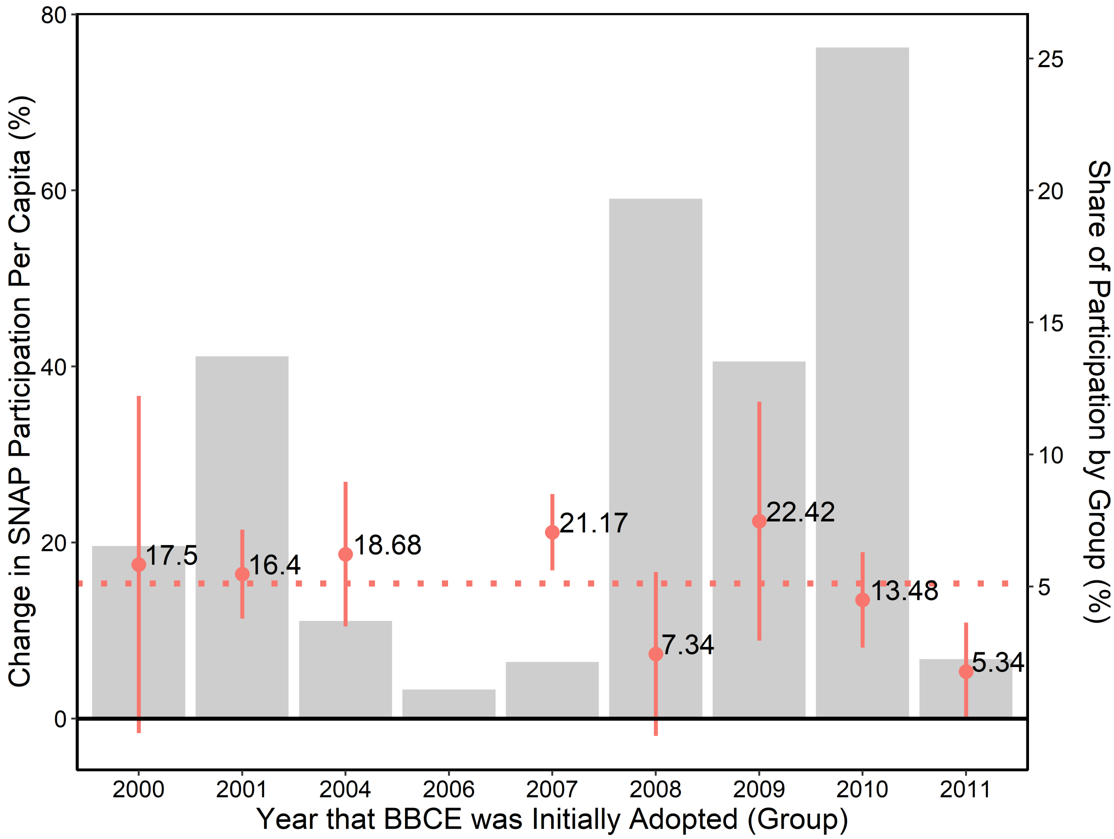

Figure A6. Estimated impacts of BBCE policy on SNAP participation across groups, CSDD with covariates

Notes: Outcome variable: Logarithm of SNAP participation per capita; Binary treatment variable: Implementation of Broad-Based Categorical Eligibility (BBCE). Other covariates used in the estimation process: SNAP policy index, unemployment rate, and percentage of population with income below 185% of the federal poverty guideline. CSDD: Callaway and Sant'Anna (2021) difference-in-differences estimator. The horizontal axis represents mutually exclusive groups of states adopting the BBCE policy in the same year (e.g., Massachusetts and Texas belong to group 2002). The right vertical axis displays gray bars indicating the percentage share of total SNAP participation for each group. On the left vertical axis, solid circles represent point estimates of the percentage change in SNAP participation per capita under CSDD, accompanied by 95% confidence bands. CSDD incorporates pre-treatment covariates via the doubly robust (DR) estimation procedure, and uses not-yet-treated states as controls (Sant'Anna and Zhao 2020). The standard errors are clustered at the state level and calculated using the multiplier-type bootstrap method proposed in Callaway and Sant'Anna (2021). Bias-corrected estimates in percentage terms and standard errors are calculated following Kennedy (1981). The dashed line represents the average treatment effect from using the static CSDD estimator. The estimate for group 2006, which comprises a single state (Minnesota), is missing due to insufficient observations to construct inverse probability weights.

