Food Benefits and Low-Income Families: Evidence from SNAP Expansion*

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Abstract

This paper examines how access to the Supplemental Nutrition Assistance Program (SNAP) has influenced the well-being of low-income families in the modern era. I exploit state-level variations in SNAP eligibility expansion under Broad-Based Categorical Eligibility (BBCE), which eliminated asset tests or increased the gross income limit. Using a difference-in-differences estimator, I find a sizable increase in SNAP participation and a decline in food insecurity among low-income households, following the BBCE expansion. While BBCE did not affect their employment status, it resulted in a small but significant reduction in hours worked. Additionally, BBCE did not significantly impact adults' health conditions, such as physical health measures and self-reported health. However, it improved access to health care, including greater access to prenatal care and primary care providers. These improvements in health outcomes were more pronounced among non-Whites compared to Whites, suggesting that BBCE contributed to reducing racial health inequities. Overall, this study provides comprehensive evidence on the effects of SNAP on near-poor families in recent decades.

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1 Introduction

One responsibility of modern governments is to protect citizens from external threats and ensure their well-being. Transfer programs help achieve this by providing financial assistance or goods to individuals facing economic hardship. Since adverse shocks often disproportionately affect disadvantaged groups and exacerbate inequality, these programs play a crucial role in protecting those in need, reducing poverty, and promoting social stability.

In the United States, many anti-poverty transfers are provided as in-kind benefits rather than cash, such as housing, medical services, and food. In particular, as the largest nutrition assistance program in the U.S.—accounting for two-thirds of the U.S. Department of Agriculture (USDA) nutrition assistance spending—the Supplemental Nutrition Assistance Program (SNAP) served 42.1 million individuals with federal spending of $112.8 billion in Fiscal Year (FY) 2023.[1] Given its scale and impact, SNAP is one of the most important safety net programs in developed countries. Therefore, understanding how the provision of SNAP benefits affects recipients is crucial for both the government and the study of public economics. However, causal evidence on the role of nutrition programs remains limited, highlighting the need to evaluate recent policy changes (Hoynes and Schanzenbach 2015).

This project examines how access to food assistance programs has affected the well-being of low-income families in the modern era, focusing on their labor and health outcomes. I evaluate this within the context of SNAP, which provides participating households with a lump-sum benefit each month to purchase food products at participating grocery stores.

Specifically, I exploit variations in the SNAP eligibility expansion known as Broad-Based Categorical Eligibility (BBCE). Prior to 1999, SNAP eligibility was primarily determined by federal rules, which made families with gross incomes below 130% of the Federal Poverty Level (FPL) eligible for the program, provided they passed both an asset test and a net income test. However, starting in the early 2000s, states were allowed to expand SNAP

[1]Participation and federal spending data are from the statistics provided by the USDA: https://www.ers.usda.gov/topics/food-nutrition-assistance/supplemental-nutrition-assistance-program-snap/key-statistics-and-research.

eligibility under BBCE by eliminating asset tests or increasing the gross income limit to as much as 200% of the FPL. This is one of the largest reforms in recent decades, designed to streamline the certification process by applying a single but broader cutoff across different households.

As of 2016, nearly 30 states had adopted BBCE by removing the asset test and relaxing the gross income test. Although the maximum income limit varied across states, ranging from 160% to 185% of the FPL, approximately 57% of states with BBCE implemented the largest expansion by raising the income limit to 200%. In sum, with a staggered adoption across states, BBCE extended SNAP eligibility to households with gross incomes above 130% of the poverty level, increasing the number of people eligible for SNAP in these states.

The main data sources consist of the 1997-2016 administrative records from the U.S. Department of Agriculture (USDA), the Current Population Survey (CPS), including its Food Security Supplement (FSS) and Annual Social and Economic Supplement (ASEC), Vital Statistics Natality Data, and the Behavioral Risk Factor Surveillance System (BRFSS). Specifically, the CPS-ASEC is utilized to create a sample of low-income families, identifying those most likely impacted by the BBCE expansion. To address potential endogeneity of income, I *predict* the FPL ratio—calculated as family income divided by the poverty level—using demographic characteristics of the sample *prior* to the implementation of BBCE. Then I define households in the lowest 35% of the predicted FPL ratio as low-income families.[2]

Given the differential timing of the BBCE expansion across states, I use a difference-in-differences (DiD) framework to compare the outcomes for low-income individuals or households before and after the BBCE expansion, relative to states without the expansion. To address the potential bias in using an ordinary least squares (OLS) regression with two-way fixed effects (De Chaisemartin and d'Haultfoeuille 2020; Sun and Abraham 2021; Goodman-Bacon 2021; Callaway and Sant'Anna 2021; Borusyak, Jaravel, and Spiess 2024; De Chaisemartin and d'Haultfoeuille 2024), I use the alternative DiD estimator developed

[2]This is because the lowest 35% corresponds to the proportion of individuals whose family income was below 200% of the poverty level before BBCE.

by De Chaisemartin and d'Haultfoeuille (2024).

The identifying assumption is that no unobserved, time-varying factors are correlated with the timing of the BBCE expansion. BBCE adoption is not significantly associated with state-level demographic and economic factors prior to the expansion, such as population, poverty rates, and unemployment rates, but rather with political stance toward welfare programs (i.e., blue or red states). Moreover, although the largest wave of BBCE adoption coincided with the Great Recession, state unemployment rates do not exhibit different trends based on BBCE adoption. Overall, my findings suggest that the decision to adopt BBCE was driven by political stance rather than economic conditions.

As the first-stage effect, I find a sharp increase in SNAP participation (averaging 7 to 12% across different datasets) and benefit amounts of $52.8 per year (a 9.76% increase). This expansion mainly benefited households with lower socioeconomic status—non-Whites, Hispanics, and individuals without a high school degree—who also had lower disposable income because of higher deductions, even though their gross income was relatively higher. Additionally, BBCE reduced the probability of low-income households experiencing low food security by 1.6 percentage points (a 7.63% decline) and very low food security by 0.8 percentage points (a 11.4% decline), which represent sizable effects.

Regarding labor market outcomes, the BBCE expansion had no substantial effect on the employment status of low-income individuals on the extensive margin of labor supply response. However, it resulted in a slight decline in their working hours by 0.3 hours per week (a 1.55% decline) on the intensive margin. The decline in hours worked was more pronounced among individuals with greater flexibility in adjusting their labor supply—those who are married, not the household head, and living with dependents under age 18. This decline in hours worked aligns with the labor supply model, which suggests that an increase in non-labor income leads to higher consumption and leisure, thereby reducing work hours when leisure is a normal good.

Concerning health outcomes, there is evidence of improved health care access among low-

income individuals following the BBCE expansion. BBCE led to a statistically significant increase of 0.21 prenatal visits during pregnancy (a 2.1% increase). It also significantly raised the likelihood of having a primary care provider, beginning one year after its implementation. This increase in health care access was more pronounced among non-Whites compared to Whites, suggesting that BBCE helped reduce racial disparities in health care access. These improvements may have been driven by the additional food budget alleviating financial pressures on available resources and reducing mental stress, thereby enabling greater investment in health care.

However, despite improvements in food security and health care access among low-income families, BBCE did not have significant effects on adults' health conditions, including physical health measures and self-reported health. While there is potential for a reduction in racial disparities in health conditions, as the effect sizes were larger for non-Whites compared to Whites—similar to the results for health care access—most of the estimates lack statistical significance, except for the decline in the probability of obesity among non-Whites. Nevertheless, an increase in the quantity and quality of food may contribute to long-term positive effects on health status, alongside improved health care access and utilization, which may not be immediately reflected in health conditions.

Prior Literature

This study contributes to two distinct strands of existing literature. The first relates to research examining the effects of the initial implementation of the Food Stamp Program (FSP) in the 1960s and 1970s. Studies find that the FSP improved birth outcomes (Almond, Hoynes, and Schanzenbach 2011), reduced labor supply (Hoynes and Schanzenbach 2012), and enhanced long-term outcomes, such as metabolic syndrome and economic sufficiency (Hoynes, Schanzenbach, and Almond 2016), human capital, residential neighborhood quality, and the likelihood of avoiding incarceration (Bailey et al. 2024).

The second strand of relevant literature focuses on the impacts of the BBCE expansion,

which serves as the treatment variable in this study. Numerous studies emphasize the role of SNAP policies, including BBCE, as key determinants of program participation (Klerman and Danielson 2011; Mulligan 2012; Ganong and Liebman 2018; Stacy, Tiehen, and Marquardt 2018; Dickert-Conlin et al. 2021; Jones et al. 2022). As more direct evidence, recent research finds that BBCE increased SNAP take-up among individuals who were *already* eligible prior to the expansion by enhancing access to information (Anders and Rafkin 2022) and reducing the transaction costs associated with applying for benefits (Lin 2024). On the administrative side, BBCE decreased government spending on program administration by over $100 million (Lin 2024). This was primarily through savings in certification processes (which account for approximately 50% of total administrative costs), benefit issuance, and fraud inspections, without increasing outreach spending or the incidence of fraud cases.

Building on two strands of literature, this study provides comprehensive evidence on the effects of SNAP eligibility expansion under BBCE on low-income families in the modern era, where evidence from participants' perspectives remains limited. The income and asset limits defining SNAP eligibility have been established in federal law since the program's introduction. However, despite the program's scale, these criteria have not been evaluated for their effectiveness over the past 50 years (Lin 2024).

More importantly, while previous studies on the BBCE expansion focus on its effects on SNAP participation and administrative costs, this study provides more thorough analyses of how the eligibility expansion influences participants' well-being across various dimensions, including food security, labor, and health outcomes. Additionally, this paper contributes to measuring the Marginal Value of Public Funds (MVPF) for SNAP in recent years, providing an estimate that can be compared to the program's introduction in the 1960s and 1970s.[3] Lastly, this study provides evidence on the effects of government transfers on near-poor families, beyond the poorest population traditionally targeted by welfare programs.

[3]MVPF is defined as the ratio of the benefits (measured as willingness to pay) to the policy's net cost to the government, serving as a unified method of assessing the policy's effect on social welfare. The initial introduction of the FSP resulted in an MVPF of 1.04 (Hendren and Sprung-Keyser 2020).

The remainder of the paper proceeds as follows. Section 2 describes institutional background on SNAP and the BBCE expansion. Section 3 describes the datasets, and Section 4 provides my empirical strategies. Section 5 presents the results on SNAP participation, household food insecurity, labor, and health outcomes, and Section 6 concludes.

2 Institutional Background

2.1 Supplemental Nutrition Assistance Program (SNAP)

SNAP is one of the largest safety net programs in the U.S., with the goal of meeting the basic needs of low-income families by supplementing their grocery budgets for nutritious food. In fiscal year (FY) 2023, the program provided food benefits to about 42.1 million individuals per month, which is roughly one in eight Americans, making it the largest food assistance program in the U.S. Total federal spending for SNAP was $112.8 billion, accounting for 68% of the U.S. Department of Agriculture (USDA) nutrition assistance spending, and the average monthly benefit per participant was $211.93.[4]

SNAP benefits are distributed monthly to participating households in a lump sum, with funds automatically loaded onto an Electronic Benefit Transfer (EBT) card, which works like a debit card. These benefits can only be spent on purchasing groceries at authorized retailers.[5] Recipients use their EBT card at regular store checkout lines to pay for their purchases and can supplement with other payment methods if their total purchase amount exceeds the card's balance or includes ineligible items.

The funding for SNAP consists of two components. First, benefit costs represent the expenditures used to provide food assistance to participants, specifically the amount spent

[4]All statistics are provided by the USDA: https://www.ers.usda.gov/topics/food-nutrition-assistance/supplemental-nutrition-assistance-program-snap/key-statistics-and-research.

[5]SNAP benefits can be used to buy any food (product) for home consumption, including fruits and vegetables, meat, poultry, fish, dairy products, breads, cereals, snacks, non-alcoholic beverages, and seeds and plants that produce food for the household to eat. However, the benefits cannot be used to purchase beer, wine, liquor, cigarettes, tobacco, vitamins, medicines, supplements, live animals (except shellfish, fish removed from water, animals slaughtered prior to pick-up from the store), hot foods at the point of sale, and any non-food items such as pet foods, cleaning supplies, paper products, other household supplies, hygiene items, and cosmetics. The information is from the USDA's website: https://www.fns.usda.gov/snap/eligible-food-items.

on food or EBT benefits. These SNAP benefits account for most of the total program costs and are funded entirely by the federal government. Although SNAP is a federal program, state agencies run the program through local offices which may oversee various aspects of the program, such as recertification length or the acceptance of online applications.[6] The second component of SNAP funding consists of administrative costs, which cover expenses for activities such as processing applications, determining eligibility, issuing benefits, and conducting fraud inspections. States receive reimbursement for half of these administrative costs from the federal government and are responsible for the remaining half.

2.2 Broad-Based Categorical Eligibility (BBCE)

Prior to 1999, SNAP eligibility was primarily determined by federal rules. However, starting in 2000, states were given the option to expand SNAP eligibility to a larger number of households through BBCE, making it one of the most significant reforms in the modern era. This change provides unique variation in SNAP eligibility criteria, which have not been evaluated since the program started in the 1960s and 1970s (Lin 2024), and enables researchers to analyze changes in state-level eligibility rules for SNAP.

SNAP eligibility is mostly determined by three criteria: assets, gross income, and net income, where net income is calculated as gross income minus deductions.[7] Specifically, federal law mandates that participating households must meet the following requirements: (i) assets—countable resources such as cash or money in a bank account—below the federal limit set by the USDA ($3,000 for most households or $4,500 if at least one household member is age 60 or older or disabled, as of March 2025); (ii) a gross monthly income below 130% of the Federal Poverty Line (FPL) ($3,380 per month for a family of four in FY 2025); and (iii) a net income below 100% of the FPL ($2,600 per month for a family of four in FY 2025).[8]

[6]Other state-level SNAP policies, which may be correlated with a state's decision to adopt BBCE or influence SNAP participation and participant outcomes, will be discussed later in Section 3.1.

[7]Examples of deductions include 20% of earned income, the standard deduction, dependent care, medical expenses, and excess shelter costs.

