Beyond the Grocery Aisle: How SNAP Expansion Shapes Health*

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November 14, 2025

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Abstract

This paper examines how access to the Supplemental Nutrition Assistance Program (SNAP) has influenced low-income families' health and economic outcomes in the modern era. Exploiting state-level expansions under Broad-Based Categorical Eligibility (BBCE)—one of the largest SNAP reforms since the 2000s—I use a difference-in-differences design with multiple large-scale data sources on program usage and population health. The expansion increased SNAP participation and generated spillovers to Medicaid and WIC enrollment. With greater available resources, I find improvements in food insecurity and health care utilization. Short-term health gains are modest overall but more pronounced among non-Whites, including declines in low birth weight and obesity. Notably, there are no significant effects on employment status, with only a slight reduction in hours worked. These findings underscore the role of benefit transfers in supporting long-term health investments and reducing racial disparities, with a substantially reduced concern for moral hazard in recent decades.

JEL Codes: H53, I18, I38

Keywords: Safety Net, SNAP, BBCE, Health

*Contact e-mail: j8shin@ucsd.edu. I deeply appreciate the mentorship and support of my advisors Gordon Dahl and Katherine Meckel throughout this research. I am also grateful for helpful comments from Marianne Bitler, Jeff Clemens, Julie Cullen, Alex Gelber, Paul Niehaus, Michael Ricks, Tom Vogl, Myunghwan Andrew Lee, as well as participants at 2025 American Society of Health Economists (ASHEcon) Annual Conference, 2025 World Congress of the Econometric Society (ESWC), 2025 All-California Labor Economics Conference (ACLEC), Yonsei University, and UCSD.

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1 Introduction

Social welfare programs are designed to improve the lives of those facing economic hardship. In the United States, many of these programs began in the 1960s or 1970s, regardless of whether the benefits were provided in cash or in kind. As one example, the Supplemental Nutrition Assistance Program (SNAP) (formerly the Food Stamp Program (FSP)) is central to discussions of U.S. anti-poverty policy as the largest nutrition assistance program.[1] The stated aim of the program is to improve food security and access to a nutritious diet among low-income households (Bronchetti, Christensen, and Hoynes 2019), by issuing monthly food vouchers redeemable at grocery stores.

However, the effects of SNAP on recipients' welfare *today* are not entirely clear, as both economic conditions and the policy context have changed substantially since its introduction.[2] This raises an empirical question of whether modern expansions of SNAP are effective in reducing food insecurity and poverty, whether they generate additional downstream effects—such as improving health or reducing labor supply—and how they interact with other government programs. While prior research has established a link between the historical implementation of SNAP and long-run outcomes (Hoynes, Schanzenbach, and Almond 2016; Bailey et al. 2024), less is known about its *immediate* effects on recipients in the *modern* era (Hoynes and Schanzenbach 2015).

This paper studies one of the largest reforms to SNAP in recent decades to provide evidence on how access to the program affects recipients' health outcomes today—including food security, health care utilization, and health status—and whether it has adverse effects on labor market outcomes. Specifically, I exploit state-level variation in SNAP eligibility expansion known as Broad-Based Categorical Eligibility (BBCE). Under BBCE, states can

[1] In Fiscal Year (FY) 2023, SNAP served 42.1 million individuals, with federal spending of $112.8 billion, accounting for two-thirds of the U.S. Department of Agriculture (USDA)'s total nutrition assistance expenditures (U.S. Department of Agriculture 2024a).

[2] For example, Gross Domestic Product (GDP) per capita has more than tripled (U.S. Bureau of Economic Analysis 2024), and safety net spending has increased more than fivefold (Urban Institute 2025), shifting toward means-tested and work-based programs. Most notably, SNAP participation—and thus program spending—has risen over time despite some fluctuations (U.S. Department of Agriculture 2024b).

choose to eliminate assets tests or increase the gross income limit, effectively streamlining the income certification process by applying a single, unified cutoff. Gradually adopted by states from 2000 and onward, BBCE expanded SNAP eligibility to households with higher gross income. Prior work shows that it increased SNAP take-up (Anders and Rafkin 2024).

To study the effects of this large expansion on household health and economic outcomes, I compile large-scale data covering 1997-2016 from the following sources: USDA administrative records, the Current Population Survey (CPS)—including its Annual Social and Economic Supplement (ASEC) and Food Security Supplement (FSS)—Vital Statistics Natality Data, and the Behavioral Risk Factor Surveillance System (BRFSS). These datasets provide variables on program participation and benefit amounts, food security, health care use, newborn and adult health conditions, and labor market outcomes. In all cases, I restrict the analysis to low-income individuals who are likely affected by the eligibility expansion, identified based on *pre*-reform demographic characteristics. I estimate the prediction model with the CPS-ASEC and apply it across all other datasets.