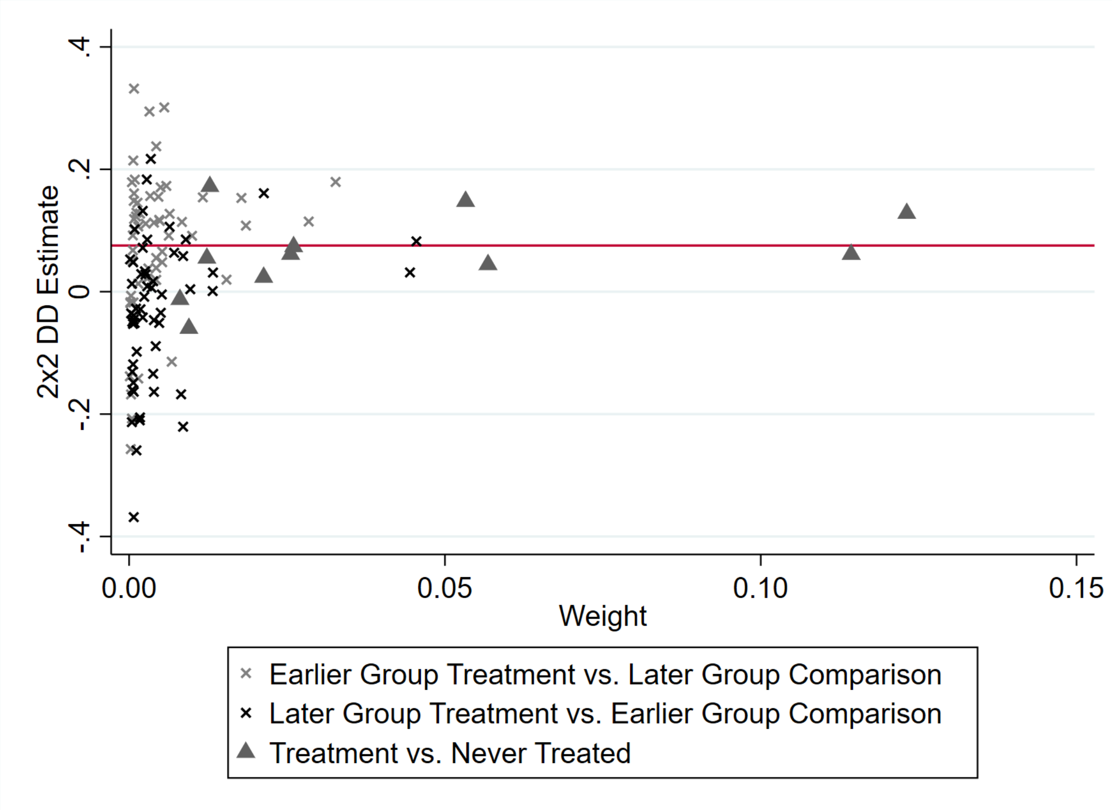

Figure A7. Goodman-Bacon decomposition of the TWFE specification without covariates, full sample

Notes: The horizontal axis represents the weight, and the vertical axis represents the estimate for each two-by-two difference-in-differences estimate. The red horizontal line shows the average effect estimated by two-way fixed effects (TWFE) estimator without covariates. The estimates are not adjusted by Kennedy (1981).

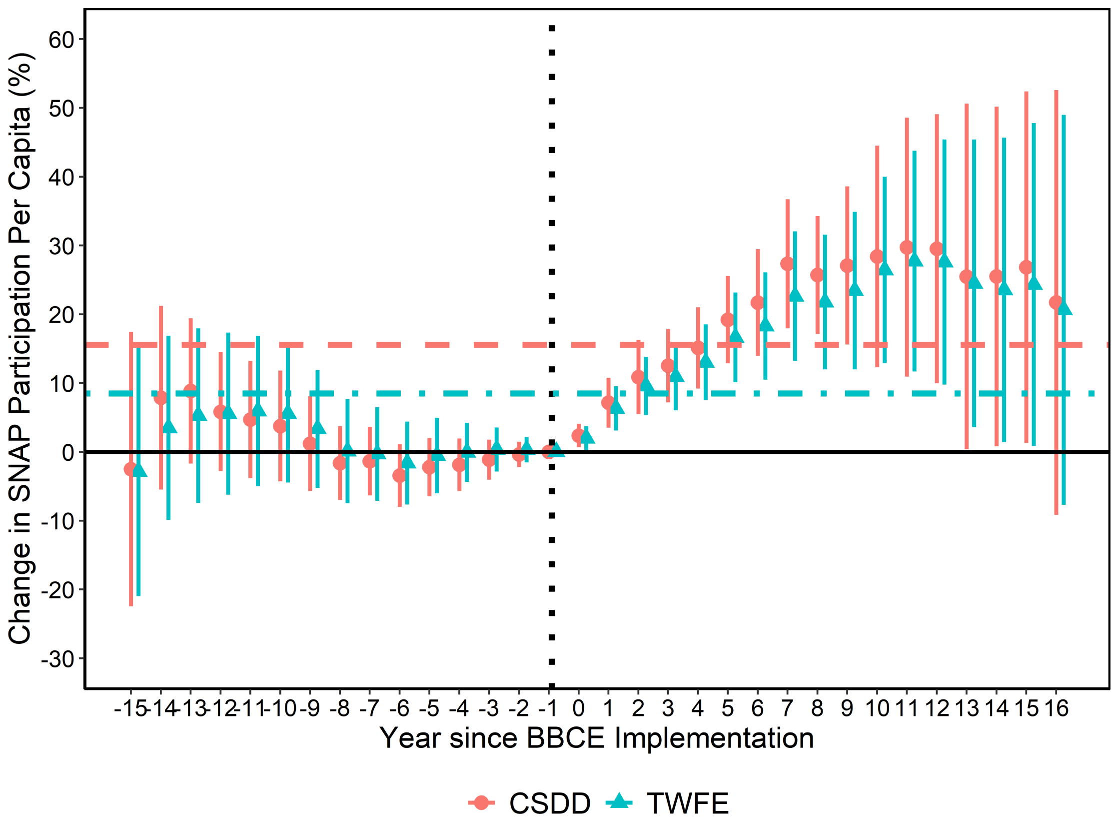

Figure A8. Event-study analysis: Estimated dynamic impacts of BBCE policy on SNAP participation, TWFE and CSDD without covariates