[8]The asset and income eligibility limits by family size are available here: https://www.fns.usda.gov/snap/recipient/eligibility (accessed in March 2025).

Under BBCE, there were no changes to the net income test. However, states were given the option to eliminate asset tests or increase the gross income limit. Since previous studies consistently indicate that asset rules affect only a small number of families and contribute minimally to the recent increase in SNAP participation (Eslami 2014; Ganong and Liebman 2018; Anders and Rafkin 2022), this study focuses on states that adopted both the elimination of asset tests and the relaxation of gross income tests.[9] Given that they passed the net income test, these policies generally make all households with incomes below a state-determined income threshold eligible for SNAP. Among states that implemented BBCE, income eligibility thresholds vary, ranging from 160% to the maximum threshold of 200% of the FPL, compared to 130% without the expansion.

Figure 1 suggests that it is feasible to use a quasi-experimental approach leveraging policy-induced temporal and spatial variations in each state's BBCE adoption. Figure 1-(a) illustrates the change in the number of states adopting the BBCE expansion of the asset test and the gross income rule over time. The time series graph highlights two notable jumps: (i) the initial implementation of BBCE in 2000 and (ii) the period during the Great Recession.

Regarding states' incentive to adopt BBCE, one driver is the desire to reduce administrative expenses by streamlining the certification process through a single but broader cutoff across different households. As described in Section 2.1, this is because states receive only partial reimbursement (50%) for administrative costs from the federal government, unlike benefit costs which are fully reimbursed. BBCE has the potential to lower administrative costs per case, particularly by eliminating asset tests. However, the increase in applications due to expanded eligibility could raise the administrative burden, making the overall effect ambiguous ex ante.[10]

Thus, the key determinant of BBCE adoption is each state's political stance toward

[9] Among 41 states that eliminated asset tests by 2016, 29 states also relaxed gross income tests, while 12 states adopted only the elimination of asset rules.

[10] This is because SNAP is an entitlement program, which guarantees funding to all eligible individuals, unlike block grants with fixed funding amounts. Thus, program spending naturally increases with the number of eligible and participating individuals.

welfare programs. Figure 1-(b) presents a map states categorized by their maximum gross income limit under the BBCE expansion as of 2016, which primarily includes coastal states with more generous government transfers.[11] Income eligibility thresholds vary across states: white states did not expand the gross income limit, dark blue states implemented the largest expansion up to 200% of the FPL, and light blue states fall in the middle, with limits ranging from 160% to 185%. By the end of the period, approximately 57% of BBCE states had expanded income limits to the maximum threshold of 200% of the FPL.

One concern is that the second major BBCE expansion coincided with the recession, which might confound the relationship between policy adoption and my findings. Moreover, previous studies demonstrate that both state policy changes and unemployment rates contribute to SNAP enrollment (Mulligan 2012; Ganong and Liebman 2018). To address this, I control for SNAP policies as well as unemployment rates in the main specification and present event study graphs for the outcomes of interest to show that there are no significant effects in the pre-treatment period. Additionally, I empirically test the identifying assumption to ensure that BBCE adoption is correlated with politics rather than economic conditions, as outlined in Section 4.2 after presenting the equations.

3 Data

3.1 U.S. Department of Agriculture (USDA) Data

For the empirical analysis, I utilize data from the USDA covering the period from 1997 to 2016. First, the administrative data on SNAP participation counts are aggregated at the level of month and participant's state of residence. I use the yearly level data to ensure consistency with other results from different data sources. In the administrative data, a participant in a given month is defined as an individual who has been issued SNAP food instruments (i.e., EBT cards) for that month. I also use the average benefit amount for SNAP-participating

[11] Specifically, when comparing the map of the 29 states that adopted BBCE by 2016 to the results of the 2000 U.S. presidential election, 20 of them were blue states. This suggests that some red states, including Texas and South Carolina, also adopted the reform, but the majority of treated states were liberal.

households in each state and year to validate the treatment effects on the reported value of SNAP benefits.

Since states administer the program, they can adopt different SNAP policies. Hence, I use the SNAP policy database to account for the effects of other SNAP policy variations during my study period. I categorize twelve policies into four groups and create four indices by taking the simple average within each group: (i) eligibility to receive benefits, (ii) transaction costs involved in applying, enrolling, or maintaining benefits, (iii) stigma associated with participation, and (iv) outreach efforts to spread information related to eligibility criteria and the process for receiving benefits (Ganong and Liebman 2018; Stacy, Tiehen, and Marquardt 2018; Dickert-Conlin et al. 2021; Jones et al. 2022).[12] My findings are robust to the construction of these indices.

To estimate the effect of BBCE on vendor participation, I use historical data on all SNAP-authorized retailers, which cover nearly all food stores.[13] The data include addresses, start and end dates of SNAP authorization, and store type variables for each vendor.[14] To identify the universe of food stores where most people usually shop (i.e., usual stores), I define non-usual stores as those including specialty stores (i.e., bakery specialty, fruits/vegetables specialty, meat/poultry specialty, and seafood specialty), non-retail stores (i.e., delivery routes, farmers' markets, and military commissaries), and small stores (i.e., convenience stores, small grocery stores, medium grocery stores, and combination groceries/others). Approximately

[12]The first category (i.e., eligibility) includes three SNAP policies: whether states exempt at least one vehicle or all vehicles from the asset test, and whether states impose eligibility restrictions for non-citizens. The second category (i.e., transaction costs) includes six policies: whether states discontinue using short certification intervals of three months or less, whether states implement the simplified reporting option that reduces requirements for reporting changes in household circumstances (e.g., only requiring households to report income changes that make them ineligible for benefits between recertification dates), whether states allow households to submit SNAP applications online, whether states ease enrollment procedures for Supplemental Security Income recipients under the Supplemental Security Income Combined Application Project (SSI CAP), whether states waive the face-to-face requirement for recertification and allow phone interviews, and whether states establish call centers to handle administrative tasks related to the program. The third category (i.e., stigma) includes two policies: whether states issue a proportion of SNAP benefits via an EBT card, and whether states require fingerprinting during the application process. The fourth category (i.e., outreach) includes one policy: whether states have federally funded TV or radio ad campaigns to raise awareness of SNAP among eligible non-participants.

[13]The data are publicly available here: https://www.fns.usda.gov/snap/retailer/historical-data.

[14]Store type definitions are available at: https://www.fns.usda.gov/snap/store-definitions.

20% of SNAP stores are classified as usual stores, which include food buying co-ops, large grocery stores, super stores, supermarkets, and wholesalers.[15] I count the number of total SNAP stores, usual stores, and non-usual stores in each state-year cell and use the participation counts as outcome variables.

3.2 Current Population Survey (CPS)

The CPS provides a rich set of demographic and economic variables for a representative sample of individuals and households. Since the BBCE expansion occurred nationwide with state-level variation over an extended period, the CPS serves as a strong data source for evaluating its effects. I use two types of CPS data from 1997 to 2016 to estimate the effects of BBCE on different outcomes and construct a sample of low-income families for my analyses.

First, I use the Food Security Supplements (CPS-FSS) to estimate the effect of BBCE on a household's probability of experiencing food insecurity in the past 12 months. The CPS-FSS provides information on the food security and food expenditures of U.S. households. The food security measures in the CPS-FSS were developed by the Food and Nutrition Service (FNS) of the USDA to identify households that experience limited or uncertain access to adequate food for economic reasons. Food security is assessed based on the number of affirmative answers to 18 questions related to food security, including 8 questions specific to households with children. Households are classified into three categories: (i) food secure, (ii) low food secure, and (iii) very low food secure. To measure the effects on food insecurity, I use the second and third categories of food security measures.

Being low food secure means that households experience a reduction in the quality, variety, and desirability of their diets, without a substantial reduction in the quantity of food intake and normal eating patterns. Being very low food secure indicates that households experience a disruption in the eating patterns of one or more household members and a reduction in food intake due to a lack of money or other resources for food. I create two

[15]The store type of 1.63% of SNAP stores is unknown and classified as usual stores.

indicators for low and very low food security in the past 12 months and use them as outcome variables.

Next, I use the Annual Social and Economic Supplements (CPS-ASEC), also known as the March Supplements. The CPS-ASEC provides SNAP-related variables, including whether an individual reports that household members receive SNAP benefits and for how long. Although self-reported program participation variables are subject to underreporting (Meyer, Mok, and Sullivan 2009), the CPS-ASEC complements the USDA's administrative data, which only provides total participation counts by state. Therefore, I use the CPS-ASEC to examine the effect of BBCE on SNAP participation, as well as heterogeneity and compositional changes in participation. The raw trends over time and the estimated treatment effects on participation and benefits from both data sources appear consistent, as discussed in later sections.

I also analyze the effects on labor market outcomes using the CPS-ASEC, including employment status, hours worked per week, and full-time status—defined as working 35 or more hours per week. Finally, I construct a sample of low-income households using a set of demographic and income variables from the CPS-ASEC, which I elaborate on in Section 4.1.

3.3 Vital Statistics Natality Data

To measure the impact of the BBCE expansion on birth outcomes, I use restricted-use Vital Statistics Natality data from 1997 to 2017. The data cover the entire universe of births in the U.S. and provide detailed information about individual births, including demographic information of mothers and fathers, maternal state of residence, and birth outcomes such as birth weight, gestation weeks, number of prenatal visits, and infant mortality.

I assign the treatment timing as the beginning of the quarter prior to birth—a proxy for the beginning of the third trimester—which is the most critical period for determining birth weight (Almond, Hoynes, and Schanzenbach 2011).[16] Then the sample is restricted to low-income households from 1997 to 2016 whose predicted FPL ratio falls within the bottom

[16]Since each observation records the date of birth and gestation weeks, I calculate the conception date and add one quarter to it for all births.

35%, as described in Section 4.1.

3.4 Behavioral Risk Factor Surveillance System (BRFSS)

The second main source of data for health-related outcomes is the BRFSS, a telephone survey that collects information on health outcomes from adults aged 18 and older. Currently, the BRFSS is the largest continuously conducted health survey system in the world, with over 400,000 interviews conducted nationwide each year.

The survey consists of core component and optional modules. The core component questions are administered in every state, while the optional modules are only conducted in states that choose to implement them. My analysis relies on data from the core modules, which include questions on various health outcomes, such as health care access and utilization, physical health measures, self-reported health, and health conditions. Additionally, the core modules provide detailed demographic characteristics and state of residence of each individual. I exclude individuals who reported being non-residents of their respective states. As with all other analyses using different datasets, I restrict the sample to low-income individuals.

3.5 Descriptive Statistics

As the first stage outcome for the BBCE expansion, Figure A.1 displays time series graphs of SNAP participation over time based on two different data sources. Figure A.1-(a) presents SNAP participation rates among low-income families using the CPS-ASEC, constructed as outlined in Section 4.1, while Figure A.1-(b) shows the total number of SNAP participants (in millions) using the USDA's administrative data. The two graphs follow a similar trend, with two significant increases in SNAP participation: when BBCE was first implemented in 2000 and around the Great Recession. These patterns are aligned with the trend in the number of states adopting BBCE over time, as shown in Figure 1-(a).

4 Empirical Strategy

This section describes the empirical strategy employed to estimate the causal effects of the BBCE expansion on SNAP participation, food insecurity, labor, and health outcomes of low-income families. I rely on the staggered treatment timing of the BBCE expansion across states, using a difference-in-differences (DiD) framework. In particular, I implement the approach of De Chaisemartin and d'Haultfoeuille (2024), which is not subject to the issue of negative weighting and remains robust to heterogeneous treatment effects. The choice of specification depends on whether the outcomes are estimated at the level of individual or household i, or at the state level s as follows:

$$Y_{ist} = \alpha + \beta BBCE_{st} + \Omega' X_i + \Gamma' Z_{st} + \lambda_s + \mu_t + \epsilon_{ist} \tag{1}$$

$$Y_{st} = \alpha + \beta BBCE_{st} + \Gamma' Z_{st} + \lambda_s + \mu_t + \epsilon_{st} \tag{2}$$

$Y_{(i)st}$ is the outcome variable for (an individual or household i) in state s and year t, including SNAP participation, indicators for household food insecurity, labor market outcomes, and health outcomes. The treatment variable, $BBCE_{st}$, is an indicator for whether state s has expanded SNAP eligibility under BBCE in year t. λ_s and μ_t are state and year fixed effects, and $\epsilon_{(i)st}$ is the error term clustered at the state level. To analyze the dynamics of treatment effects and assess the presence of confounding pre-trends, I also estimate event study versions of Equations 1 and 2. These models allow for the estimation of dynamic effects up to $t = 2$ and pre-treatment (placebo) effects up to $t = -3$ to construct a balanced panel at the state and year levels.[17]

I consider various specifications with different sets of covariates. X_i represents a vector of individual- or household-level covariates, including age, gender, race/ethnicity, marital status, and education level (for households, this refers to the household head). Z_{st} is

[17]Since Illinois adopted the BBCE expansion of the gross income limit in 2016, which is the last year of my data period, I exclude Illinois from the analysis to estimate dynamic treatment effects in the post-treatment period.

a set of state-level covariates, including unemployment rates and four SNAP policy indices—eligibility, transaction costs, stigma, and outreach—defined in Section 3.1. They are included to control for their potential influence on SNAP participation and the outcomes of program participants. For health outcomes, I also control for Medicaid expansion under the Affordable Care Act (ACA) to account for differential effects across states due to variations in insurance coverage generosity for low-income individuals. I use the specification with the full set of controls as the main specification, while estimates from alternative specifications with different covariates are reported in the Appendix as robustness checks.

The identifying assumption is that there are no unobserved, time-varying factors correlated with the timing of BBCE adoption. In the specifications defined by Equations 1 and 2, given this assumption, β is the coefficient of interest representing the effect of the BBCE expansion (on individuals or households) in treated states relative to (those in) non-treated states, before and after adoption. For all specifications, I apply person- or household-level weights from the data where applicable.