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. I track states three years after adoption to construct a balanced panel of state-years. To address the potential bias in using an ordinary least squares regression with two-way fixed effects (TWFE), I use the alternative DiD estimator developed by De Chaisemartin and d'Haultfoeuille (2024) to address heterogeneous treatment effects.[3]

The identifying assumption is that no unobserved, time-varying factors are correlated with the timing of the BBCE expansion. To assess the validity of my identification strategy, I estimate event-study versions of my design and find flat pre-trends across outcomes. I also control for a large number of state-level variables, including economic conditions and other

[3]See De Chaisemartin and d'Haultfoeuille (2020), Sun and Abraham (2021), Goodman-Bacon (2021a), Callaway and Sant'Anna (2021), Borusyak, Jaravel, and Spiess (2024), and De Chaisemartin and d'Haultfoeuille (2024) for details on the bias problem.

policies, as robustness checks. Because the largest wave of BBCE adoption coincided with the Great Recession, I further test that there is no correlation between implementation timing and economic variables.

I first document a sharp increase in SNAP participation (an 8-12% increase across datasets) and in benefit amounts of $52.8 per year (a 9.76% increase), statistically significant at the 1% and 5% levels, respectively. There is no evidence of pre-trends, and the results remain robust across multiple specifications and extensions, including models that control for unemployment rates and other SNAP policies, and test for underreporting of SNAP participation in the CPS (Meyer, Mok, and Sullivan 2009). In line with evidence of "woodwork effects" in SNAP under BBCE (Anders and Rafkin 2024)—*already* eligible households become more likely to enroll, in addition to those at the margin of eligibility—I evaluate the reform's impact on the entire low-income population throughout the paper.

I next turn to spillovers of the reform to other safety net programs. BBCE also increased enrollment in Medicaid—which offers public health insurance—and the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC)—which provides nutrition assistance, health screenings, and referrals. Enrollment rose by 1.7 percentage points (a 6.24% increase) for Medicaid and 1.5 percentage points (a 10.03% increase) for WIC, statistically significant at the 1% and 5% levels, respectively. These increases primarily occurred among SNAP participants, highlighting spillover effects across programs—likely driven by increased awareness of program benefits and eligibility or reduced administrative burden through streamlined applications. These findings further provide a potential mechanism for downstream effects on health.

Next, I estimate the effects of the BBCE expansion on health outcomes: food security, health care use, and health status—separately for birth outcomes and adult health conditions. BBCE reduced the probability of low-income households experiencing low food security by 1.8 percentage points (a 8.28% decline) and very low food security by 0.8 percentage points (a 10.86% decline), representing sizable and statistically significant effects. These findings

suggest improvements in the quantity, quality, and variety of food consumed among low-income households.

Furthermore, the BBCE expansion improved health care utilization across the entire low-income population. 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 use is more pronounced among non-Whites compared to Whites, suggesting that BBCE helped reduce racial disparities in health care utilization. Additionally, the lower likelihood of missing doctor visits due to cost after BBCE supports the positive effects of increased health care provision and available resources on access to care and doctor visits.

Regarding health status, BBCE did not have statistically significant effects on birth weight or adult health conditions—medical diagnoses and self-reported health—in the overall low-income sample. Still, effects are consistently larger for non-Whites across outcomes. Most notably, BBCE significantly increased birth weight by 5.25 grams and reduced the incidence of low birth weight by 0.36 percentage points (a 2.48% decline) among Black mothers—strong indicators of infant and future health—even comparable to the effects observed during the program's initial rollout in the 1960s and 1970s (Almond, Hoynes, and Schanzenbach 2011). There is also suggestive decline in the likelihood of obesity among non-Whites.

Although the findings indicate several positive effects of anti-poverty transfers, concerns remain that safety net programs may reduce work incentives. 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. It led to only 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—and was roughly ten times smaller than during the program's early rollout (Hoynes and Schanzenbach 2012).

In sum, this paper provides novel evidence on the impacts of a major SNAP eligibility expansion on a wide range of household outcomes, including participation in social assistance programs, health, and labor supply. The findings highlight the continued role of benefit transfers in alleviating poverty and reducing inequality, with a reduced concern for moral hazard relative to the past. They also capture the effects of extending benefits to near-poor families as well as to the poorest populations traditionally targeted by welfare programs.

This paper contributes to research on the causal effects of the Supplemental Nutrition Assistance Program (SNAP) on household health and economic outcomes. A first set of studies examines the program's initial rollout in the 1960s and 1970s, showing improvements in birth outcomes (Almond, Hoynes, and Schanzenbach 2011), reductions in labor supply (Hoynes and Schanzenbach 2012), and long-run gains in health and economic well-being (Hoynes, Schanzenbach, and Almond 2016; Bailey et al. 2024). By contrast, evidence on the effects of SNAP participation in the modern era is more limited. Two exceptions are (East 2020), who examines the long-run health impacts of early-life SNAP access among children of recent immigrants, and (Bronchetti, Christensen, and Hoynes 2019), who show that changes in the real value of SNAP benefits due to local food prices increase the use of preventive care among children. My study complements this work by focusing on a major eligibility reform that directly expanded program access for a broad share of low-income households, allowing for estimation of policy-relevant effects on health and economic well-being.[4]

A second strand of research studies the Broad-Based Categorical Eligibility (BBCE) reform specifically.[5] Anders and Rafkin (2024) find that BBCE raised participation among already eligible households by lowering information frictions, and Lin (2024) shows that simplifying program administration reduced application burdens and generated government savings of more than $100 million. As a related study on the participants' side, Han (2016)

[4]Additional studies examine outcomes for narrow groups, such as childless, non-elderly, non-disabled adults: see Dodini, Larrimore, and Tranfaglia (2024) on financial outcomes and Gray et al. (2023) on labor supply responses.