Notes: Outcome variable: Logarithm of SNAP participation per capita; Binary treatment variable: Implementation of Broad-Based Categorical Eligibility (BBCE). TWFE: two-way fixed effects. CSDD: Callaway and Sant'Anna (2021) difference-in-differences estimator. The horizontal axis indicates the length of exposure to BBCE (i.e., the number of years since BBCE was implemented first in a state or group of states), whereas the vertical axis represents the estimated impact in each year relative to the baseline year immediately preceding the introduction of BBCE. The solid circles and triangles represent point estimates using dynamic CSDD and TWFE respectively for various lead and lag years, accompanied by 95% confidence intervals. Dashed and dashed-dotted lines represent the average estimates using static CSDD and TWFE estimators without covariates. The standard errors are clustered at the state level, and CSDD's standard errors are calculated using the multiplier-type bootstrap method proposed in Callaway and Sant'Anna (2021). Bias-corrected estimates in percentage terms and standard errors are calculated following Kennedy (1981). Results under CSDD are estimated using not-yet-treated as controls and pre-treatment covariates only.

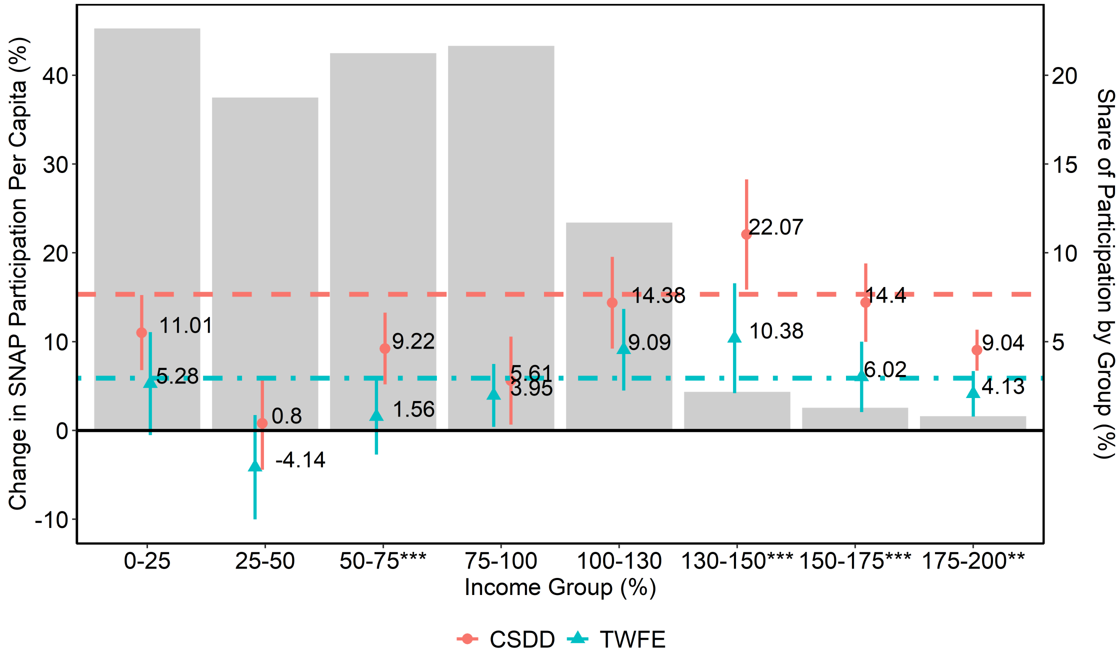

Figure A9. Estimated impacts of BBCE policy on SNAP participation by household income level, CSDD and TWFE with covariates

Notes: Outcome variable: Logarithm of SNAP participation per capita; Binary treatment variable: Implementation of Broad-Based Categorical Eligibility (BBCE). Other covariates used in the estimation process: SNAP policy index, unemployment rate, and percentage of population with income below 185% of the federal poverty guideline. TWFE: two-way fixed effects; CSDD: Callaway and Sant'Anna (2021) difference-in-differences estimator. The horizontal axis represents different subgroups of SNAP participation across different income levels, ranging from 0 to 200% with roughly 25% increments. The right vertical axis displays gray bars indicating the percentage share of total SNAP participation for each subgroup. On the left vertical axis, solid circles and triangles represent point estimates of the percentage change in SNAP participation per capita under CSDD and TWFE respectively, accompanied by 95% confidence bands. Dashed and dashed-dotted lines represent the average estimates using static CSDD and TWFE estimators with covariates. CSDD incorporates pre-treatment covariates via the doubly robust (DR) estimation procedure, and uses not-yet-treated states as controls (Sant'Anna and Zhao 2020). The standard errors are clustered at the state level and calculated by the multiplier-type bootstrap method proposed in Callaway and Sant'Anna (2021). Bias-corrected estimates in percentage terms and standard errors are calculated following Kennedy (1981). Asterisks (*,**,***) next to each income category indicate statistically significant differences between TWFE and CSDD estimates at the 10%, 5%, and 1% significance levels, respectively.