The literature on potential biases in using ordinary least squares regression with two-way fixed effects (TWFE) has expanded, particularly in cases where (i) the timing of treatment adoption varies and (ii) treatment effects are heterogeneous across units and over time (De Chaisemartin and d'Haultfoeuille 2020; Sun and Abraham 2021; Goodman-Bacon 2021; Callaway and Sant'Anna 2021; Borusyak, Jaravel, and Spiess 2024; De Chaisemartin and d'Haultfoeuille 2024). Given that states adopted the BBCE expansion at different times, I use the estimator developed by De Chaisemartin and d'Haultfoeuille (2024) (DCDH) to address potential biases associated with the TWFE estimator.[18]

The parameter of interest is defined as a weighted average of the average treatment effects for groups that switched into and those switched out of treatment. Specifically, states adopting the BBCE expansion are compared to states that remained untreated in both years, rather than to those that had already adopted it in both years. Similarly, states that revoked

[18] Approximately 20% of the weights are negative across all outcomes, further supporting the adoption of this method.

the expansion are compared to those that remained treated in both years. Unlike other alternative DiD estimators, the DCDH estimator accommodates the estimation of treatment effects when a treatment can both "turn on" and "turn off," as observed with the BBCE expansion.[19]

4.1 Identifying a Low-Income Sample

Throughout the paper, I construct a sample of low-income individuals or families to identify those most likely to be affected by the BBCE expansion to ensure sufficient statistical power for the estimation. A key challenge is that income may be endogenous to the BBCE expansion. To address this, I predict the FPL ratio—calculated as family income divided by the poverty level—using characteristics of the sample prior to the implementation of BBCE, so that these predictions remain unaffected by the policy. I follow the approach proposed by Rittenhouse (2023).[20]

I begin with a sample of households with children under age 18 from the pre-treatment period of the CPS-ASEC from 1997 to 1999.[21] Next, I divide the sample into a training set (75%) and a validation set (25%) and run a linear regression on the training set using the following equation:

$$Y_i = \alpha + \beta X_i + \delta X_i \times X_i \tag{3}$$

Y_i is the FPL ratio of household i, serving as the outcome variable of interest. X_i is a vector of observable characteristics, including the household head's and spouse's age, gender, race and ethnicity, education, number of children under age 18, number of family members, and state, with one level of interaction included. I obtain predicted values of the FPL ratio by applying the estimated regression coefficients to the entire dataset. Finally, I define households in the lowest 35% of the predicted FPL ratio as low-income families, as this

[19] This is particularly noteworthy because South Carolina revoked its expansion in 2009.

[20] In the referenced paper, this procedure aims to estimate the tax value of birth and define "low-income" births by predicting household income.

[21] This is because SNAP benefits may be limited to three months within a three-year period for households without a child under age 18, unless they meet work requirements or qualify for an exemption.

corresponds to the proportion of individuals whose family income was below 200% of the poverty level before BBCE. This procedure is repeated for all analyses using different data, except for the USDA's administrative data on statewide SNAP participation counts.

The scatter plots in Figure A.2 compare predicted values to true values in the validation sample (25%) of the CPS-ASEC for the FPL ratio. Each blue dot in Figure A.2-(a) corresponds to an observation, while Figure A.2-(b) displays the average predicted values within bins of actual FPL ratios, with bin lengths of 50 percentage points. Both figures demonstrate that the estimation strategy is effective in ordering observations by the FPL ratio, particularly within the low-income population. The out-of-sample R-squared is 0.351.

The widening gap in SNAP participation counts (Figure A.1-(b)) between treated and never-treated states may be driven by changes in population size or the underlying composition of people rather than the BBCE expansion, particularly around the Great Recession. To address this, Figure 2 presents time series graphs of the share of the SNAP-eligible population based on the gross income rule over time, separately for each state's BBCE adoption decision. The SNAP-eligible population is defined as individuals whose predicted FPL ratio falls within the lowest portion of the distribution across several thresholds. These thresholds correspond to the population share with incomes below each income threshold based on the gross income limit in the pre-treatment period.[22]

As shown by the red line, the fraction of predicted SNAP-eligible individuals remains stable in states without BBCE adoption. However, the blue line, representing states with BBCE adoption, follows a different pattern, leading to a widening gap between treated and never-treated states. In addition to the two significant jumps observed in the number of states adopting BBCE (Figure 1-(a)) and in SNAP participation (Figure A.1), another sharp increase in the predicted SNAP-eligible population share occurs in 2014. This is when California adopted BBCE, accounting for about 10% of the sample—the largest share among states that implemented BBCE.

[22]This corresponds to 20% for 130% of the FPL as the income limit; 27% for 160% of the FPL; 28% for 165% of the FPL; 32% for 185% of the FPL; and 35% for 200% of the FPL.

4.2 Determinants of the BBCE Expansion

The validity of my research design relies on the assumption that BBCE adoption is as good as random. In addition to testing the robustness of my results using various controls, I directly examine whether state-level characteristics prior to the BBCE expansion can predict a state's BBCE adoption as a binary outcome. Figure A.3 shows that BBCE adoption is not significantly associated with unemployment rates, poverty rates, or population size, but is strongly linked to whether a state is a blue state—as determined by the results of the 2020 U.S. presidential election. The coefficient for per capita expenditure on welfare programs is slightly larger than those of the first three variables, reflecting the influence of political stance on BBCE adoption.[23] [24]

As briefly discussed in Section 3.5, the largest wave of BBCE adoption occurred around the Great Recession. The potential confounding effects of state economic conditions on BBCE adoption could threaten the causal interpretation of my findings. To address this concern, I estimate the event-study version of the main specification based on Equation 2 without controls, using unemployment rates as the outcome. In Figure A.4, I do not find strong evidence that state unemployment rates follow different trends based on BBCE adoption, both over the entire data period (Figure A.4-(a)) and in the restricted period from 2007 onward (Figure A.4-(b)). Notably, there are no positive pre-trends, even when I restrict the sample to later years. This suggests that unemployment rates, as a key variable representing each state's economic conditions, were not a primary driver of BBCE adoption.[25]

[23] Government expenditure on welfare programs indicates per capita transfer spending—such as cash assistance, medical care, and retirement and disability payments—and is from the State and Local Finance Data, available at: https://state-local-finance-data.taxpolicycenter.org/pages.cfm.

[24] Consistent with these findings, Lin (2024) also demonstrates that state BBCE adoption cannot be predicted using pre-expansion state characteristics, such as voters' preferences for welfare programs, voters' negative attitudes toward Black Americans, state economic conditions, fiscal reliance on federal grants, or SNAP administrative costs and error rates.

[25] Another potential confounder is the SNAP Provisions of the American Recovery and Reinvestment Act of 2009 (ARRA). The temporary increase in maximum SNAP benefits and additional federal funding for SNAP administration applied uniformly across all states and did not vary at the state level. State-level differences in other SNAP policies—such as enrollment processes, administrative flexibility, and outreach efforts—are accounted for in the main specification, except for the suspension of the time limit for able-bodied adults without dependents (ABAWDs). ARRA initially suspended the three-month time limit for

To sum up, although many states adopted BBCE around the time of the Great Recession, the decision to adopt it was driven by political stance, rather than by economic conditions.

5 Results

This section presents the main estimation results on SNAP participation, household food insecurity, labor market outcomes, and health outcomes resulting from the BBCE expansion using the DCDH estimator. I begin by presenting the first-stage effect on SNAP participation, for both individuals and retailers.

5.1 SNAP Participation

Table 1 shows the DiD estimates for SNAP participation using different data sources. The DiD estimate in column (1) shows the effect of BBCE on SNAP participation among low-income individuals as a binary outcome, using individual level data from the CPS-ASEC and estimated with Equation 1. Following the BBCE expansion, I found a significant increase in SNAP participation of 2.5 percentage point. This corresponds to an 11.74% increase, when using the average participation rate of low-income individuals during the pre-treatment periods as the baseline.

The outcome variable in columns (2) and (3) are the natural log of the number of individuals (column (2)) and households (column (3)) participating in SNAP (i.e., participation counts), based on administrative data from the USDA and estimated with Equation 2. BBCE increased SNAP participation by 7.2 to 7.5% on average for both individuals and households. These estimates are slightly smaller than the estimate based on CPS data in column (1), and the discrepancy likely stems from differences in sample construction and the inclusion of

ABAWDs nationwide until September 2010. After the nationwide suspension expired, states could either continue waiving the time limits or reinstate them, leading to some state-level variation. However, my results remain robust to controlling for the effects of ABAWD waivers, based on the database of Harris (2021). To maintain consistency with previous studies on BBCE, I do not control for them in my specification. The information on the ABAWD time limit is available at: https://www.cbpp.org/research/food-assistance/waivers-add-key-state-flexibility-to-snaps-three-month-time-limit.

individual-level controls. Table A.1 demonstrates that this increase in SNAP participation is robust to the inclusion of different covariates when using both participation rates (Panel A) and counts (Panel B) as outcomes.

The identifying assumption is that the timing of the BBCE expansion across states is uncorrelated with each state's time-varying determinants of the outcomes of interest. To test this assumption, Figure 3 shows my main event study estimates of the impact of BBCE on SNAP participation from both data sources. I set the period $t = -1$ as the reference period. At each period, blue dots represent the DiD estimates for SNAP participation, exploiting spatial and temporal variations in the BBCE expansion along with a 95% confidence interval. Since the estimates in the pre-treatment periods are close to zero and statistically insignificant for all pre-periods, they are consistent with the parallel trends assumption, allowing for causal inference from the estimates. The estimates for post-treatment periods in Figure 3 show a sharp increase in SNAP participation over time, which is consistent with the average increase following the BBCE expansion previously shown in Table 1.

Next, I estimate the effects of BBCE expansion on SNAP benefit amounts, including 0 for non-participants. Column (1) of Table 2 shows that BBCE increased the average household benefit amount by \$52.8 per year, or 9.76% relative the pre-treatment mean of \$541.1. As a robustness check, column (2) presents the estimate for winsorized benefit amounts, where extreme values are replaced at the 2.5th percentile in each tail of the distribution. After winsorization, the average yearly benefit for each household prior to adoption is \$509.2, which is slightly lower than the reported values but similar in magnitude. The DiD estimate of \$47.4 corresponds to a 9.32% increase, suggesting that the result is robust to winsorization of extreme values. Corresponding event study figures are presented in Figure 4.[26]

[26]Since the estimates are based on survey participants' reported values, I also compare them to the average benefit amount for SNAP-participating households from the USDA's administrative data. Prior to BBCE adoption, the average yearly benefit amount for participating households is \$3,167 (in 2016 dollars), and the SNAP participation rate of low-income families from the CPS-ASEC is 0.211. Following the policy adoption, SNAP participation rates increased by 11.7% (CPS-ASEC) and 7.5% (USDA data), as shown in Table 1. Adjusting the average benefit amount using the sample means and the treatment effects results in increases of \$78.1 (CPS-ASEC) and \$50.1 (USDA data) in household SNAP benefit amounts, respectively. This suggests that the effect sizes of reported benefits align with those from the administrative data.

5.1.1 Heterogeneity Analyses

I examine heterogeneity by demographic characteristics to evaluate the targeting properties of the reform using the CPS-ASEC. Despite states' autonomy in eliminating asset rules and increasing gross income limits, the net income test of 100% of the FPL and the benefit schedule—the maximum allowance less than 30% of net income—remained unchanged. Consequently, the expanded eligibility primarily applies to households with large deductions to gross income, particularly those with high child care, medical care, and shelter costs (Hoynes and Schanzenbach 2015).

In Table A.2, Panel A presents the effects on SNAP participation rates, while Panel B presents the effects on SNAP benefit amounts. For both outcomes, I find larger increases among non-Whites (column (2)), Hispanics (column (3)), and individuals with low education levels who have not completed high school (column (5)). These demographic groups, who were disproportionately affected by the expansion, are generally more socioeconomically disadvantaged.

Put differently, beyond increasing overall participation and benefits received, this expansion primarily benefited households with lower socioeconomic status, also characterized by lower disposable income due to higher deductions despite relatively higher gross income.

5.1.2 Continuous Treatment

I estimate the same specification using two measures of continuous treatment, rather than a binary treatment, to better capture the differential effect of treatment intensity given the variation in income thresholds across states. The average coefficients from the CPS-ASEC (column (1)) and the USDA data (column (2)) are presented in Table A.3.

Panel A shows the estimates for the first treatment measure, which is constructed based on the gross income limit, ranging from 130% to 200% of the FPL. I assign a value of 0 to states and years without the BBCE expansion (i.e., 130% of the FPL) and assign the change in the gross income limit as a percentage of the FPL to treated states after adoption, scaling

it to represent the effect of a 10 percentage-point increase in the income limit. Columns (1) and (2) show that a 10 percentage-point increase in the gross income limit (i.e., from 130% to 140% of the FPL) increased SNAP participation by 0.4 percentage points (a 2.03% increase) and 1.3%, respectively for each data source. With the maximum increase in the income threshold from 130% to 200% of the FPL, the estimates indicate a 14.04% and 8.82% increase in SNAP participation.

In Panel B, the other continuous treatment measure is based on the share of the SNAP-eligible population in terms of the gross income limit.[27] As discussed in Section 4.1, during the pre-treatment period, the lowest 20% of survey respondents in the CPS-ASEC had predicted family incomes below 130% of the FPL, while the lowest 35% had predicted incomes below 200% of the FPL. I assign a value of 0 to states and years without the BBCE expansion and assign the change in the eligible population share to treated states after adoption, scaling it to represent the effect of a 1 percentage-point increase in the eligible population share.

Panel B shows that a 1 percentage-point increase in the share of the eligible population (i.e., from the bottom 20% of the income distribution to 21%) increased SNAP participation by 0.2 percentage points (a 0.93% increase) (column (1)) and 0.06% (column (2)). With the maximum increase in the eligible population share from the lowest 20% to 35% of the FPL ratio, the estimates indicate a 14% and 8.72% increase in SNAP participation, which are very similar in magnitude to those in Panel A.

The estimates are slightly larger than those in Table 1, which are obtained using a binary treatment: 11.7% from the CPS-ASEC and 7.5% from the USDA data. Considering that 16 out of the 28 states that adopted the BBCE gross income rule in my sample chose the maximum limit of 200%, the treatment effects from different types of treatment variables are consistent with each other. Thus, I use the binary treatment throughout the remaining analyses in this paper.

[27] These values are also used to plot a time series graph of the share of the SNAP-eligible population in Figure 2.