[5]A set of 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).

documents that SNAP eligibility expansion during the Great Recession reduced nonfood hardships—such as difficulties in paying for utilities and rent—among near-poor families with gross incomes between 100% and 200% of the FPL. Han (2020) also finds increased participation in other nutritional assistance programs, including free school lunch and WIC. This paper extends this literature by providing one of the first comprehensive analyses of the health effects of SNAP expansion, a novel contribution in the modern era, and by examining the underlying mechanisms through which BBCE influences recipients' well-being.

A complementary body of work examines the effects of benefit transfers on health and household economic outcomes more broadly. Quasi-experimental evidence shows that increases in household resources improve birth outcomes, children's long-run health and educational attainment, and reduce material hardship (Dahl and Lochner 2012; Hoynes, Miller, and Simon 2015; Aizer et al. 2016; Boudreaux, Golberstein, and McAlpine 2016; Cohodes et al. 2016; Bastian and Michelmore 2018; Miller and Wherry 2019; Brown, Kowalski, and Lurie 2020; Goodman-Bacon 2021b). This paper contributes to the literature by providing new causal evidence on the effects of a large eligibility expansion in the nation's primary food assistance program, highlighting how changes in the generosity and reach of SNAP influence well-being among low-income households.

Finally, this analysis relates to broader work on the design of transfer programs. SNAP's income and asset tests have remained largely unchanged since the program's introduction, yet their effectiveness has not been rigorously reassessed in fifty years (Lin 2024). Hence, the reform provides a unique opportunity to study whether eligibility rules in SNAP effectively target resources to those in need and extend benefits to less poor families.

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 the empirical strategy. Section 5 presents the results on program participation, and Section 6 covers food security, health care utilization, and health status. Section 7 discusses labor market outcomes, and Section 8 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 on SNAP was $112.8 billion, accounting for 68% of the U.S. Department of Agriculture's (USDA) nutrition assistance spending, and the average monthly benefit per household was about $400 (U.S. Department of Agriculture 2024a).

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.[6] 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. Most households spend more on SNAP-eligible items than their SNAP benefits cover, so they are not constrained by the in-kind nature of SNAP (relative to an equivalent transfer in cash) (Hoynes, McGranahan, and Schanzenbach 2015; Hastings and Shapiro 2018). Still, consistent with the hypothesis of mental accounting—that households treat different sources of income differently (Thaler 1999)—recent empirical evidence shows that people use SNAP benefits differently from cash assistance (Hastings and Shapiro 2018; Finkelstein, Chorniy, and Notowidigdo 2025).[7]

[6]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.

[7]Using novel retail data, Hastings and Shapiro (2018) find that the marginal propensity to consume

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 on food or EBT benefits. These SNAP benefits account for more than 90 percent of total program costs and are entirely funded by the federal government (Pew Research Center 2023). Although SNAP is a federal program, it is administered by state agencies through local offices, which are responsible for various operational aspects of the program—such as determining recertification periods or accepting online applications.[8] To support these activities, the second component of SNAP funding covers administrative costs, including expenses related to 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.

SNAP is designed to prevent food insecurity, but its regulations also emphasize the role of work and responsibility. To that end, the program imposes two types of work requirements, unless an individual qualifies for an exemption. First, the general requirements apply to individuals aged 16–59 and involve registering for work, participating in Employment and Training (E&T) or workfare, accepting suitable job offers, and avoiding voluntary job loss or reductions in work hours below 30 per week without valid cause. Next, able-bodied adults (age 18-54) without dependents (ABAWDs) need to meet an additional requirement to receive SNAP benefits for more than three months within a three-year period. They must work, or participate in a work program or workfare, for at least 80 hours per month.[9]

(MPC) food out of SNAP—that is, the increase in food expenditure from an additional dollar—is much greater than the MPC out of cash. Also, Finkelstein, Chorniy, and Notowidigdo (2025) corroborate the non-fungibility of SNAP benefits, as SNAP does not increase emergency department visits for drug or alcohol use, unlike Supplemental Security Income (SSI) benefits provided in cash. This stands in contrast to earlier work, which aligns with theoretical predictions for inframarginal households. Hoynes and Schanzenbach (2009) find that the MPC food out of SNAP is higher, although not statistically different from the MPC food out of cash income.

[8]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 2.3.

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

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 introduces a unique state-level variation in SNAP—particularly in eligibility criteria, which have not been evaluated since the program's inception in the 1960s and 1970s—within a context of limited variation for program evaluation (Hoynes and Schanzenbach 2018; Lin 2024).

SNAP eligibility is mostly established by three criteria: assets, gross income, and net income, where net income equals gross income minus deductions such as 20% of earned income, dependent care, medical expenses, and excess shelter costs. 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 Level (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) (U.S. Department of Agriculture 2024c).