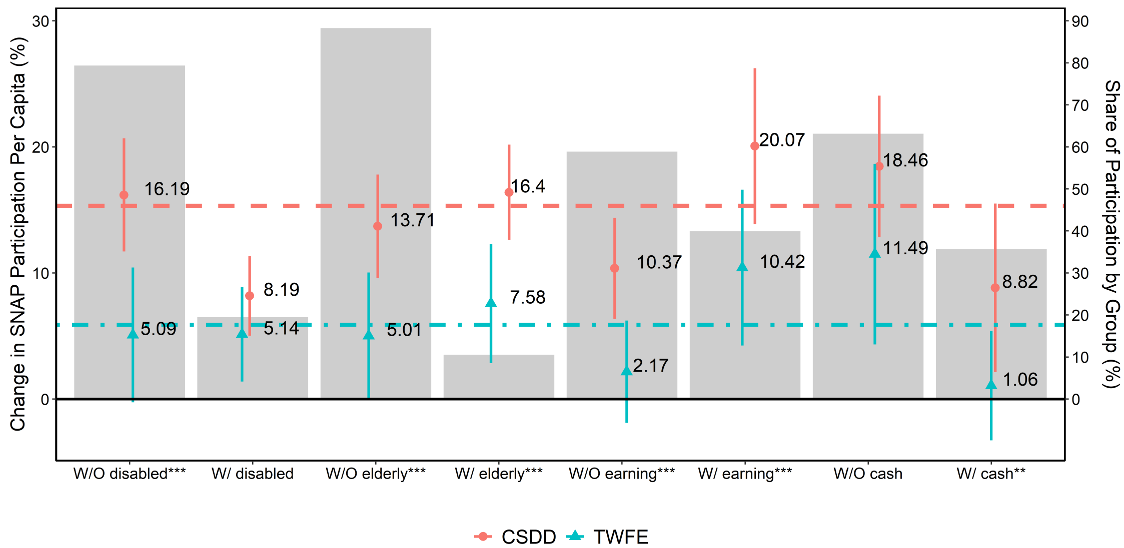

Figure A10. Estimated impacts of BBCE policy on SNAP participation by household socioeconomic characteristics, CSDD and TWFE with covariates

Notes: Outcome variable: Logarithm of SNAP participation per capita; Binary treatment variable: Implementation of Broad-Based Categorical Eligibility (BBCE). Other covariates used in the estimation process: SNAP policy index, unemployment rate, and percentage of population with income below 185% of the federal poverty guideline. TWFE: two-way fixed effects; CSDD: Callaway and Sant'Anna (2021) difference-in-differences estimator. The horizontal axis represents different subgroups of SNAP caseloads based on household socioeconomic characteristics, including the presence of disabled members, earning status, the presence of elderly members, and receipt of cash assistance from other welfare programs (i.e.,TANF/AFDC, SSI, or state-funded General Assistance). The right vertical axis displays gray bars indicating the percentage share of total SNAP participation for each subgroup. On the left vertical axis, solid circles and triangles represent point estimates of the percentage change in SNAP participation per capita under CSDD and TWFE respectively, accompanied by 95% confidence bands. Dashed and dashed-dotted lines represent the average estimates using static CSDD and TWFE estimators with covariates. CSDD incorporates pre-treatment covariates via the doubly robust (DR) estimation procedure, and uses not-yet-treated states as controls (Sant'Anna and Zhao 2020). The standard errors are clustered at the state level and calculated by the multiplier-type bootstrap method proposed in Callaway and Sant'Anna (2021). Bias-corrected estimates in percentage terms and standard errors are calculated following Kennedy (1981). Asterisks (*,**,***) next to each socioeconomic category indicate statistically significant differences between TWFE and CSDD estimates at the 10%, 5%, and 1% significance levels, respectively.