5.1.3 Permutation Test

To ensure that my results capture true policy effects, I perform a permutation test as a falsification method to evaluate the impact of BBCE expansion on SNAP participation, using the two data sources mentioned earlier. In this test, I randomly reassign states to the treated or untreated groups, while keeping the original BBCE adoption dates unchanged. The average effect of BBCE on SNAP participation under these counterfactual assignments should be close to zero.

I reassign treatment status 1,000 times and plot the estimates of each counterfactual policy effect as a histogram in Figure A.5, separately for each data source. Figure A.5-(a) presents the results from the CPS-ASEC data, where the distribution is bell-shaped with a mean of -0.001 and a standard deviation of 0.008. The vertical red line represents the original DiD estimate of 0.025 for the effect of the BBCE expansion on low-income individuals' SNAP participation rates as a binary outcome (column (1) of Table 1).

Figure A.5-(b) presents the results from USDA's administrative data, showing the coefficients on the natural log of SNAP participation counts. The distribution closely resembles that in Figure A.5-(a), with a mean of 0 and a standard deviation of 0.021. Again, the original DiD estimate of 0.075, repsented by the vertical red line (column (2) of Table 1), falls in the right tail of the distribution. The p-values from the two permutation tests are 0.003 (Figure A.5-(a)) and 0.001 (Figure A.5-(b)), suggesting that my findings are unlikely to be the result of spurious effects.

5.1.4 SNAP Retailer Participation

I present evidence on vendor participation following the BBCE expansion. While there is a huge increase in the number of individuals participating in SNAP, Table A.4 and Figure A.6 present no significant effects on the number of stores participating in SNAP (column (1) and Figure A.6-(a)). By store type, as defined in Section 3.1, there are also no significant changes in the number of SNAP vendors, for both usual stores (column (2) and Figure A.6-

(b)) and non-usual stores (column (3) and Figure A.6-(c)). This implies an increase in the number of SNAP participants each SNAP retailer should serve, as an increase in the number of SNAP participants due to eligibility expansion was not accompanied by an increase in the number of SNAP stores. Moreover, I find a 0.6 percentage point decline in the share of usual stores (a 2.93% decline) (column (4)). Though an economic significance of the estimate is not huge, my findings suggest that overall shopping experience for SNAP participants may have become less convenient after the BBCE expansion.

5.2 Food Insecurity

To measure one of the most direct effects of SNAP expansion, I estimate how BBCE affected low-income households' access to food, using two indicators for food insecurity. Table 3 shows that the BBCE expansion reduced the probability of households experiencing low food security in the past 12 months by 1.6 percentage points (column (1)) and very low food security by 0.8 percentage points (column (2)). These point estimates correspond to a 7.63% and 11.4% decline in food insecurity relative to the pre-treatment means, representing sizable effects in percentage terms.

Additionally, event study estimates in Figure 5 show a reduction in the probability of low-income households' experiencing food insecurity, preceded by flat pre-trends for both outcome indicators. Thus, the decrease in the fraction of households with food insecurity indicates improvements in access to nutritious foods among low-income households following the BBCE expansion.

5.3 Labor Market Outcomes

Table 4 presents the results of the BBCE expansion's impact on labor market outcomes among low-income individuals, focusing on employment status and weekly hours of work. The definition of hours worked per week includes zero hours for individuals who did not report any employment during the year. Column (1) of Table 4 indicates that BBCE had

no substantial effect on the probability of being employed for low-income individuals as a binary outcome. The 0.3 percentage point decline is neither statistically nor economically significant relative to the pre-treatment mean.

In contrast, column (2) reveals that the BBCE expansion led to a slight reduction in weekly working hours by 0.3 hours (a 1.55% decline). This finding highlights a modest but significant adjustment in labor supply on the intensive margin, driven by the additional food budget provided through SNAP expansion, without notable changes on the extensive margin. Figure 6 confirms the absence of confounding pre-trends for both employment status (Figure 6-(a)) and weekly hours of work (Figure 6-(b)).

Next, I examine the heterogeneous effects of the BBCE expansion on hours worked, considering household structure and demographic characteristics of low-income families. In Table 5, columns (1) and (2) show that the decline in working hours is concentrated among individuals living with dependents under age 18. This group may reduce their labor supply to spend more time with children, facilitated by easier access to food. For SNAP recipients specifically, individuals without dependents can only receive benefits for three months during a three-year period if they do not meet work requirements.[28] Thus, it may be more challenging for this group to reduce their labor supply while maintaining SNAP benefits beyond the three-month limit.

Additionally, the decline is greater among individuals who are not the household head (columns (3) and (4)) and are thus more likely to be secondary earners, as well as among married individuals (columns (5) and (6)), although the latter two estimates are not statistically significant. These findings suggest that labor supply responses tend to be larger among individuals with greater flexibility in adjusting their labor supply.

Hoynes and Schanzenbach (2012) found that the initial introduction of the Food Stamp Program (FSP) in the 1960s and 1970s had no significant impact on the labor supply of the overall sample but reduced both employment and hours worked among single mothers,

[28]Information about specific requirements and exemptions is available here: https://www.fns.usda.gov/snap/work-requirements.

who were more likely to participate in the program. Their estimates for the overall sample, though very small in magnitude, do not indicate a negative effect. This is likely due to the composition of their sample, which includes higher-income individuals who are less relevant to SNAP and its expansion, with only 3% of the sample reporting food stamp receipt.

As another distinction, I found that the decline was more pronounced among married individuals than unmarried ones. Consistent with the findings from all of my heterogeneity analyses, married individuals may find it easier to reduce their labor supply due to the presence of a partner who can also work or contribute financially, unlike unmarried individuals who may still need to work. Since my sample consists only of those likely to be affected by the reform in terms of predicted income—unlike that of Hoynes and Schanzenbach (2012)—household structure may play a larger role in determining the effects of benefit receipt.

According to Hoynes and Schanzenbach (2012), the implementation of the FSP led to a reduction in annual work hours by 238 hours (a 22.3% decline) among families headed by an unmarried woman. This reduction is significantly larger than my estimate of 14.82 hours—calculated as 0.285 hours per week $\times$ 52 weeks per year—resulting from the BBCE expansion's effect on all low-income families. The smaller magnitude of my estimate likely reflects that it captures the impacts of program expansion, rather than initial implementation, and includes effects on less poor families.

Altogether, the decline in hours worked is consistent with the theoretical predictions of the neoclassical labor supply model, which suggests that an increase in non-labor income leads to higher consumption and more leisure, resulting in fewer working hours (assuming that leisure is a normal good). In addition, when comparing the treatment effects of program implementation in earlier periods to recent program expansions, the potential adverse effects of transfer programs—such as reducing work incentives, discouraging labor supply, and lowering tax revenues—appear to have been mitigated.

5.4 Health Care Access

In terms of health-related outcomes, I first estimate the effect of the BBCE expansion on health care access and utilization among low-income families. Figure 7-(a) and column (1) of Table 6 show that the number of prenatal visits during pregnancy increases by 0.21, with strong statistical significance at the 1% level (a 2.1% increase). Column (2) indicates a 1.1 percentage point increase in the probability of low-income adults having a personal doctor or health care provider. While this average effect is not statistically strong, Figure 7-(b), which illustrates dynamic effects, shows a statistically significant increase of 2.2% starting one year after the BBCE expansion.

When investigating heterogeneous effects by race, Table 7 reports greater improvements in health care access among non-Whites compared to Whites, both for prenatal care and access to health care providers. Columns (1) and (2) show that the increase in the number of prenatal visits is 0.24 for non-Whites (a 2.42% increase), which is larger than the 0.13 percentage-point increase for Whites (a 1.23% increase), both in absolute terms and as a percentage. In columns (3) and (4), the BBCE expansion increased the probability of having a primary health care provider for both non-Hispanic Whites and non-Whites. However, the 2 percentage point increase for non-Whites (a 3.05% increase) is more than twice greater than the increase for Whites and exhibits stronger statistical significance. Since non-Whites had lower average values in the pre-treatment period and experienced greater increases in both outcomes following the BBCE expansion, these findings suggest that BBCE also reduced racial disparities in health care access while improving overall access.

My findings on health care access align with those of Bronchetti, Christensen, and Hoynes (2019), although their focus is on *children's* outcomes. They report that higher SNAP purchasing power, driven by changes in local prices, led to increased utilization of preventive health care among children, including a greater likelihood of having an annual checkup and any doctor's visit. Similarly, this increase in health care access can be attributed to the expansion of available resources resulting from an income effect. This is because additional

access to SNAP enables participating households to consume not only more nutritious foods but also other goods and services, including health care, even though it is not directly provided by SNAP. This channel is further supported by the slight decline in hours worked, as reported in Section 5.3, which may allow individuals to invest more time in receiving medical care. Moreover, with reduced financial constraints, low-income families may experience less mental stress and be more likely to prioritize things that are not urgent but important in the long run, such as regular check-ups.

5.5 Health Conditions

In the previous sections, I present evidence that BBCE significantly reduced food insecurity and increased health care access among low-income families, suggesting potential improvements in health status. To verify this, this section provides estimates of health conditions among the low-income population.

I first estimate the effect of the BBCE expansion on physical health measures and self-reported health among adults aged 18 or older. In Table 8, columns (1) and (2) show that BBCE resulted in a slight decline in body mass index (BMI)—measured as weight (in kilograms) divided by height (in meters) squared—and a reduction in the probability of being obese (BMI > 30), although the coefficients are not statistically significant.[29] Regarding self-reported health, columns (3) and (4) indicate no significant impacts of the BBCE expansion on indicators of poor health in the past 30 days, assessed separately for physical and mental health.

Table 9 shows that, compared to Whites, non-Whites experienced a greater decline in the probability of being obese (columns (1) and (2)), as well as in reporting poor physical health (columns (3) and (4)) and mental health (columns (5) and (6)). Although the estimates for self-reported health are imprecise, the 1.1 percentage point decline in obesity is statistically significant at the 5% level and represents a 3.95% reduction relative to the pre-treatment

[29]When estimating the treatment effect on BMI, observations in the top 1% of the distribution—those with a BMI greater than 48.55—are coded as missing values and excluded from the analyses.

mean.

To sum up, BBCE did not lead to significant improvements in health conditions for the entire sample of low-income families, despite larger effects observed among the non-White population, which are not always statistically significant. Similar to the results on health care access, my findings on health status are also consistent with those of Bronchetti, Christensen, and Hoynes (2019), although I focus on health outcomes for adults rather than children. They found that the local purchasing power of SNAP was not significantly associated with children's health status, except for fewer school days missed due to illness. While it is challenging to detect substantial effects on health outcomes within just a few years of policy implementation, there may be positive effects in the long run, reflecting improvements in food security and health care utilization.

6 Conclusion

In this project, I provide comprehensive evidence on how access to food assistance programs has impacted the well-being of low-income families in recent decades, with a focus on their labor and health outcomes. I exploit variations in the expansion of the Supplemental Nutrition Assistance Program (SNAP), which offers vouchers to low-income households for purchasing food. Since the early 2000s, states have had the option to eliminate asset tests or raise the gross income limit through Broad-Based Categorical Eligibility (BBCE). I employ a difference-in-differences (DiD) estimator to account for the variation in the timing of BBCE adoption across states.

Following the BBCE expansion, I find a sharp increase in SNAP participation and benefit amounts, and a meaningful decline in food insecurity among low-income individuals. Although BBCE had no substantial impact on employment status, it resulted in a small but significant reduction in hours worked. These effects were more concentrated among individuals with greater flexibility to adjust their labor supply, such as those who are married, not the household head, and living with dependents.

There is evidence of improved health care access among low-income individuals following the BBCE expansion, including greater access to prenatal care and primary care providers. However, BBCE did not significantly impact adults' health conditions, as measured by physical health indicators and self-reported health. These improvements in health outcomes were more pronounced among non-Whites compared to Whites, suggesting that BBCE contributed to reducing racial disparities in health-related outcomes, despite its limited effects on immediate improvements in health status.

Overall, this study enhances our understanding of the role and effects of nutrition assistance programs in the modern era, which aim to prevent individuals from falling into extreme poverty, alleviate hardships, and help them manage risks by redistributing resources to those in need.