Under BBCE, there were no changes to the net income test. However, states were given the option to eliminate the asset test 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 2024), this study focuses on the 28 states and the District of Columbia that chose to increase the gross income limit.[10] The new gross income eligibility thresholds vary, ranging from 160% to the maximum threshold of 200% of the FPL, compared

[10]Each of them additionally chose to eliminate the asset test. An additional 12 states eliminated the asset test only. 10 states did not make any changes.

to the pre-existing limit of 130%. The expanded eligibility primarily affected households with lower disposable income due to large deductions from gross income, particularly those with high medical, child care, and shelter costs (Hoynes and Schanzenbach 2015).[11]

Figure 1 suggests that a quasi-experimental approach is feasible by leveraging policy-induced temporal and spatial variation in states' BBCE adoption. Figure 1-(a) plots the change in the number of states adopting BBCE. With the exception of South Carolina, which revoked its expansion in 2009, the number of BBCE states has steadily increased. The time series graph highlights two notable jumps: (i) the initial implementation of BBCE in 2000 and (ii) the period around the Great Recession in 2009.

Regarding states' incentive to adopt BBCE, one driver could be the desire to reduce program costs. However, as described in Section 2.1, most of the total program costs consist of food benefits, which are fully reimbursed by the federal government. Although a small portion, states may seek to reduce administrative costs, as they receive only partial reimbursement (50%) from the federal government. BBCE has the potential to lower administrative costs per case, particularly by eliminating the asset test. Nevertheless, the increase in applications from expanded eligibility could raise administrative burdens, making the overall effect ambiguous ex ante. In short, the financial incentive to adopt BBCE is limited given SNAP's funding structure.

Instead, a key determinant of BBCE adoption appears to be each state's political stance toward 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.[12] Income eligibility thresholds vary across states: white states did not expand the gross income limit, dark blue states implemented the

[11] This is because both the net income test and the benefit schedule—the maximum allowance minus 30% of net income—remained unchanged.

[12] Specifically, when comparing the map of the 29 states that adopted BBCE by 2016 with the results of the 2000 U.S. presidential election, 20 of them were blue states. This suggests that while some red states, including Texas and South Carolina, also adopted the reform, the majority of treated states were liberal. Consistent with this, the BBCE adoption rate among blue states increased rapidly over time and reached 95% by 2016, compared to just over 25% in red states.

largest expansion up to 200% of the FPL, and other states fall in the middle, with limits ranging from 160% to 185%. By the end of the period, 55% of BBCE states had expanded income limits to the maximum threshold of 200% of the FPL.

2.3 Other SNAP Policies

Since states administer the program, they can adopt different SNAP policies, leading to other SNAP policy variations during my study period. To account for these effects, I categorize twelve policies in the SNAP policy database 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).[13]

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 (SSI) recipients, 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

[13]The data are available here: https://www.ers.usda.gov/data-products/snap-policy-data-sets. My findings are robust to the construction of these indices. Examples include treating the twelve policies individually without averaging, creating a simple average of all policies as a single variable, and applying the same variations to subsets of policies following Ganong and Liebman (2018).

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.[14]

3 Data

To measure the impacts of BBCE adoption on household outcomes, I combine microdata on individual- and household-level program usage and health outcomes from the Current Population Survey (CPS), Vital Statistics Natality Data, and the Behavioral Risk Factor Surveillance System (BRFSS). Details on USDA administrative data are provided in the Appendix (Section A.2.2). Summary statistics for key outcome variables are presented in Table 1.

3.1 Current Population Survey (CPS)

The CPS provides a rich set of demographic and economic variables for a representative sample of individuals and households. I use two types of CPS data from 1997 to 2016 to estimate the effects of BBCE on various outcomes and construct a prediction model that identifies a sample of low-income families for my analyses.

First, 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

[14] 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 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 preferred 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.

self-reported program participation variables are subject to underreporting (Meyer, Mok, and Sullivan 2009), the CPS-ASEC complements USDA administrative data, which only report total participation counts and average benefit per recipient by state. Therefore, I use the CPS-ASEC to examine the effect of BBCE on SNAP participation and benefit amounts, participation in other safety net programs, and labor market outcomes such as employment status and weekly hours worked.

Throughout the paper, I focus on low-income families most likely to be affected by the BBCE expansion to ensure sufficient statistical power. Since income may be endogenous to the policy, I *predict* the FPL ratio—family income divided by the FPL—using *pre*-BBCE characteristics from the CPS-ASEC (1997-1999). I then apply the same estimated prediction model to subsequent datasets to identify the low-income sample, defined as the lowest 35% of the predicted FPL ratio.[15] The full derivation, following the approach of Rittenhouse (2023), is provided in Section A.1. Using the CPS-ASEC from 1997 to 2016, Table 2 presents average demographic characteristics for low-income individuals compared to the overall population in the dataset. Low-income individuals are slightly younger, more likely to be Black or Hispanic, and less likely to have a high school degree or be married, reflecting characteristics correlated with low socioeconomic status.

Next, 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.[16] 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 measured by the number of affirmative responses to 18 related questions, and households are classified into 3 categories: (i) food secure, (ii) low food secure, and (iii) very low food secure. To measure the effects on food insecurity, I

[15] This threshold corresponds to the share of individuals whose family income was below 200% of the FPL prior to BBCE.