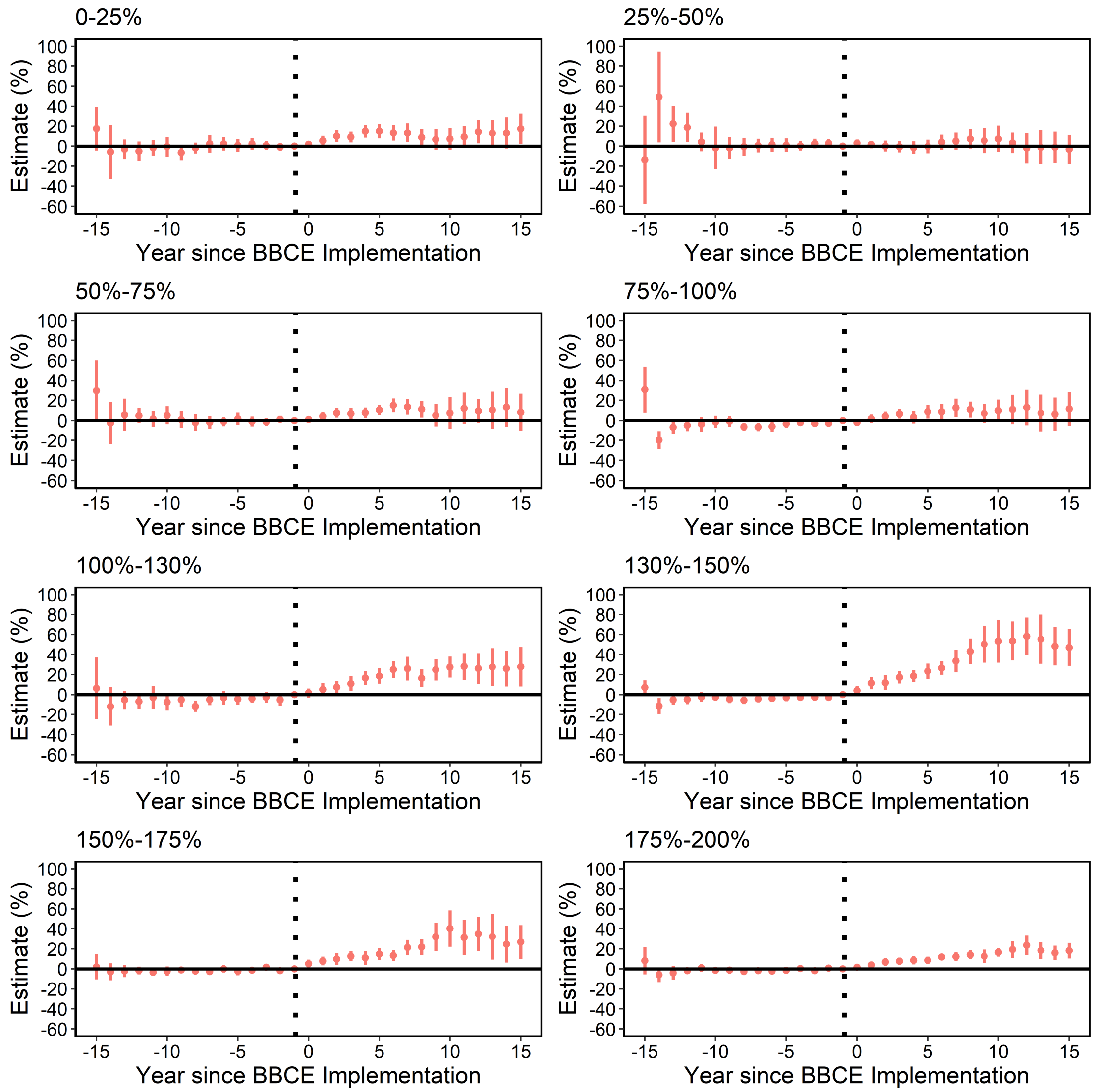

Figure A11. Event-study analysis: Estimated dynamic impacts of BBCE policy on SNAP participation by household gross income level, CSDD with covariates

Notes: Outcome variable: Logarithm of SNAP participation per capita; Binary treatment variable: Implementation of Broad-Based Categorical Eligibility (BBCE). Other covariates used in the estimation process: SNAP policy index, unemployment rate, and percentage of population with income below 185% of the federal poverty guideline. CSDD: Callaway and Sant'Anna (2021) difference-in-differences estimator. Each panel illustrates the dynamic effects of BBCE on SNAP participation for each mutually exclusive group. The horizontal axis indicates the length of exposure to BBCE (i.e., the number of years since BBCE was implemented first in a state or group of states), whereas the vertical axis represents the estimated impact at each year relative to the baseline year immediately preceding the introduction of BBCE. The solid circles represent point estimates using dynamic CSDD for various lead and lag years, accompanied by 95% confidence intervals. CSDD incorporates pre-treatment covariates via the doubly robust (DR) estimation procedure, and uses not-yet-treated states as controls (Sant'Anna and Zhao 2020). The standard errors are clustered at the state level and calculated using the multiplier-type bootstrap method proposed in Callaway and Sant'Anna (2021). Bias-corrected estimates in percentage terms and standard errors are calculated following Kennedy (1981).