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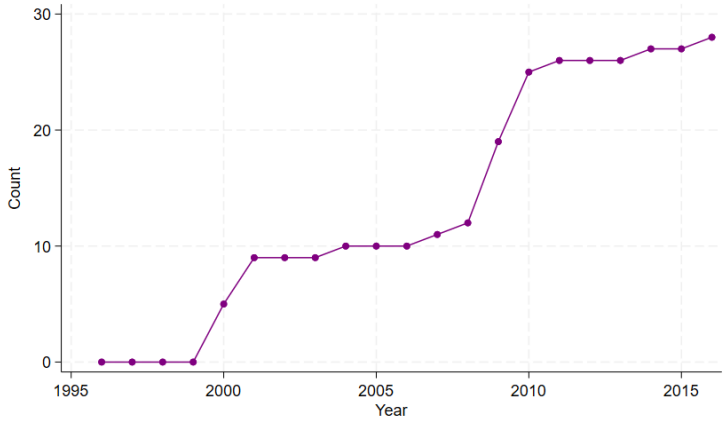
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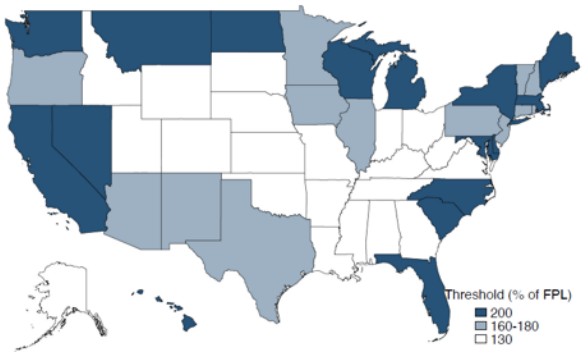
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Figures and Tables

Figure 1: States with BBCE Expansion



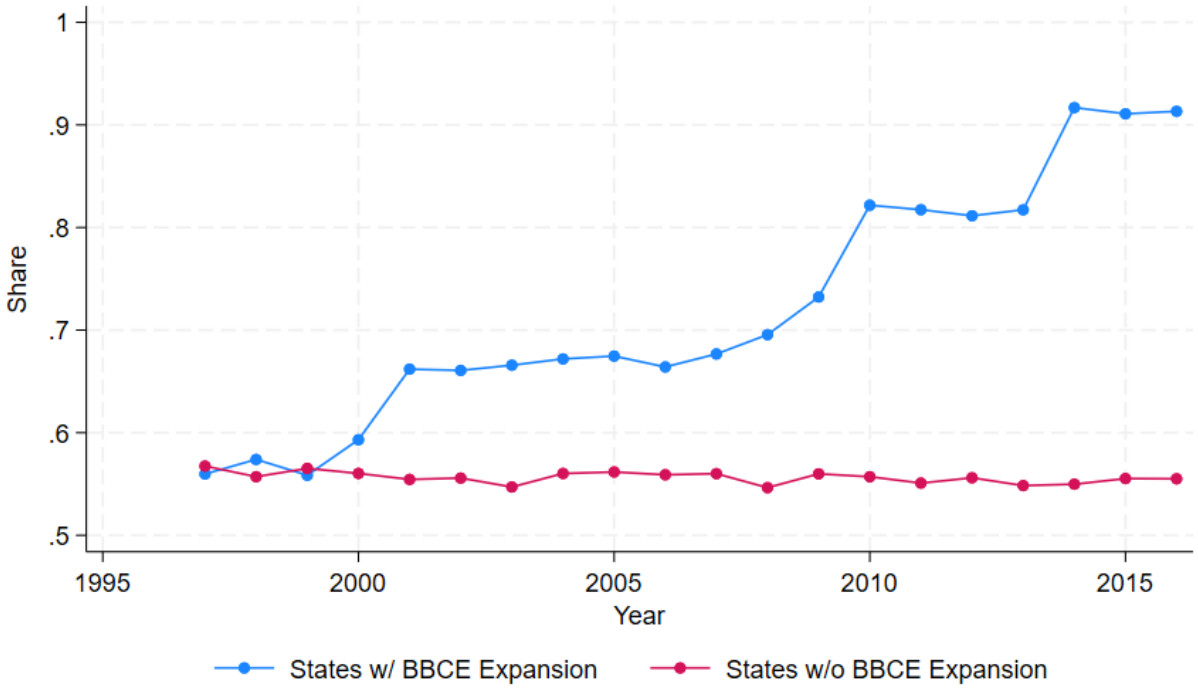
(a) Number of States with BBCE Expansion



(b) Map of States with BBCE Expansion (Anders and Rafkin 2022)

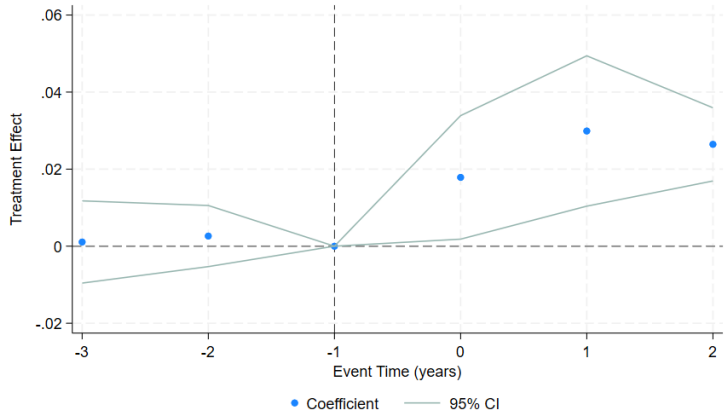
Notes: Figure 1-(a) displays time series graphs showing the number of states that adopted the BBCE expansion of the asset test and the gross income rule over time. The x-axis represents calendar years. Figure 1-(b) presents a state-level map from Anders and Rafkin (2022), illustrating the maximum gross income limit under the BBCE expansion up to 2016. States in dark blue implemented the largest expansion up to 200% of the FPL, those in light blue expanded the limit to between 160% and 185%, and those in white maintained the gross income limit at 130%, with no expansion.

Figure 2: Time Series Graphs of SNAP-Eligible Population Share

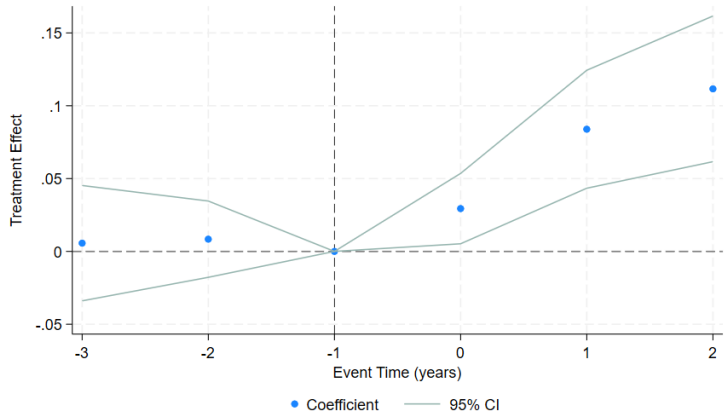


Notes: Figure 2 displays time series graphs of the share of the SNAP-eligible population based on the gross income rule over time, separately for each state's BBCE adoption decision. The SNAP-eligible population is defined as individuals whose predicted FPL ratio falls within the lowest portion of the distribution across several threshold. These threshold correspond to the population share with incomes below each income threshold based on the gross income limit in the pre-treatment period (i.e., 20% for 130% of the FPL as the income limit; 27% for 160% of the FPL; 28% for 165% of the FPL; 32% for 185% of the FPL; and 35% for 200% of the FPL). The sample consists of low-income individuals, as defined in Section 4.1, using the CPS-ASEC from 1997 to 2016. The x-axis represents calendar years. The blue line shows the average share of SNAP-eligible population for states that adopted BBCE at some point during the sample period (i.e., treated). The red line shows the average share of SNAP-eligible population for states that have never adopted BBCE (i.e., never-treated).

Figure 3: Effect of BBCE Expansion on SNAP Participation



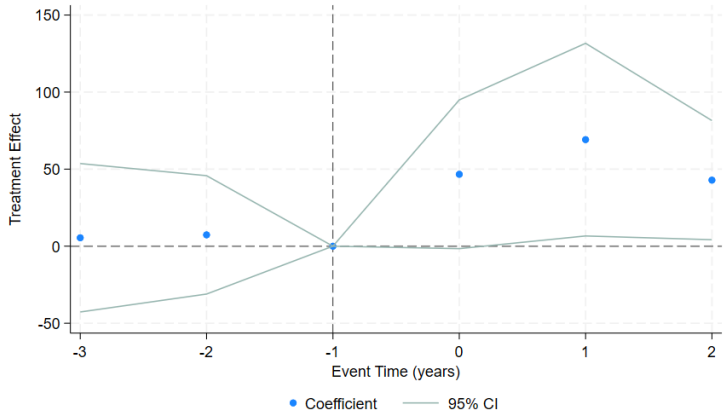
(a) SNAP Participation = 1 (binary)



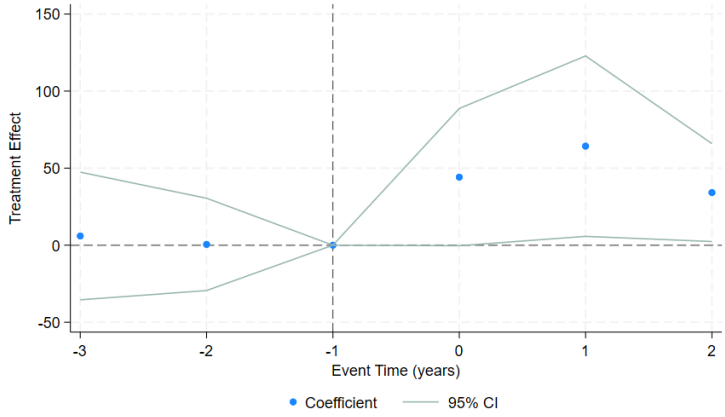
(b) log(SNAP Participation Count)

Notes: Figure 3 displays the estimation results of the impact of the BBCE expansion on SNAP participation using the event study framework developed by De Chaisemartin and d'Haultfoeuille (2024). Each figure shows the effect on low-income individuals' SNAP participation as a binary outcome based on Equation 1 (Figure 3-(a)) and the natural log of the number of individuals participating in SNAP based on Equation 2 (Figure 3-(b)). The x-axis represents the number of years since the BBCE expansion (with negative numbers indicating pre-intervention placebo effects). The 95% confidence intervals are represented by light green lines. The sample consists of low-income individuals, as defined in Section 4.1, using the CPS-ASEC (Figure 3-(a)) and all SNAP participants using the USDA's administrative data (Figure 3-(b)) from 1997 to 2016. Standard errors are clustered at the state level. CPS-ASEC person-level weights are applied (Figure 3-(a) only). Individual-level covariates include age, gender, race/ethnicity, marital status, and education level (Figure 3-(a) only). State-level covariates include unemployment rates and four SNAP policy indices (i.e., eligibility, transaction costs, stigma, and outreach), as defined in Section 3.1.

Figure 4: Effect of BBCE Expansion on SNAP Benefit Amounts



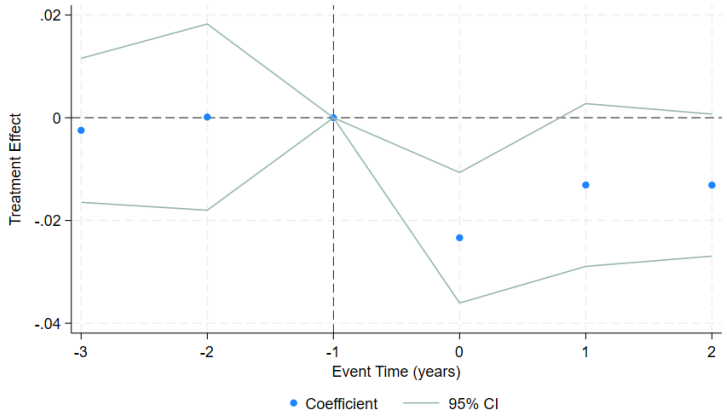
(a) Reported Amount



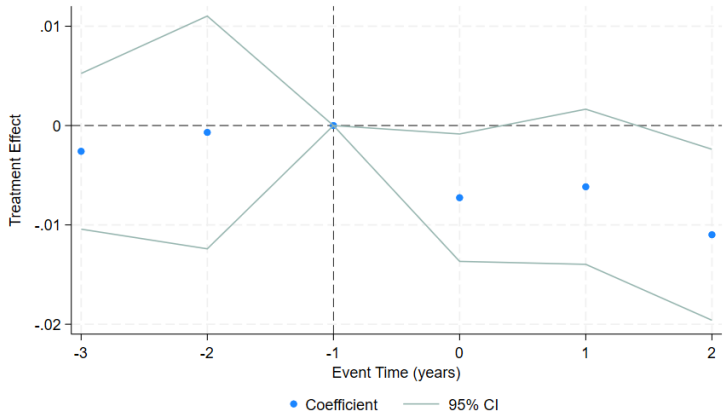
(b) Winsorized Amount (2.5th percentile)

Notes: Figure 4 displays the estimation results of the impact of the BBCE expansion on household SNAP benefit amounts per year (in 2016 dollars) using the event study framework developed by De Chaisemartin and d'Haultfoeuille (2024) based on Equation 1. Figure 4-(a) shows the effect on reported SNAP benefit amounts, while Figure 4-(b) shows the effect on winsorized benefit amounts, where extreme values are replaced at the 2.5th percentile in each tail of the distribution. The x-axis represents the number of years since the BBCE expansion (with negative numbers indicating pre-intervention placebo effects). The 95% confidence intervals are represented by light green lines. The sample consists of low-income individuals, as defined in Section 4.1, using the CPS-ASEC from 1997 to 2016. Standard errors are clustered at the state level. CPS-ASEC person-level weights are applied. Individual-level covariates include age, gender, race/ethnicity, marital status, and education level. State-level covariates include unemployment rates and four SNAP policy indices (i.e., eligibility, transaction costs, stigma, and outreach), as defined in Section 3.1.

Figure 5: Effect of BBCE Expansion on Household Food Insecurity



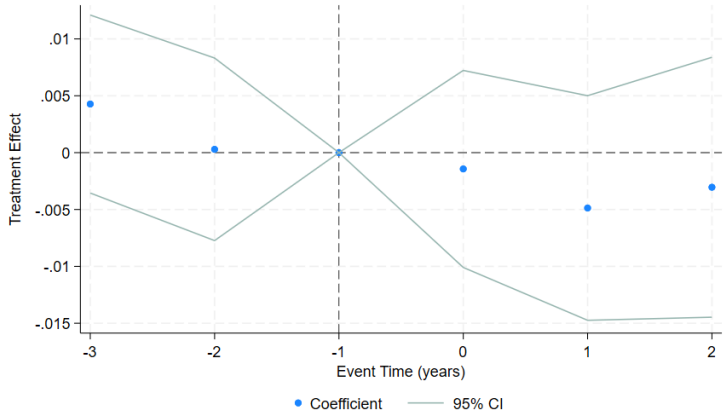
(a) Having Low Food Insecurity (binary)



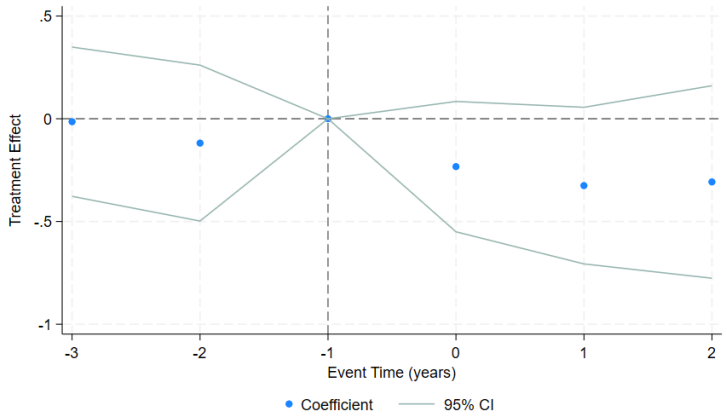
(b) Having Very Low Food Insecurity (binary)

Notes: Figure 5 displays the estimation results of the impact of the BBCE expansion on household food insecurity using the event study framework developed by De Chaisemartin and d'Haultfoeuille (2024) based on Equation 1. Each figure shows the effect on the probability of households experiencing low food security (Figure 5-(a)) and very low food security (Figure 5-(b)), as defined in Section 3.2. The x-axis represents the number of years since the BBCE expansion (with negative numbers indicating pre-intervention placebo effects). The 95% confidence intervals are represented by light green lines. The sample consists of low-income households, as defined in Section 4.1, using the CPS-FSS from 1997 to 2016. Standard errors are clustered at the state level. CPS-FSS household-level weights are applied. Household-level covariates include gender, race/ethnicity, marital status, and education level of household head, number of children, and number of family members. State-level covariates include unemployment rates and four SNAP policy indices (i.e., eligibility, transaction costs, stigma, and outreach), as defined in Section 3.1.