[16] Between 70% and 76% of households interviewed in the December CPS complete the FSS, with rates consistent over time. For example, the 76% FSS response rate in 2022 is based on the number of households, as reported at: https://ers.usda.gov/sites/default/files/_laserfiche/DataFiles/50764/techdoc2022.pdf?v=51640.

create two indicators. The first measure captures low or very low food security in the past 12 months, and the other captures very low food security only.[17]

3.2 Vital Statistics Natality Data

To measure the impact of the BBCE expansion on birth weight and prenatal care, I use restricted-use individual-level 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 characteristics of mothers and fathers, maternal state of residence, and birth outcomes such as birth weight, gestation weeks, and prenatal care. As outcomes for birth weight among low-income births, I use a continuous measure of birth weight and an indicator for low birth weight (birth weight $<$ 2,500 grams, approximately 5.5 lb). I also estimate the effects on the total number of prenatal visits, a potential driver of improvements in birth outcomes.

I assign the treatment timing to the beginning of the third trimester, which is the most critical period for determining birth weight (Almond, Hoynes, and Schanzenbach 2011). Since each observation reports the date of birth and gestation weeks, I calculate the conception date and add two quarters to it for all births. Then the sample is restricted to low-income households from 1997 to 2016 whose predicted FPL ratio falls within the bottom 35%, as described in Section A.1.

3.3 Behavioral Risk Factor Surveillance System (BRFSS)

The second main source of data on health outcomes is the BRFSS (1997–2016), an annual cross-sectional telephone survey that collects individual-level health information from adults aged 18 and older. The BRFSS is currently the largest continuously conducted health survey system in the world, with more than 400,000 interviews conducted nationwide each year.

[17]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.

My analysis relies on the core modules conducted in every state, which include questions on various health outcomes such as medical diagnosis, physical health measures, self-reported health, and health care access and utilization. Specifically, the outcomes include indicators for asthma, diabetes, and coronary heart disease; body mass index (BMI)—calculated as weight (in kilograms) divided by height (in meters) squared; an indicator for obesity (BMI > 30); indicators of poor physical or mental health in the past 30 days; and an indicator for having a primary health care provider. They largely overlap with measures used in prior studies of SNAP's effects on health (Hoynes, Schanzenbach, and Almond 2016; Bronchetti, Christensen, and Hoynes 2019) and are consistently available in the BRFSS across all years.

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 as the lowest 35% of the predicted FPL ratio.

3.4 Time Series: SNAP Participation

Figure A.1 shows time series graphs of SNAP participation from two different data sources. Figure A.1-(a) presents SNAP participation rates among low-income families using the CPS-ASEC, while Figure A.1-(b) displays the total number of SNAP participants (in millions) using USDA 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 align with the trend in state-level BBCE adoption over time, as shown in Figure 1-(a).

The widening gap in SNAP participation counts between treated and never-treated states may be driven by changes in population size or the composition of people rather than the BBCE expansion, particularly around the Great Recession. To address this, Figure 2 presents a time series graph of the share of the predicted SNAP-eligible population among the low-income sample of the CPS-ASEC (see Section A.1), separately by each state's BBCE

adoption decision. The predicted SNAP-eligible population is defined as individuals whose predicted FPL ratio—family income divided by the FPL—falls below the gross income limit for SNAP eligibility in the pre-treatment period (1997-1999): 130% of the FPL without BBCE, and 160%, 165%, 180%, or 200% of the FPL with BBCE.

As shown by the red line, the fraction of predicted SNAP-eligible individuals remains stable in states without BBCE adoption. In contrast, 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.

4 Identification Strategy

This section describes the identification strategy employed to estimate the causal effects of the BBCE expansion on household well-being and economic 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. 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 program participation and SNAP benefit amounts, household food insecurity, health care use, health status, and labor market outcomes. The treatment variable, $BBCE_{st}$,

is an indicator for whether state s has expanded SNAP eligibility under BBCE in year t.[18] 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 test the validity of the parallel trends assumption in the pre-treatment period, I also estimate event-study versions of Equations 1 and 2. Across all datasets, I observe two years of post-period and three years of pre-period data for treated states to construct a balanced panel of state-years.[19]

I consider various specifications with different sets of covariates. X_i represents a vector of individual- or household-level covariates, including age, gender, race and ethnicity, marital status, and education level (for households, this refers to the household head). Z_{st} is a set of state-level covariates, including unemployment rates and SNAP policy indices—eligibility, transaction costs, stigma, and outreach—defined in Section 2.3. They are included to control for their potential influence on SNAP participation (Mulligan 2012; Ganong and Liebman 2018) 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 as robustness checks. For all specifications, I apply person- or household-level weights from the data where applicable.

The identifying assumption is that there are no unobserved, time-varying factors correlated with the timing of BBCE adoption. Given this assumption, β is the coefficient of interest in Equations 1 and 2, capturing the effect of the BBCE expansion (on individuals or households) in treated states relative to (those in) non-treated states before and after adoption. One concern is that the largest wave of BBCE adoption occurred around the Great

[18] I also consider alternative specifications that model program participation using continuous treatment variables. These continuous treatments are defined as interactions between the BBCE indicator and either (i) the gross income limit, which increases under BBCE, or (ii) the predicted SNAP-eligible population in the given state. The results are presented in Section A.3 and imply similar magnitudes, so I use a binary indicator in my preferred specification.