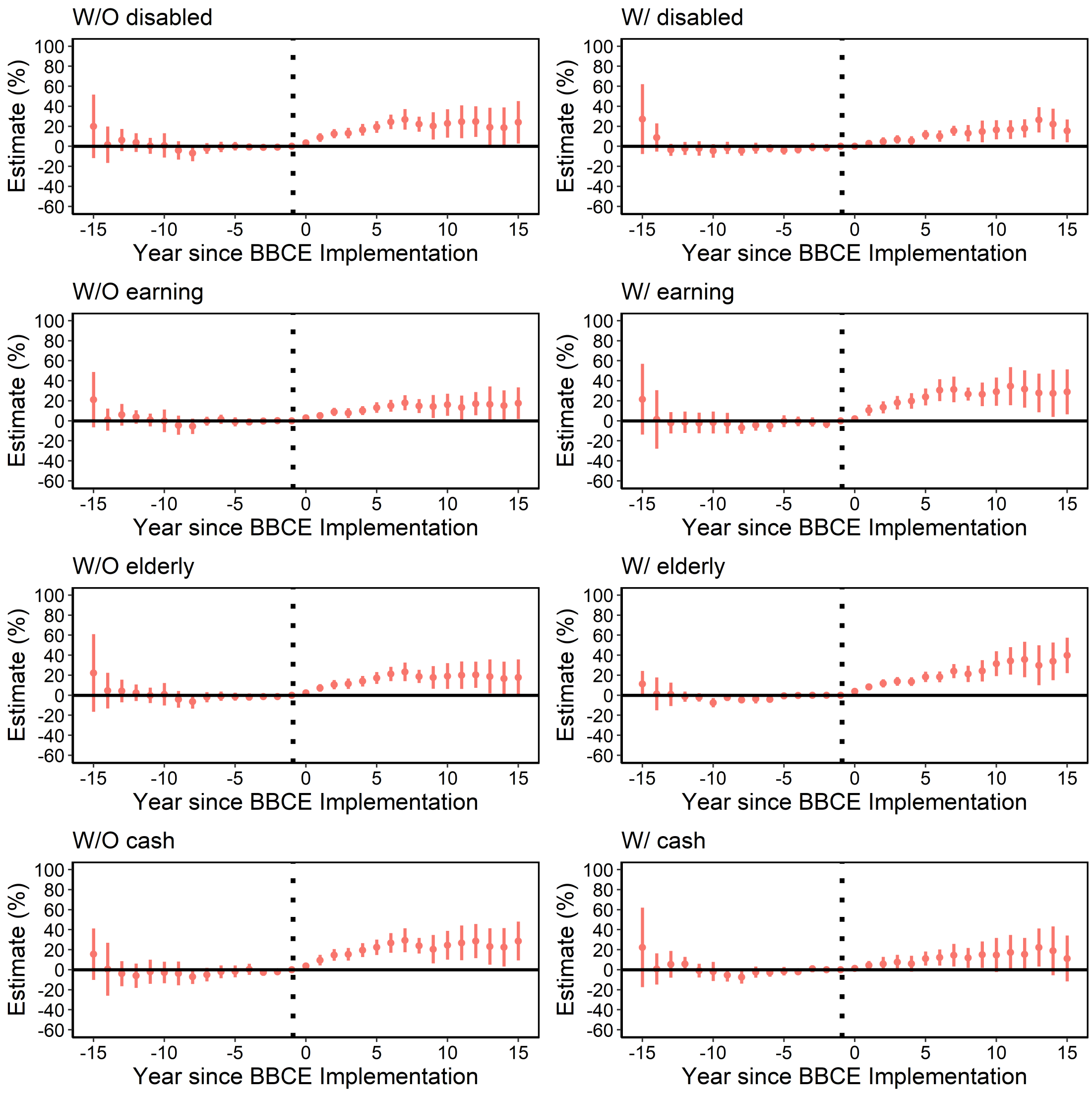

Figure A12. Event-study analysis: Estimated dynamic impacts of BBCE policy on SNAP participation by demographics and welfare statuses, CSDD with covariates

Notes: Outcome variable: Logarithm of SNAP participation per capita; Binary treatment variable: Implementation of Broad-Based Categorical Eligibility (BBCE). Other covariates used in the estimation process: SNAP policy index, unemployment rate, and percentage of population with income below 185% of the federal poverty guideline. CSDD: Callaway and Sant'Anna (2021) difference-in-differences estimator. For each row, the two panels illustrate the dynamic effects of BBCE on SNAP participation for households with or without the characteristic. The horizontal axis indicates the length of exposure to BBCE (i.e., the number of years since BBCE was implemented first in a state or group of states), whereas the vertical axis represents the estimated impact at each year relative to the baseline year immediately preceding the introduction of BBCE. The solid circles represent point estimates using dynamic CSDD for various lead and lag years, accompanied by 95% confidence intervals. CSDD incorporates pre-treatment covariates via the doubly robust (DR) estimation procedure, and uses not-yet-treated states as controls (Sant'Anna and Zhao 2020). The standard errors are clustered at the state level and calculated using the multiplier-type bootstrap method proposed in Callaway and Sant'Anna (2021). Bias-corrected estimates in percentage terms and standard errors are calculated following Kennedy (1981).