Figure 6: Effect of BBCE Expansion on Labor Market Outcomes



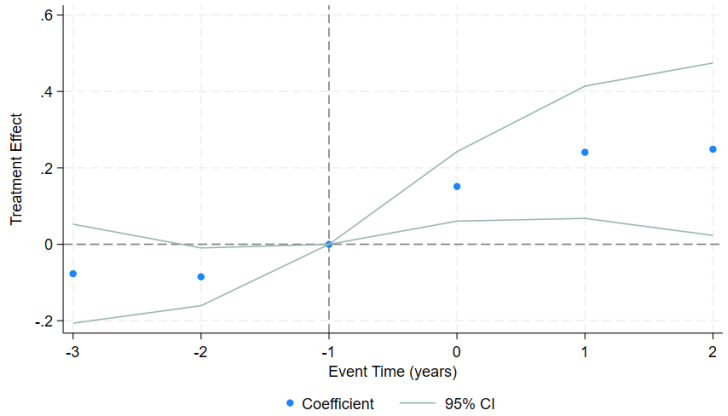
(a) Employment Status (binary)



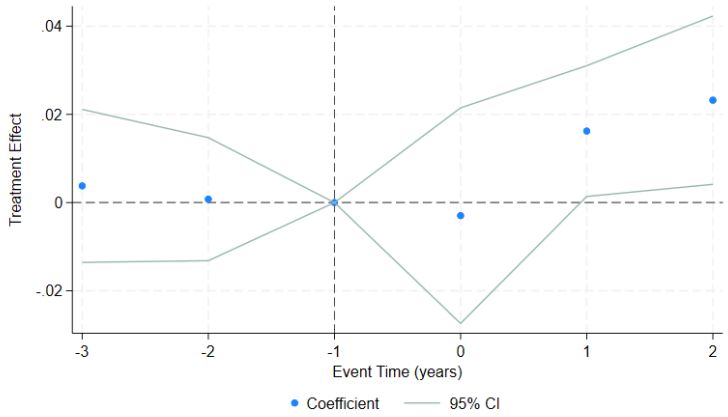
(b) Hours Worked (per week)

Notes: Figure 6 displays the estimation results of the impact of the BBCE expansion on labor market outcomes using the event study framework developed by De Chaisemartin and d'Haultfoeuille (2024) based on Equation 1. Each figure shows the effect on employment status (binary) (Figure 6-(a)) and hours worked (per week) (Figure 6-(b)). The x-axis represents the number of years since the BBCE expansion (with negative numbers indicating pre-intervention placebo effects). The 95% confidence intervals are represented by light green lines. The sample consists of low-income individuals, as defined in Section 4.1, using the CPS-ASEC from 1997 to 2016. Standard errors are clustered at the state level. CPS-ASEC person-level weights are applied. Individual-level covariates include age, gender, race/ethnicity, marital status, and education level. State-level covariates include unemployment rates and four SNAP policy indices (i.e., eligibility, transaction costs, stigma, and outreach), as defined in Section 3.1.

Figure 7: Effect of BBCE Expansion on Health Care Acess



(a) Number of Prenatal Visits



(b) Any Primary Care Provider (binary)

Notes: Figure 7 displays the estimation results of the impact of the BBCE expansion on health care access using the event study framework developed by De Chaisemartin and d'Haultfoeuille (2024). Each figure shows the effect on the number of prenatal visit during pregnancy based on Equation 2 (Figure 7-(a)) and whether having a personal doctor or health care provider (binary) based on Equation 1 (Figure 7-(b)). The x-axis represents the number of years since the BBCE expansion (with negative numbers indicating pre-intervention placebo effects). The 95% confidence intervals are represented by light green lines. The sample consists of low-income individuals, as defined in Section 4.1, using the restricted-use Vital Statistics Natality Data (Figure 7-(a)) and the BRFSS (Figure 7-(b)) from 1997 to 2016. Standard errors are clustered at the state level. BRFSS person-level weights are applied (Figure 7-(b) only). Individual-level covariates include age, gender, race/ethnicity, marital status, and education level (Figure 7-(b) only). State-level covariates include unemployment rates, four SNAP policy indices (i.e., eligibility, transaction costs, stigma, and outreach), as defined in Section 3.1, and indicators for Medicaid expansion as part of the Affordable Care Act (ACA).

Table 1: Effect of BBCE Expansion on SNAP Participation

	Binary	Count	
	(1)	(2)	(3)
	Part. = 1	log(indiv)	log(HH)
BBCE	0.025***	0.075***	0.072***
	(0.007)	(0.018)	(0.018)
CONTROLS			
Individual	YES	N/A	N/A
State			
Unemployment	YES	YES	YES
SNAP Policies	Yes	YES	YES
Pre-Period Mean	0.211	522,612.5	235,063.8
Data Source	CPS-ASEC	USDA	USDA

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Notes: Table 1 reports the estimation results of the impact of the BBCE expansion on SNAP participation using the difference-in-differences (DiD) estimator developed by De Chaisemartin and d'Haultfoeuille (2024). Each column presents the DiD estimate for low-income individuals' SNAP participation as a binary outcome based on Equation 1 (column (1)) and the natural log of the number of individuals (column (2)) and households (column (3)) participating in SNAP based on Equation 2. The sample consists of low-income individuals, as defined in Section 4.1, using the CPS-ASEC (column (1)) and all SNAP participants using the USDA's administrative data (columns (2) and (3)) from 1997 to 2016. Standard errors are clustered at the state level. CPS-ASEC person-level weights are applied (column (1) only). Individual-level covariates include age, gender, race/ethnicity, marital status, and education level (column (1) only). State-level covariates include unemployment rates and four SNAP policy indices (i.e., eligibility, transaction costs, stigma, and outreach), as defined in Section 3.1.

Table 2: Effect of BBCE Expansion on SNAP Benefit Amounts

	(1) Reported Amount	(2) Winsorized Amount
BBCE	52.809**	47.431**
	(21.391)	(19.254)
CONTROLS		
Individuals	YES	YES
State		
Unemployment	YES	YES
SNAP Policies	YES	YES
Pre-Period Mean	541.088	509.164

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Notes: Table 2 reports the estimation results of the impact of the BBCE expansion on household SNAP benefit amounts per year (in 2016 dollars) using the difference-in-differences (DiD) estimator developed by De Chaisemartin and d'Haultfoeuille (2024) based on Equation 1. Each column presents the DiD estimate for reported SNAP benefit amounts (column (1)) and winsorized benefit amounts (column (2)), where extreme values are replaced at the 2.5th percentile in each tail of the distribution. The sample consists of low-income individuals, as defined in Section 4.1, using the CPS-ASEC from 1997 to 2016. Standard errors are clustered at the state level. CPS-ASEC person-level weights are applied. Individual-level covariates include age, gender, race/ethnicity, marital status, and education level. State-level covariates include unemployment rates and four SNAP policy indices (i.e., eligibility, transaction costs, stigma, and outreach), as defined in Section 3.1.

Table 3: Effect of BBCE Expansion on Household Food Insecurity

	(1) Low Food Security	(2) Very Low Food Security
BBCE	-0.016***	-0.008**
	(0.006)	(0.003)
CONTROLS		
Household	YES	YES
State		
Unemployment	YES	YES
SNAP Policies	YES	YES
Pre-Period Mean	0.213	0.072

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Notes: Table 3 reports the estimation results of the impact of the BBCE expansion on household food insecurity using the difference-in-differences (DiD) estimator developed by De Chaisemartin and d'Haultfoeuille (2024) based on Equation 1. Each column presents the DiD estimate for the probability of households experiencing low food security (column (1)) and very low food security (column (2)), which are defined in Section 3.2 as binary outcomes. The sample consists of low-income individuals, as defined in Section 4.1, using the CPS-FSS from 1997 to 2016. Standard errors are clustered at the state level. CPS-FSS household-level weights are applied. Household-level covariates include gender, race/ethnicity, marital status, and education level of household head, number of children, and number of family members. State-level covariates include unemployment rates and four SNAP policy indices (i.e., eligibility, transaction costs, stigma, and outreach), as defined in Section 3.1.

Table 4: Effect of BBCE Expansion on Labor Market Outcomes

	(1) Employment	(2) Hours Worked
BBCE	-0.003	-0.285*
	(0.004)	(0.158)
CONTROLS		
Individual	YES	YES
State		
Unemployment	YES	YES
SNAP Policies	YES	YES
Pre-Period Mean	0.501	18.455

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Notes: Table 4 reports the estimation results of the impact of the BBCE expansion on labor market outcomes using the difference-in-differences (DiD) estimator developed by De Chaisemartin and d'Haultfoeuille (2024) based on Equation 1. Each column presents the DiD estimate for employment status (binary) (column (1)) and hours worked (per week) (column (2)). The sample consists of low-income individuals, as defined in Section 4.1, using the CPS-ASEC from 1997 to 2016. Standard errors are clustered at the state level. CPS-ASEC person-level weights are applied. Individual-level covariates include age, gender, race/ethnicity, marital status, and education level. State-level covariates include unemployment rates and four SNAP policy indices (i.e., eligibility, transaction costs, stigma, and outreach), as defined in Section 3.1.

Table 5: Heterogeneous Effects of BBCE Expansion on Hours Worked

	Living w/ Dependents		Relation to HH Head		Marital Status	
	(1)	(2)	(3)	(4)	(5)	(6)
	Yes	No	Head	Other	Married	Unmarried
BBCE	-0.368***	-0.201	-0.173	-0.388**	-0.588	-0.112
	(0.126)	(0.284)	(0.290)	(0.162)	(0.486)	(0.218)
CONTROLS						
Individual	YES	YES	YES	YES	YES	YES
State						
Unemployment	YES	YES	YES	YES	YES	YES
SNAP Policies	YES	YES	YES	YES	YES	YES
Pre-Period Mean	21.599	13.421	19.000	17.880	23.363	16.115

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Notes: Table 5 reports the estimation results of the heterogeneous impacts the BBCE expansion on hours worked (per week) using the difference-in-differences (DiD) estimator developed by De Chaisemartin and d'Haultfoeuille (2024) based on Equation 1. The sample consists of low-income individuals, as defined in Section 4.1, using the CPS-ASEC from 1997 to 2016. Columns (1) and (2) present the DiD estimates after splitting the sample into those living with dependents under age 18 and those without dependents, respectively. Columns (3) and (4) present the DiD estimates by relationship to household head. Columns (5) and (6) present the DiD estimates by marital status. Standard errors are clustered at the state level. CPS-ASEC person-level weights are applied. Individual-level covariates include age, gender, race/ethnicity, marital status, and education level. State-level covariates include unemployment rates and four SNAP policy indices (i.e., eligibility, transaction costs, stigma, and outreach), as defined in Section 3.1.

Table 6: Effect of BBCE Expansion on Health Care Access

	(1) Number of Prenatal Visits	(2) Any Primary Care Provider
BBCE	0.213***	0.011
	(0.080)	(0.009)
CONTROLS		
Individual	N/A	YES
State		
Unemployment	YES	YES
SNAP Policies	YES	YES
Pre-Period Mean	10.163	0.727

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Notes: Table 6 reports the estimation results of the impact the BBCE expansion on health care access using the difference-in-differences (DiD) estimator developed by De Chaisemartin and d'Haultfoeuille (2024). Each column presents the DiD estimate for the number of prenatal visit during pregnancy based on Equation 2 (column (1)) and whether having a personal doctor or health care provider (binary) based on Equation 1 (column (2)). The sample consists of low-income individuals, as defined in Section 4.1, using the restricted-use Vital Statistics natality data (column (1)) and the BRFSS (column (2)) from 1997 to 2016. Standard errors are clustered at the state level. BRFSS person-level weights are applied (column (2) only). Individual-level covariates include age, gender, race/ethnicity, marital status, and education level (column (2) only). State-level covariates include unemployment rates, four SNAP policy indices (i.e., eligibility, transaction costs, stigma, and outreach), as defined in Section 3.1, and indicators for Medicaid expansion as part of the Affordable Care Act (ACA).

Table 7: Heterogeneous Effects of BBCE Expansion on Health Care Access

	Number of Prenatal Visits		Any Primary Care Provider	
	(1) White	(2) Others	(3) White	(4) Others
BBCE	0.130*	0.240***	0.008	0.020*
	(0.070)	(0.088)	(0.008)	(0.011)
CONTROLS				
Individual	N/A	N/A	YES	YES
State				
Unemployment	YES	YES	YES	YES
SNAP Policies	YES	YES	YES	YES
Pre-Period Mean	10.591	9.950	0.785	0.668

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Notes: Table 7 reports the estimation results of the heterogeneous impacts the BBCE expansion on health care access by race using the difference-in-differences (DiD) estimator developed by De Chaisemartin and d'Haultfoeuille (2024). Each column presents the DiD estimate for the number of prenatal visit during pregnancy based on Equation 2 (columns (1) and (2)) and whether having a personal doctor or health care provider (binary) based on Equation 1 (columns (3) and (4)). The sample consists of low-income individuals, as defined in Section 4.1, using the restricted-use Vital Statistics Natality Data (columns (1) and (2)) and the BRFSS (columns (3) and (4)) from 1997 to 2016. Standard errors are clustered at the state level. BRFSS person-level weights are applied (columns (3) and (4) only). Individual-level covariates include age, gender, race/ethnicity, marital status, and education level (columns (3) and (4) only). State-level covariates include unemployment rates, four SNAP policy indices (i.e., eligibility, transaction costs, stigma, and outreach), as defined in Section 3.1, and indicators for Medicaid expansion as part of the Affordable Care Act (ACA).