[19] 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.

Recession, as shown in Figure 1-(a). The potential confounding effects of state economic conditions on BBCE adoption could threaten the causal interpretation of my findings. However, when I estimate the event-study model with the unemployment rate as the dependent variable, I do not find that the timing of BBCE adoption is correlated with unemployment rates (Figure A.7). See Section A.2 for details.

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 2021a; Callaway and Sant'Anna 2021; Borusyak, Jaravel, and Spiess 2024; De Chaisemartin and d'Haultfoeuille 2024). Since 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 from the negative weighting problem in the TWFE estimator.[20]

The parameter of interest is defined as a weighted average of the average treatment effects for groups that switched into or out of treatment. Specifically, states adopting BBCE are compared with states that remained untreated in both years, rather than with those that had already adopted it in both years. Similarly, states that revoked the expansion are compared with those that remained treated in both years.[21]

5 Results: Program Participation

The following three sections present the main estimation results for program participation (Section 5), health outcomes (Section 6), and labor market outcomes (Section 7) following the BBCE expansion, using the DCDH estimator. In this section, I begin with the most direct effect of BBCE on SNAP participation and then examine how this effect extends to

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

[21] Unlike other alternative DiD estimators, the DCDH estimator allows for the estimation of treatment effects when a treatment can both "turn on" and "turn off." This is relevant for BBCE, as South Carolina revoked its expansion in 2009.

participation in other safety net programs.

5.1 SNAP Participation

Table 3 shows the DiD estimates for SNAP participation and benefit amounts from the CPS-ASEC, estimated using Equation 1. The DiD estimate in column (1) shows the effect of BBCE on SNAP participation among low-income individuals as a binary outcome. Following the BBCE expansion, I find that SNAP participation rises sharply by 2.5 percentage points, statistically significant at the 1% level. This represents an 11.74 percent increase relative to the baseline participation rate among individuals predicted to be low-income in the pre-treatment period.[22]

In columns (2) and (3), I additionally examine effects on SNAP benefit amounts (in 2016 dollars)—including zero for non-participants—and find an increase of $47.4 to $52.8 per year (a 9-10% increase across specifications), all statistically significant at the 5% level. Since the benefit schedule did not change under BBCE, this increase is driven by higher participation.

Figure 3 shows my main event-study estimates of the impact of BBCE on SNAP participation and benefit amounts. I set the period $t = -1$ as the reference period. In each period, the blue dots show the DiD estimates for the outcome with 95% confidence intervals, based on spatial and temporal variation in the BBCE expansion. I do not find evidence of differential trends in the pre-period, supporting the identifying assumption. The estimates for post-treatment periods in Figure 3 show a significant increase in both outcomes over time, which is consistent with the average increase following the BBCE expansion previously shown in Table 3.

Table A.1 demonstrates that the increases in SNAP participation (Panel A) and benefit amounts (Panel B) are robust to the inclusion of different covariates. In the Appendix, Sections A.2, and A.3 present additional robustness tests and extensions that further support

[22]Since SNAP participation increased not only among the newly eligible but also among the *previously* eligible population, consistent with Anders and Rafkin (2024) (i.e., woodwork effects), I estimate the effect of BBCE on the entire low-income population throughout the paper.

the validity of my results, including: (i) similar results when compared with USDA administrative data; (ii) evidence that underreporting of SNAP participation in the CPS (Meyer, Mok, and Sullivan 2009) is not affected by BBCE; (iii) confirmatory results from several falsification tests; (iv) similar magnitudes when using a continuous treatment measure; and (v) no effect of BBCE on vendor participation.

5.2 SNAP Retailer Participation

In addition to examining the effects of the BBCE expansion on individual and household SNAP participation, I also present evidence on vendor participation. This analysis helps assess whether the reform affected access to authorized retailers, which could serve as another channel driving increased SNAP participation.

I use historical data on all SNAP-authorized retailers, which cover nearly all food stores. The data include addresses, start and end dates of SNAP authorization, and store type variables for each vendor.[23] 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 20% of SNAP stores are classified as usual stores, which include food buying co-ops, large grocery stores, super stores, supermarkets, and wholesalers.[24] I count the total number of SNAP stores, usual stores, and non-usual stores in each state-year cell and use participation counts as outcome variables.

While there is a huge increase in the number of individuals and households participating in SNAP, Table A.2 and Figure A.2 present no significant effects on the number of stores participating in SNAP (column (1) and Figure A.2-(a)). By store type, there are also no

[23]The data are publicly available here: https://www.fns.usda.gov/snap/retailer/historical-data. Store type definitions are available at: https://www.fns.usda.gov/snap/store-definitions.

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

significant changes in the number of SNAP vendors, for both usual stores (column (2) and Figure A.2-(b)) and non-usual stores (column (3) and Figure A.2-(c)). The results suggest no meaningful change in access to SNAP stores following BBCE.