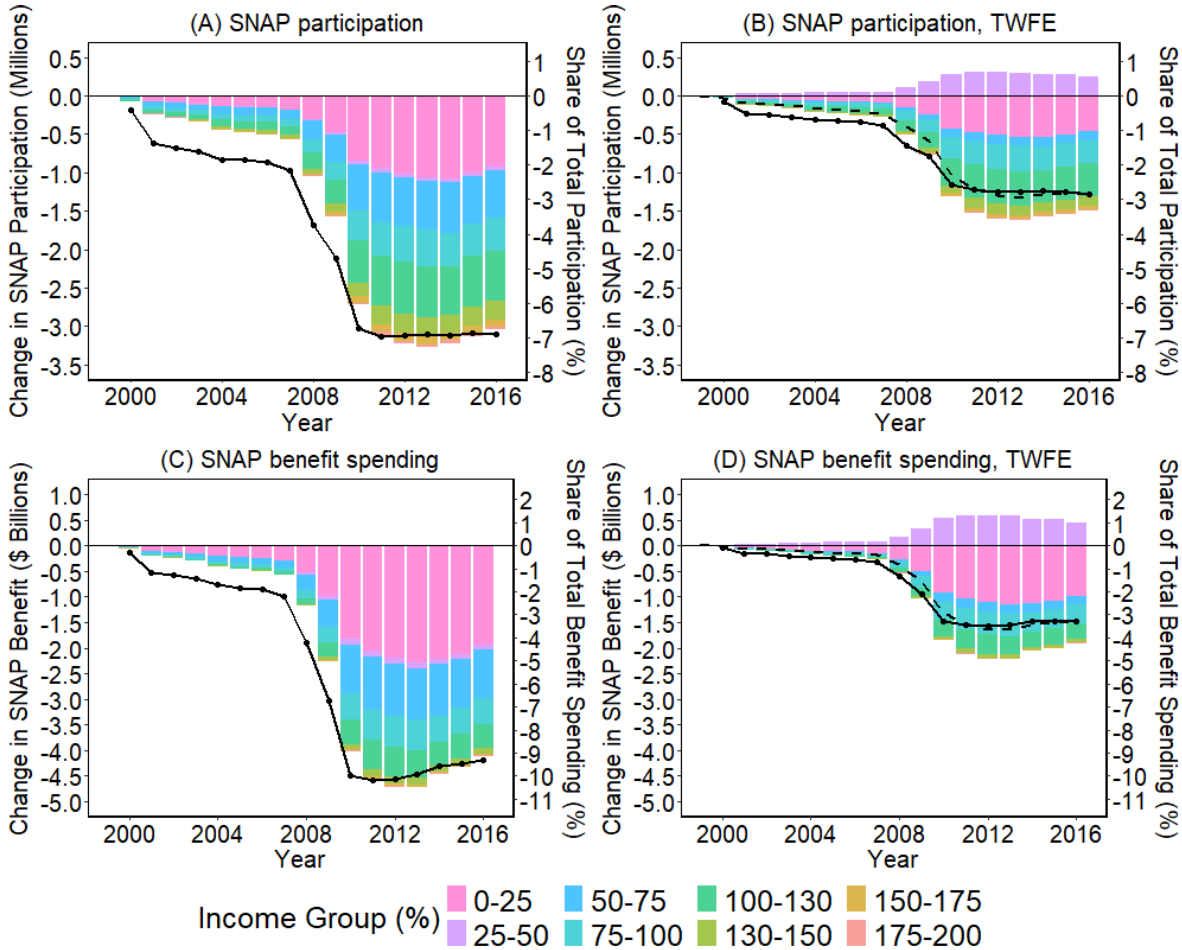

Figure A13. Simulated annual reduction in total SNAP participation and benefit spending in the absence of BBCE, 2000-2016, CSDD and TWFE with covariates

Notes: Panels A and B show the simulated annual reduction in SNAP participation and benefit spending under the counterfactual scenario that BBCE was never implemented using the income-group-specific CSDD estimates. Panels C and D show the simulated annual reduction in annual SNAP participation and benefit spending under the counterfactual scenario that BBCE was never implemented using the income-group-specific TWFE estimates. TWFE: two-way fixed effects; CSDD: Callaway and Sant'Anna (2021) difference-in-differences estimator. The horizontal axis represents the year. The left vertical axis represents the simulated annual reduction in SNAP participation measured in millions of participants and benefit spending measured by billion dollars. The right vertical axis displays a solid line indicating the share of SNAP participants. Different colors indicate the change incurred by different income groups. The dashed line in panels B and D represents the net change in the simulated annual reductions in SNAP participation and benefit spending. The simulated changes in SNAP participation and benefit spending under TWFE for the income group [25%, 50%) are based on the statistically insignificant coefficient estimate for this group (see Figure A9).

Table A1. SNAP participation per capita by socioeconomic characteristics by states' BBCE adoption status, 1996–2016

	Non-BBCE states	BBCE states	Difference	p-value
Gross income level of household				
0-25%	2.33	2.27	-0.07	0.54
25%-50%	1.54	1.98	0.44	<0.01
50%-75%	1.98	2.17	0.19	<0.01
75%-100%	2.08	2.34	0.26	<0.01
100%-130%	1.21	1.28	0.07	0.10
130%-150%	0.12	0.26	0.14	<0.01
150%-175%	0.08	0.15	0.07	<0.01
175%-200%	0.05	0.09	0.04	<0.01
Presence of a household member with a disability				
No	7.26	8.14	0.88	<0.01
Yes	1.93	2.23	0.30	<0.01
Presence of an elderly household member				
No	8.34	9.26	0.92	<0.01
Yes	0.86	1.12	0.26	<0.01
Presence of earned income				
No	5.24	6.26	1.02	<0.01
Yes	3.95	4.11	0.16	0.19
Receipt of cash assistance				
No	6.25	6.60	0.35	0.16
Yes	2.94	3.77	0.83	<0.01
Observations (state-year)	210	861		

Notes: BBCE: Broad-Based Categorical Eligibility. A state is considered as a BBCE adopter in any given year if it adopts BBCE for at least one month in that year. p-values represent a statistical two-sample t-test for equality of means between BBCE and non-BBCE states.

Table A2. Robustness check: Estimated impacts of BBCE policy on state-level per-capita SNAP participation using the CSDD estimator with not-yet-treated and never-treated states as controls, without and with covariates

	Not-yet-treated		Never-treated	
Log(SNAP participation per capita)	(1)	(2)	(3)	(4)
CSDD	15.52***	15.34***	14.97***	14.74***
	(2.97)	(2.07)	(2.84)	(2.07)
Covariates	NO	YES	NO	YES
Observations (state-by-year)	1071	1071	1071	1071

Notes: Outcome variable: Logarithm of SNAP participation per capita; Binary treatment variable: Implementation of Broad-Based Categorical Eligibility (BBCE). Other covariates used in the estimation process: SNAP policy index, unemployment rate, and percentage of population with income below 185% of the federal poverty guideline. TWFE: two-way fixed effects. CSDD: Callaway and Sant'Anna (2021) difference-in-differences estimator. CSDD incorporates pre-treatment covariates via the doubly robust (DR) estimation procedure, and uses not-yet-treated (columns (1) and (2)) and never-treated (columns (3) and (4)) as controls (Sant'Anna and Zhao 2020). The standard errors are clustered at the state level and calculated using the multiplier-type bootstrap method proposed in Callaway and Sant'Anna (2021). Bias-corrected estimates in percentage terms and standard errors are calculated following Kennedy (1981). *p < 0.10, **p < 0.05, ***p < 0.01.