Table 8: Effect of BBCE Expansion on Health Conditions

	Physical Health		Poor Health (30 days)	
	(1)	(2)	(3)	(4)
	BMI	Obesity	Physical	Mental
BBCE	-0.015	-0.006	-0.001	-0.005
	(0.077)	(0.005)	(0.009)	(0.014)
CONTROLS				
Individual	YES	YES	YES	YES
State				
Unemployment	YES	YES	YES	YES
SNAP Policies	YES	YES	YES	YES
Pre-Period Mean	27.115	0.267	0.371	0.378

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Notes: Table 8 reports the estimation results of the impact the BBCE expansion on health conditions using the difference-in-differences (DiD) estimator developed by De Chaisemartin and d'Haultfoeuille (2024) based on Equation 1. Each column presents the DiD estimate for BMI (column (1)), the probability of being obese (binary) (column (2)), whether reported having poor physical health in the past 30 days (binary) (column (3)), and having poor mental health in the past 30 days (binary) (column (4)). The sample consists of low-income individuals, as defined in Section 4.1, using the BRFSS from 1997 to 2016. Standard errors are clustered at the state level. BRFSS person-level weights are applied. Individual-level covariates include age, gender, race/ethnicity, marital status, and education level. State-level covariates include unemployment rates, four SNAP policy indices (i.e., eligibility, transaction costs, stigma, and outreach), as defined in Section 3.1, and indicators for Medicaid expansion as part of the Affordable Care Act (ACA).

Table 9: Heterogeneous Effects of BBCE Expansion on Health Conditions

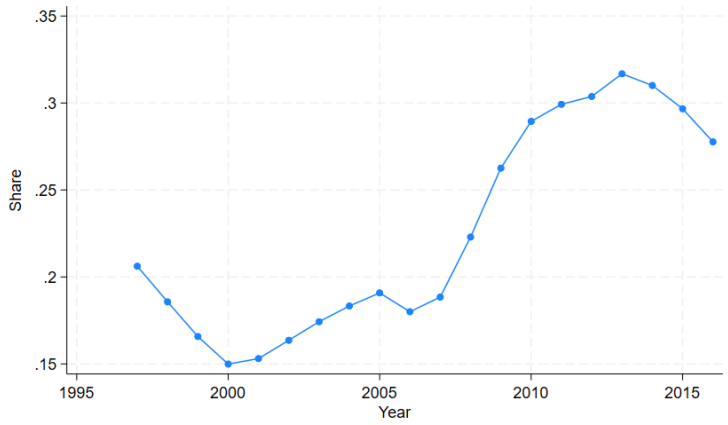
	Obesity		Poor Physical Health		Poor Mental Health	
	(1) White	(2) Others	(3) White	(4) Others	(5) White	(6) Others
BBCE	0.002	-0.011**	-0.000	-0.005	-0.007	-0.014
	(0.412)	(0.006)	(0.008)	(0.010)	(0.011)	(0.013)
CONTROLS						
Individual	YES	YES	YES	YES	YES	YES
State						
Unemployment	YES	YES	YES	YES	YES	YES
SNAP Policies	YES	YES	YES	YES	YES	YES
Pre-Period Mean	0.236	0.294	0.378	0.363	0.386	0.372

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

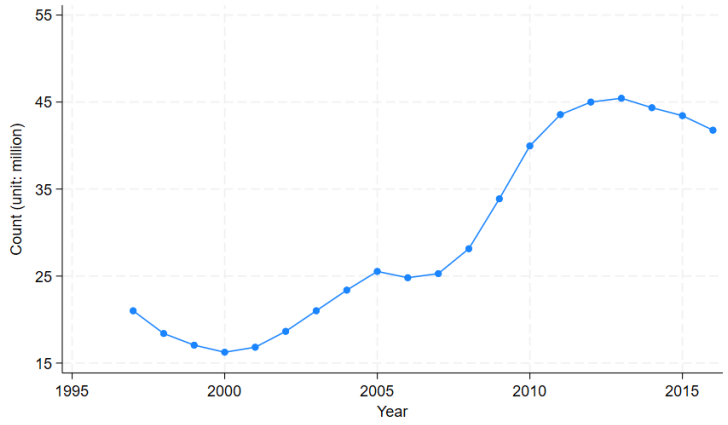
Notes: Table 9 reports the estimation results of the heterogeneous impacts the BBCE expansion on health conditions using the difference-in-differences (DiD) estimator developed by De Chaisemartin and d'Haultfoeuille (2024) based on Equation 1. Each column presents the DiD estimate for the probability of being obese (binary) (columns (1) and (2)), whether reported having poor physical health in the past 30 days (binary) (columns (3) and (4)), and having poor mental health in the past 30 days (binary) (columns (5) and (6)). The sample consists of low-income individuals, as defined in Section 4.1, using the BRFSS from 1997 to 2016. Standard errors are clustered at the state level. BRFSS person-level weights are applied. Individual-level covariates include age, gender, race/ethnicity, marital status, and education level. State-level covariates include unemployment rates, four SNAP policy indices (i.e., eligibility, transaction costs, stigma, and outreach), as defined in Section 3.1, and indicators for Medicaid expansion as part of the Affordable Care Act (ACA).

Appendix

Figure A.1: Time Series Graphs of SNAP Participation



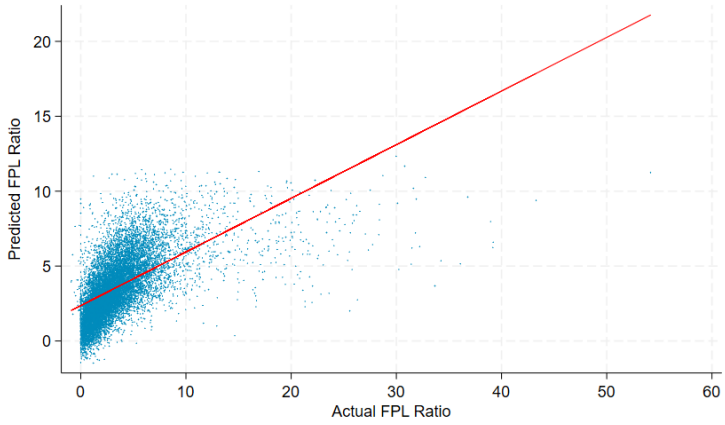
(a) SNAP Participation Rate



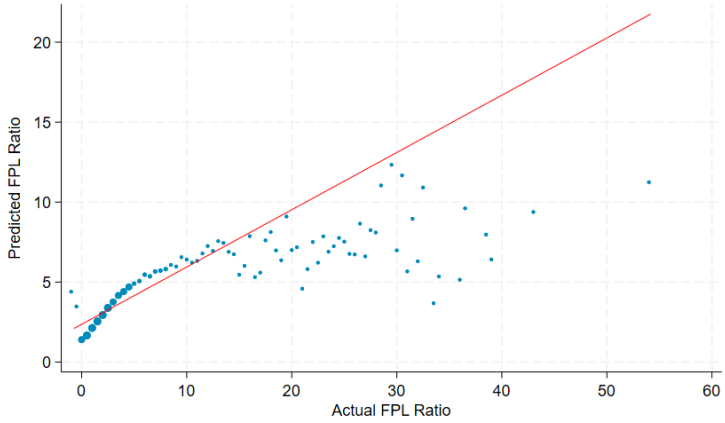
(b) SNAP Participation Count

Notes: Figure A.1 displays time series graphs of SNAP participation based on two different data sources. Figure A.1-(a) presents SNAP participation rates over time among low-income individuals, as defined in Section 4.1, using the CPS-ASEC from 1997 to 2016. Figure A.1-(b) shows the total number of SNAP participants (in millions) using the USDA's administrative data from 1997 to 2016. In both figures, the x-axis represents calendar years.

Figure A.2: Out-of-Sample CPS-ASEC Predictions



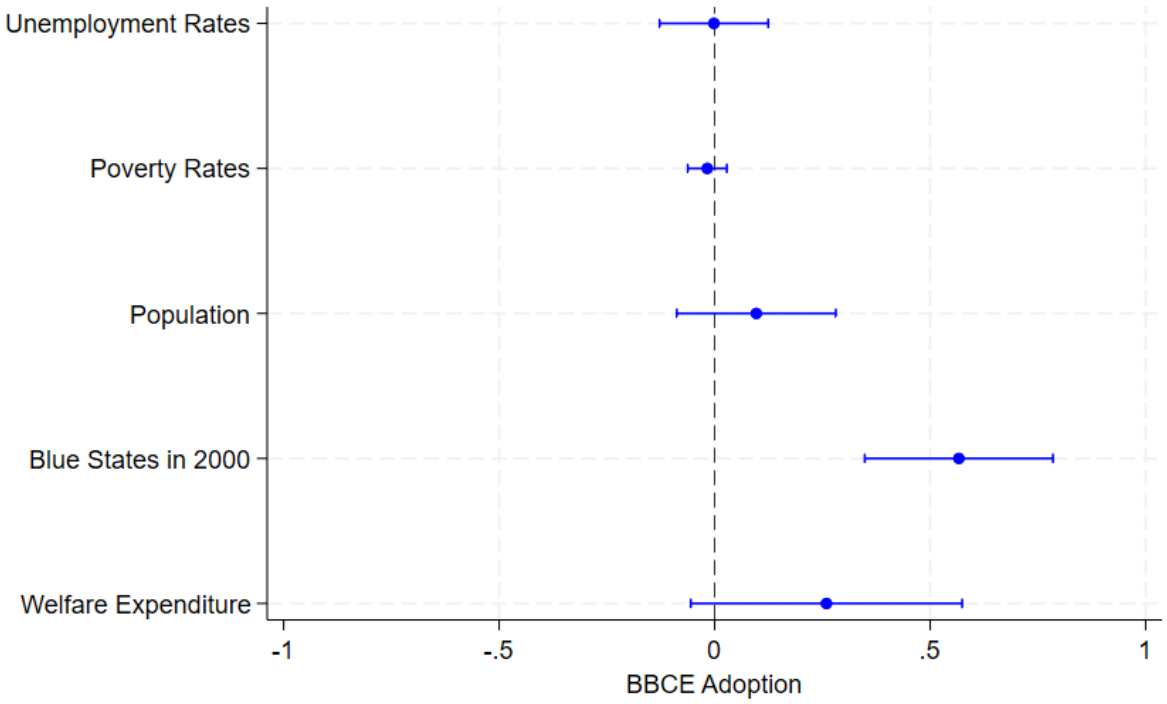
(a) Scatter Plot of Raw Data



(b) Binned Scatter Plot

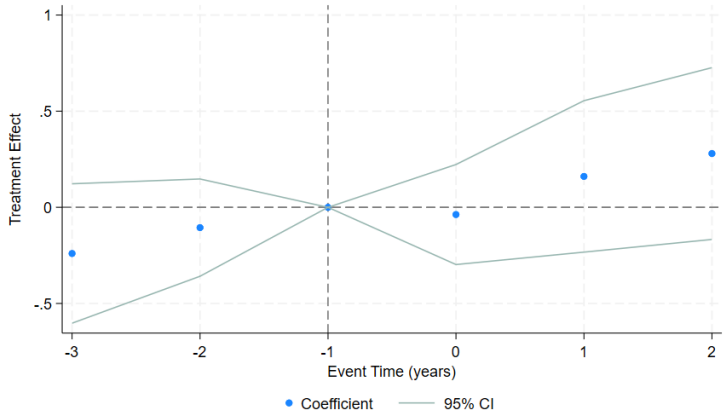
Notes: Figure A.2 compares the predicted and true values of the FPL ratio in the validation sample (25%) of the CPS-ASEC. The predicted FPL ratio is estimated using Equation 3. The x-axis represents the true FPL ratio, while the y-axis shows the predicted value. In Figure A.2-(a), each blue dot represents an individual observation. In Figure A.2-(b), each blue dot represents the average predicted values within bins of actual FPL ratios, with bin widths of 50 percentage points. In both figures, the red line represents the line of best fit through the data. The out-of-sample R-squared is 0.351.

Figure A.3: Determinants of BBCE Adoption

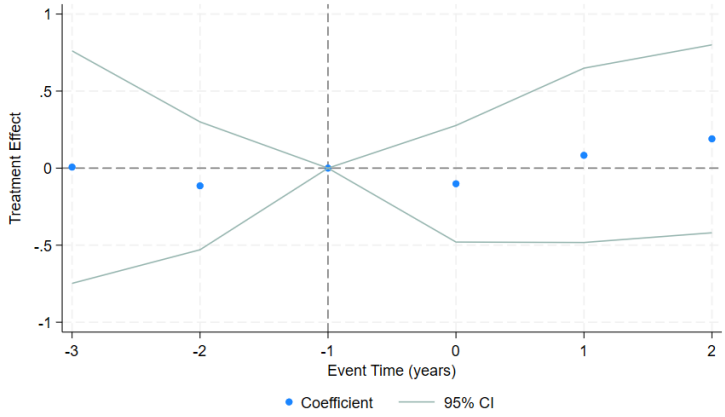


Notes: Figure A.3 presents the estimation results of the impact of state-level characteristics during the pre-treatment period (1997–1999) on BBCE adoption. The dependent variable is an indicator of whether each state adopted BBCE by 2016. The regression coefficients for each variable are represented by dots, with 95% confidence intervals shown as bars. The state-level characteristics include unemployment rates, poverty rates, population size, whether a state is a blue state (as determined by the results of the 2020 U.S. presidential election), and per capita expenditure on welfare programs, including cash assistance, medical care, and retirement and disability payments.