5.3 Medicaid and WIC Participation

Before examining the effects on health outcomes, I investigate whether the SNAP eligibility expansion—and the resulting increase in SNAP participation—increased take-up of other welfare programs for low-income families, using the CPS-ASEC. This approach allows for a more accurate interpretation of effects on downstream outcomes and informs broader policy design by highlighting the reform's cross-program impacts. Specifically, I examine whether BBCE increased participation in Medicaid and the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC).

Medicaid is a federal and state public health insurance program that offers free or low-cost coverage to eligible low-income adults, children, the elderly, and people with disabilities. It provides more affordable insurance and health care services to enrollees, including prenatal doctor visits. WIC is a federal nutrition assistance program, designed to address nutritional deficiencies and improve the health outcomes of low-income pregnant and postpartum women and their young children. WIC benefits include monthly vouchers for nutritious foods, nutrition education, health screenings, and referrals to other social services.

Figure 4 and Table 4 show that the BBCE expansion increased Medicaid participation by 1.7 percentage points (a 6.24% increase) and WIC participation by 1.5 percentage points (a 10.03% increase).[25] The estimates are statistically significant at the 1% level for Medicaid participation and at the 5% level for WIC participation. Given that the SNAP participation rate among low-income individuals increased by 2.5 percentage points (an 11.74% increase) due to the expansion (column (1) of Table 3), the increases in Medicaid and WIC participa-

[25]Since the variable for WIC participation is only available for females in the CPS-ASEC, I restrict the sample to females aged 15 to 39 with children in the household.

tion are also substantial.[26] Additional analysis in Table A.4 examines the impact of BBCE on participation in Medicaid and WIC, accounting for whether individuals *also* participate in SNAP. The estimates suggest that the rise in Medicaid and WIC participation following BBCE is driven primarily by increased SNAP take-up—a pattern indicative of potential program spillovers.[27]

These findings motivate a further investigation of the mechanisms that enable enrollment in multiple safety net programs. SNAP participation facilitates WIC enrollment through adjunctive eligibility (Randall et al. 1998), which allows WIC applicants to bypass income documentation requirements if they are already enrolled in other means-tested programs (e.g., SNAP and Medicaid) with verified income. This highlights the role of transaction costs in reducing take-up, while also suggesting that information costs matter (Moffitt 1983; Currie 2004; Anders and Rafkin 2024), since information about WIC may be provided during SNAP enrollment.

Also, Table A.5 provides suggestive evidence that the increase in Medicaid participation is greater in states that (i) use SNAP data to verify Medicaid eligibility, particularly for children, to facilitate enrollment or renewal (e.g., Express Lane Eligibility), and (ii) offer a combined application portal for SNAP and Medicaid.[28] In sum, these findings support the role of both the information and transaction cost channels in promoting multi-program participation through SNAP.[29]

[26]Medicaid has expanded to include pregnant women and children with higher incomes, with the most significant expansion occurring under the Affordable Care Act (ACA) in 2014—which extended eligibility to individuals with family incomes at or below 138% of the FPL. As a robustness check for Medicaid participation, the estimates in Table A.3—which exclude indicators for the ACA expansion and limit the data to pre-ACA years—show that while the ACA expansion slightly increases Medicaid participation, most of the effect is driven by the BBCE expansion itself, rather than by the ACA. The results also remain robust when controlling for state Medicaid income eligibility limits, which vary over time.

[27]In Table A.4, the effect on Medicaid participation (column (1)) can be expressed as the sum of the estimates for those who also participate in SNAP (column (2)) and those who do not (column (3)); the same logic applies to WIC participation (columns (4)–(6)). The increases in the share of low-income individuals participating in both Medicaid and SNAP (column (2)) and in both WIC and SNAP (column (5)) account for most of the observed increases in single program participation (columns (1) and (4)).

[28]For example, Indiana's benefits application portal is available here: https://fssabenefits.in.gov/bp/.

[29]These findings align with cross-enrollment patterns between SNAP and Medicaid among already eligible groups (incomes below 125% of the FPL), which are correlated with state policies to reduce administrative burden, such as presumptive and continuous eligibility for Medicaid (Schmidt, Shore-Sheppard, and Watson

6 Results: Health Outcomes

In previous sections, I present evidence that BBCE significantly increased participation in SNAP, Medicaid, and WIC among low-income families, suggesting the potential for improvements in food security, health care utilization, and health status. For example, greater or higher-quality food consumption can directly improve both food security and health status. Increased participation in Medicaid and WIC provides health care–related support, enhancing access to services and, in turn, improving health. Moreover, increased economic security and reduced stress from additional resources for food and medical care can facilitate better health management and investment.

To examine the effects of the modern SNAP expansion beyond nutrition assistance, this section estimates the impact of BBCE on health-related outcomes among the low-income population. I separately assess the effects on food security (Section 6.1), health care utilization (Section 6.2), and health status (Section 6.3).

6.1 Food Security

As a food assistance program, a primary goal of SNAP is to improve nutritional security. Thus, I estimate how BBCE affected low-income households' access to food and take-up as the first group of health outcomes, using the CPS-FSS. The definitions of each food security measure are provided in detail in Section 3.1.