Table A3. Robustness check: Estimated impacts of the BBCE policy on SNAP participation under alternative aggregation schemes of monthly data, using CSDD without and with covariates

Log(SNAP participation per capita)	(1)	(2)	(3)	(4)	(5)	(6)
CSDD	15.52***	15.34***	14.80***	14.23***	15.16***	14.99***
	(2.97)	(2.07)	(2.28)	(1.96)	(2.99)	(2.29)
Covariates	NO	YES	NO	YES	NO	YES
Aggregation scheme	Primary		Full-year		Majority-year	
Observations (state-by-year)	1071	1071	1071	1071	1071	1071

Notes: Outcome variable: Logarithm SNAP participation per capita; Binary treatment variable: Implementation of Broad-Based Categorical Eligibility (BBCE). Other covariates used in the estimation process: SNAP policy index, unemployment rate, and percentage of population with income below 185% of the federal poverty guideline. CSDD: Callaway and Sant'Anna (2021) difference-in-differences estimator. CSDD incorporates pre-treatment covariates via the doubly robust (DR) estimation procedure (columns 2, 4, and 6), and uses not-yet-treated states as controls (Sant'Anna and Zhao 2020). The standard errors are clustered at the state level and calculated using the multiplier-type bootstrap method proposed in Callaway and Sant'Anna (2021). Bias-corrected estimates in percentage terms and standard errors are calculated following Kennedy (1981).

Estimates in columns (1) and (2): define a state as a BBCE adopter in a given year if this state adopts BBCE for at least one month in that year, which serves as the primary aggregation scheme of the analysis.

Estimates in columns (3) and (4): define a state as a BBCE adopter only if this state adopts BBCE throughout that year (full-year aggregation scheme).

Estimates in columns (5) and (6): define a state as a BBCE adopter in a given year only if this state adopts BBCE for at least six months in that year (majority aggregation scheme). *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table A4. Robustness check: Estimated impacts of the BBCE policy on state-level per-capita SNAP participation using different CSDD estimators with covariates

Log(SNAP participation per capita)	(1)	(2)	(3)
CSDD	15.34***	15.87***	15.57***
	(2.07)	(2.65)	(2.32)
Estimation method	DR	OR	IPW
Observations (state-by-year)	1071	1071	1071

Notes: Logarithm of SNAP participation per capita; Binary treatment variable: Implementation of Broad-Based Categorical Eligibility (BBCE). Other covariates used in the estimation process: SNAP policy index, unemployment rate, and percentage of population with income below 185% of the federal poverty guideline. The Callaway and Sant'Anna (2021) difference-in-differences (CSDD) estimator is applied under alternative estimation procedures—doubly robust (DR) (Sant'Anna and Zhao 2020) (column 1), outcome regression (OR) (Heckman, Ichimura, and Todd 1997) (column 2), and inverse probability weighting (IPW) (Abadie 2005) (column 3)—using not-yet-treated states as controls and incorporating only pre-treatment covariates. The standard errors are clustered at the state level and calculated using the multiplier-type bootstrap method proposed in Callaway and Sant'Anna (2021). Bias-corrected estimates in percentage terms and standard errors are calculated following Kennedy (1981). *p $<$ 0.10, **p $<$ 0.05, ***p $<$ 0.01.

Table A5. Robustness check: Estimated impacts of the BBCE policy on state-level per-capita SNAP participation using CSDD with covariates, based on samples that either keep or exclude Louisiana in 2015 and 2016

Log(SNAP participation per capita)	(1)	(2)
CSDD	15.34***	17.73***
	(2.07)	(3.17)
Estimation method	DR	IPW
Louisiana (2015 and 2016)	Keep	Drop
Observations (state-by-year)	1071	1069

Notes: Outcome variable: Logarithm of SNAP participation per capita; Binary treatment variable: Implementation of Broad-Based Categorical Eligibility (BBCE). Other covariates used in the estimation process: SNAP policy index, unemployment rate, and percentage of population with income below 185% of the federal poverty guideline. CSDD: Callaway and Sant'Anna (2021) difference-in-differences estimator. Results are estimated using samples keeping (column 1) and dropping (column 2) Louisiana in 2015 and 2016, using not-yet-treated as controls and pre-treatment covariates via the doubly robust (DR) (Sant'Anna and Zhao 2020) and inverse probability weighting (IPW) (Abadie 2005) respectively. The standard errors are clustered at the state level and calculated using the multiplier-type bootstrap method proposed in Callaway and Sant'Anna (2021). Bias-corrected estimates in percentage terms and standard errors are calculated following Kennedy (1981). *p < 0.10, **p < 0.05, ***p < 0.01.

Table A6. Robustness check: Estimated impacts of the BBCE policy on state-level per-capita SNAP participation using CSDD with covariates, under different approaches for handling single-state groups g=2006 (Minnesota, MN) and g=2007 (Arizona, AZ)

Log(SNAP participation per capita)	Drop MN&AZ	Drop MN	Drop AZ	Move MN to g=2007	Move AZ to g=2006
	(1)	(2)	(3)	(4)	(5)
CSDD	15.20***	15.32***	15.21***	15.54***	15.54***
	(2.20)	(2.36)	(2.37)	(2.18)	(2.32)
Observations (state-by-year)	1029	1050	1050	1071	1071

Notes: Outcome variable: Logarithm of SNAP participation per capita; Binary treatment variable: Implementation of Broad-Based Categorical Eligibility (BBCE). Other covariates used in the estimation process: SNAP policy index, unemployment rate, and percentage of population with income below 185% of the federal poverty guideline. CSDD: Callaway and Sant'Anna (2021) difference-in-differences estimator. CSDD incorporates pre-treatment covariates via the doubly robust (DR) estimation procedure, and uses not-yet-treated states as controls (Sant'Anna and Zhao 2020). The standard errors are clustered at the state level and calculated using the multiplier-type bootstrap method proposed in Callaway and Sant'Anna (2021). Bias-corrected estimates in percentage terms and standard errors are calculated following Kennedy (1981). *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.