Figure A.4: Effect of BBCE Expansion on Unemployment Rates



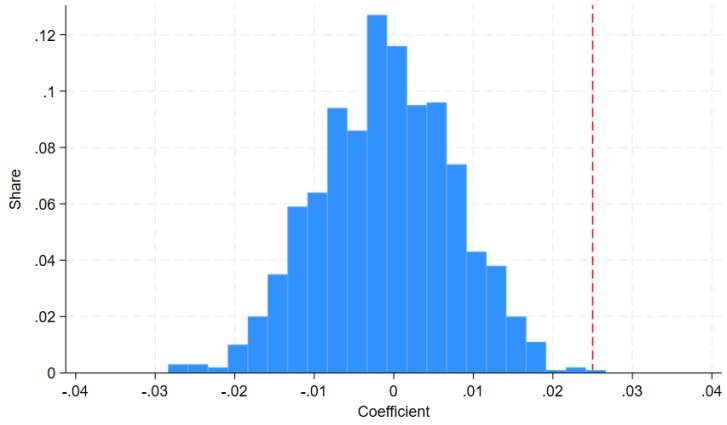
(a) Unemployment Rates (1997-2016)



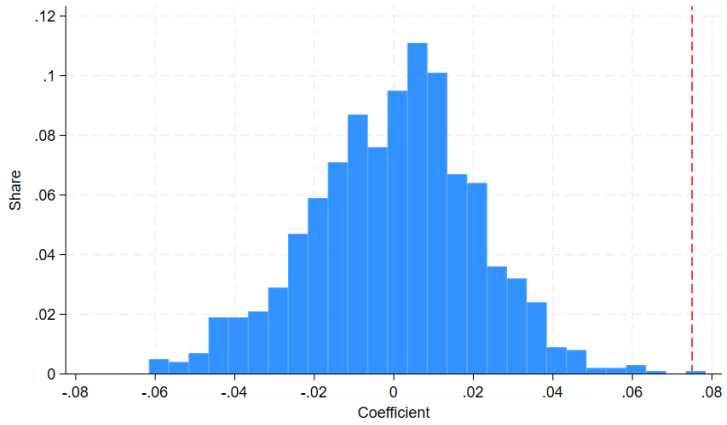
(b) Unemployment Rates (2007-2016)

Notes: Figure A.4 displays the estimation results of the impact of the BBCE expansion on state unemployment rates using the event study framework developed by De Chaisemartin and d'Haultfoeuille (2024) based on Equation 2. Each figure shows the effect over the entire data period (Figure A.4-(a)) and in the restricted period from 2007 onward (Figure A.4-(b)). Standard errors are clustered at the state level.

Figure A.5: Effect of BBCE Expansion on SNAP Participation: Permutation Test



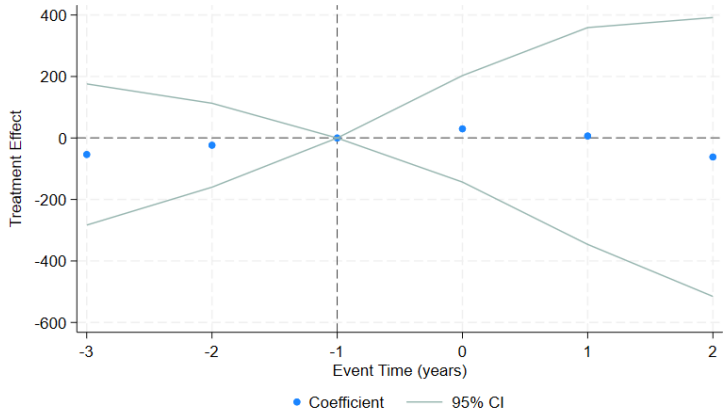
(a) SNAP Participation Rates (binary)



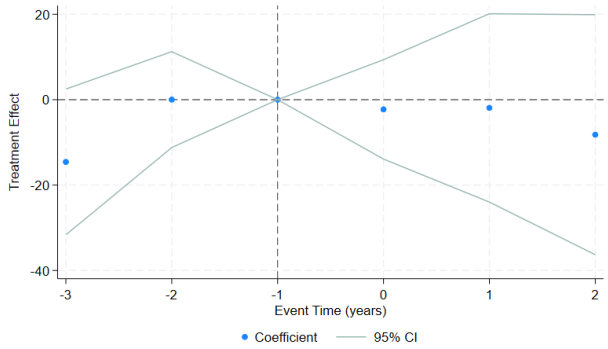
(b) log(SNAP Participation Counts)

Notes: Figure A.5 displays the distribution of the average effect of the BBCE expansion on SNAP participation, using the CPS-ASEC data (Figure A.5-(a)) and the USDA's data (Figure A.5-(b)). This is done by randomizing the treated states 1,000 times with the adoption dates fixed, using the event study framework developed by De Chaisemartin and d'Haultfoeuille (2024) based on Equation 1 (Figure A.5-(a)) and Equation 2 (Figure A.5-(b)). The numbers on the x-axis correspond to the estimates from each replication, and each bar shows the relative frequency within the given interval of estimates. The vertical red lines represent the original DiD estimate of 0.025 (column (1) of Table 1) and 0.075 (column (2) of Table 1) for the effect of BBCE on SNAP participation. The p-values of the two permutation tests are 0.003 (Figure A.5-(a)) and 0.001 (Figure A.5-(b)), respectively.

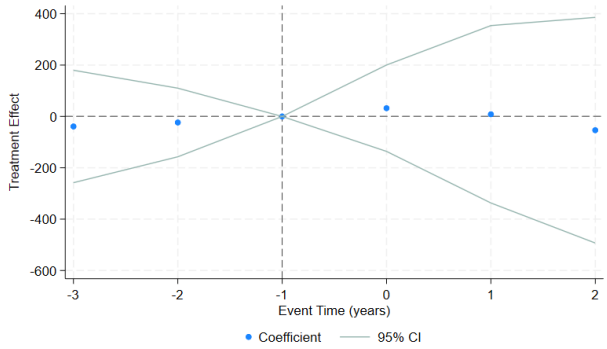
Figure A.6: Effect of BBCE Expansion on SNAP Retailer Participation



(a) All Stores



(b) Usual Stores (20%)



(c) Non-Usual Stores (80%)

Notes: Figure A.6 displays the estimation results of the impact of the BBCE expansion on SNAP vendor counts using the event study framework developed by De Chaisemartin and d'Haultfoeuille (2024) based on Equation 2. Each figure shows the effect on the number of all stores (Figure A.6-(a)), usual stores (Figure A.6-(b)), and non-usual stores (Figure A.6-(c)) participating in SNAP, which are defined in Section 3.1. The x-axis represents the number of years since the BBCE expansion (with negative numbers indicating pre-intervention placebo effects). The 95% confidence intervals are represented by light green lines. The sample consists of SNAP-authorized retailers, using the Historical SNAP Retailer Locator Data from 1997 to 2016. Standard errors are clustered at the state level. State-level covariates include unemployment rates and four SNAP policy indices (i.e., eligibility, transaction costs, stigma, and outreach), as defined in Section 3.1.

Table A.1: Effect of BBCE Expansion on SNAP Participation: Robustness

	(1)	(2)	(3)	(4)	(5)
A. SNAP Part. = 1					
BBCE	0.019***	0.024***	0.024***	0.025***	0.025***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)
CONTROLS					
Individual	NO	YES	YES	YES	YES
State					
Unemployment	NO	NO	YES	NO	YES
SNAP Policies	NO	NO	NO	YES	YES
Pre-Period Mean			0.211		
B. log(SNAP Part. Count)					
BBCE	0.081***	N/A	0.076***	0.081***	0.075***
	(0.019)	N/A	(0.018)	(0.019)	(0.018)
CONTROLS					
Individual	NO	YES	YES	YES	YES
State					
Unemployment	NO	NO	YES	NO	YES
SNAP Policies	NO	NO	NO	YES	YES
Pre-Period Mean			522,612.5		

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Notes: Table A.1 reports the estimation results of the impact of the BBCE expansion on SNAP participation using the difference-in-differences (DiD) estimator developed by De Chaisemartin and d'Haultfoeuille (2024) with a different combination of covariates. Panel A presents the DiD estimates for low-income individuals' SNAP participation as a binary outcome based on Equation 1, while Panel B presents the DiD estimates for the natural log of the number of individuals participating in SNAP based on Equation 2. The sample consists of low-income individuals, as defined in Section 4.1, using the CPS-ASEC (Panel A) and all SNAP participants using the USDA's administrative data (Panel B) from 1997 to 2016. Standard errors are clustered at the state level. CPS-ASEC person-level weights are applied (Panel A only). Individual-level covariates include age, gender, race/ethnicity, marital status, and education level (Panel A only). State-level covariates include unemployment rates and four SNAP policy indices (i.e., eligibility, transaction costs, stigma, and outreach), as defined in Section 3.1.

Table A.2: Heterogeneous Effects of BBCE Expansion on SNAP Participation and Benefit Amounts

	Race		Ethnicity		Education	
	(1) White	(2) Others	(3) Hispanic	(4) Others	(5) $<$ HS	(6) $\geq$ HS
A. Participation *(binary)*						
BBCE	0.019***	0.026***	0.045***	0.014**	0.024***	0.020***
	(0.007)	(0.006)	(0.008)	(0.006)	(0.006)	(0.003)
Baseline Controls	YES	YES	YES	YES	YES	YES
Pre-Period Mean	0.164	0.250	0.201	0.214	0.252	0.152
B. Benefit *(in 2016 dollars)*						
BBCE	37.675	71.544***	136.806***	28.031	46.691**	38.903***
	(27.768)	(19.791)	(38.415)	(25.201)	(22.795)	(14.933)
Baseline Controls	YES	YES	YES	YES	YES	YES
Pre-Period Mean	388.425	668.689	523.006	547.375	680.985	340.006

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Notes: Table A.2 reports the estimation results of the heterogeneous impacts the BBCE expansion on SNAP participation (Panel A) and household SNAP benefit amounts per year (in 2016 dollars) (Panel B) using the difference-in-differences (DiD) estimator developed by De Chaisemartin and d'Haultfoeuille (2024) based on Equation 1. The sample consists of low-income individuals, as defined in Section 4.1, using the CPS-ASEC from 1997 to 2016. Columns (1) and (2) present the DiD estimates after splitting the sample by race. Columns (3) and (4) present the DiD estimates by Hispanic ethnicity. Columns (5) and (6) present the DiD estimates by education level: those with (column (6)) and without (column (5)) high school degree or equivalent. Standard errors are clustered at the state level. CPS-ASEC person-level weights are applied. Individual-level covariates include age, gender, race/ethnicity, marital status, and education level. State-level covariates include unemployment rates and four SNAP policy indices (i.e., eligibility, transaction costs, stigma, and outreach), as defined in Section 3.1.

Table A.3: Effect of BBCE Expansion on SNAP Participation: Continuous Treatment

	(1)	(2)
	Part. = 1	log(Part. Count)
A. Gross Income Limit		
$BBCE_{Inc\ Limit}$	0.004***	0.013***
	(0.001)	(0.003)
Baseline Controls	YES	YES
Pre-Period Mean	0.211	522,613
B. Eligible Population Share		
$BBCE_{Pop\ Share}$	0.002***	0.006***
	(0.0005)	(0.001)
Baseline Controls	YES	YES
Pre-Period Mean	0.211	522,613

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Notes: Table A.3 reports the estimation results of the impact of the BBCE expansion on SNAP participation using the difference-in-differences (DiD) estimator developed by De Chaisemartin and d'Haultfoeuille (2024) with continuous treatment measures. Panel A presents the estimates for the first treatment measure, which is constructed based on the gross income limit, ranging from 130% to 200% of the FPL. I assign a value of 0 to states and years without the BBCE expansion (i.e., 130% of the FPL) and assign the change in the gross income limit, expressed as a percentage of the FPL, to treated states after adoption. The measure is scaled to represent the effect of a 10 percentage-point increase in the income limit. Panel B presents the estimates for the second treatment measure, which is constructed based on the share of the SNAP-eligible population as determined by the gross income limit. Specifically, during the pre-treatment period, the lowest 20% of survey respondents in the CPS-ASEC had predicted family incomes below 130% of the FPL; 27% for 160% of the FPL; 28% for 165% of the FPL; 32% for 185% of the FPL; and 35% for 200% of the FPL. I assign a value of 0 to states and years without the BBCE expansion and assign the change in the eligible population share to treated states after adoption. The measure is scaled to represent the effect of a 1 percentage-point increase in the eligible population share. In each panel, Column (1) presents the DiD estimates for low-income individuals' SNAP participation as a binary outcome based on Equation 1, while Column (2) presents the DiD estimates for the natural log of the number of individuals participating in SNAP based on Equation 2. The sample consists of low-income individuals, as defined in Section 4.1, using the CPS-ASEC (column (1)) and all SNAP participants using the USDA's administrative data (column (2)) from 1997 to 2016. Standard errors are clustered at the state level. CPS-ASEC person-level weights are applied (column (1) only). Individual-level covariates include age, gender, race/ethnicity, marital status, and education level (column (1) only). State-level covariates include unemployment rates and four SNAP policy indices (i.e., eligibility, transaction costs, stigma, and outreach), as defined in Section 3.1.

Table A.4: Effect of BBCE Expansion on SNAP Retailer Participation

	Count			Share
	(1)	(2)	(3)	(4)
	All	Usual	Non-Usual	Usual
BBCE	-8.482	-4.133	-4.349	-0.006**
	(165.353)	(10.299)	(160.897)	(0.003)
CONTROLS				
Individual	N/A	N/A	N/A	N/A
State				
Unemployment	YES	YES	YES	YES
SNAP Policies	YES	YES	YES	YES
Pre-Period Mean	3,917.017	802.660	3,114.357	0.205

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Notes: Table A.4 reports the estimation results of the impact of the BBCE expansion on SNAP vendor counts using the difference-in-differences (DiD) estimator developed by De Chaisemartin and d'Haultfoeuille (2024) based on Equation 2. Each column presents the DiD estimate for the number of all stores (column (1)), usual stores (column (2)), and non-usual stores (column (3)) participating in SNAP, which are defined in Section 3.1. The sample consists of SNAP-authorized retailers, using the Historical SNAP Retailer Locator Data from 1997 to 2016. Standard errors are clustered at the state level. State-level covariates include unemployment rates and four SNAP policy indices (i.e., eligibility, transaction costs, stigma, and outreach), as defined in Section 3.1.