Table 5 shows that the BBCE expansion reduced the probability of households experiencing low food security in the past 12 months by 1.8 percentage points (column (1)) and very low food security by 0.8 percentage points (column (2)), statistically significant at the 1% and 5% levels, respectively. These point estimates correspond to a 8.28 percent and 10.86 percent decline in food insecurity relative to the pre-treatment means, representing sizable effects in percentage terms. The event-study estimates in Figure 5 confirm this reduction in

2024). Prior work also examines joint participation in the other direction, showing that Medicaid participation can facilitate SNAP participation, either through randomly assigned coverage (Baicker et al. 2014) or the ACA expansion (Schmidt, Shore-Sheppard, and Watson 2021; Cha and Escarce 2022).

food insecurity, preceded by flat pre-trends for both outcome indicators.[30]

The decrease in the fraction of households with food insecurity indicates improvements in access to food following BBCE. This can be attributed to increased participation in SNAP and WIC providing nutrition benefits, with the latter driven by potential spillovers within the social safety net, as discussed in Section 5.3. Participation in Medicaid can also play a role by reducing out-of-pocket medical costs and increasing available resources.

6.2 Health Care Utilization

The increase in program participation (Section 5)—including Medicaid and WIC, which directly facilitate health care access—motivates examining the effects of BBCE on health care utilization. This analysis helps illuminate the frictions that low-income households face in obtaining medical care—distinct from health status—with the potential to further improve health in the long run.

For health care utilization, I examine two outcomes from restricted-use Natality data and the BRFSS: the number of prenatal visits and the likelihood of having a personal doctor or primary health care provider. Figure 6-(a) and column (1) of Table 6 show that the number of prenatal visits increased by 0.21 (a 2.1% increase), with strong statistical significance at the 1% level. Column (4) indicates a 1.1 percentage-point increase in the probability of low-income adults having a health care provider. While this average effect is imprecise, Figure 6-(b), which illustrates dynamic effects, shows a statistically significant increase of 2.2 percent starting one year after the expansion.

When investigating heterogeneous effects by race, Table 6 reports greater improvements

[30]Unlike my findings, Han (2016) finds no decline in food insecurity and Han (2020) finds no increase in Medicaid. Both papers use the Survey of Income and Program Participation (SIPP), with around 7,300 and 24,000 observations, whereas I use data sets 40 to 55 times larger, covering 20 years and providing greater statistical power. Moreover, both papers restrict their samples to households with gross income between 100% and 200% of the FPL and define the treatment variable as the share of newly eligible households. As a result, they miss potential woodwork effects Anders and Rafkin (2024), where *already* eligible households respond to BBCE. I instead include *all* already eligible groups to capture full effects of the policy. Finally, my sample construction is based on *predicted* income—unlike actual income, where the treatment sample is not held fixed—to avoid potential endogenous responses to the policy, such as participation in other government programs or changes in labor supply.

in health care utilization among non-Whites compared to Whites, both for prenatal care and access to health care providers. Columns (2) and (3) show that the number of prenatal visits increased by 0.24 for non-Whites (a 2.42% increase), which is larger than the 0.13 increase for Whites (a 1.23% increase), both in absolute terms and as a percentage.

In columns (5) and (6), the BBCE expansion increased the probability of having a health care provider for both Whites and non-Whites. However, the 2 percentage-point increase for non-Whites (a 3.05% increase) is more than double the increase for Whites and is estimated with greater precision. 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 utilization while improving overall use.

Also, Figure A.3 shows a decline in the share of low-income adults who report missing doctor visits due to cost in the past year. The 0.5 percentage point decline represents roughly a 3 percent reduction relative to the pre-treatment period mean of 18.7%. The increase in household resources, along with the reduction in out-of-pocket medical expenses (through Medicaid or WIC), may explain the decline in the financial burden of doctor visits.

My findings on health care utilization are consistent with those of Bronchetti, Christensen, and Hoynes (2019), although their focus is on *children's* outcomes. The authors estimate that a 10 percent increase in SNAP's purchasing power—driven by changes in local food prices—increases annual checkups by 8.1 percent and any doctor's visits by 3.4 percent.

6.3 Health Status

I then examine how BBCE influenced the health status of low-income individuals, separately for birth outcomes (Section 6.3.1) and adult health conditions (Section 6.3.2).

6.3.1 Birth Outcomes

Using restricted-use birth certificate data, I first examine the effect of BBCE on birth weight, which is a common indicator of newborn health (Almond, Hoynes, and Schanzenbach 2011) and is also linked to later life human capital formation. Table 7 shows that BBCE did not lead to significant improvements in birth weight for the overall low-income sample. The DiD estimates for the the continuous measure of birth weight below 3,200 grams (approximately 7.1 lb; column (1)) and for the indicator of low birth weight (birth weight $<$ 2,500 grams, approximately 5.5 lb; column (5)) are both small in magnitude, along with small standard errors.

When estimating heterogeneous impacts by race, however, I find larger and statistically significant improvements among Black mothers (columns (3) and (7)) following the BBCE expansion, who represent the most vulnerable group, compared to modest effects among White mothers (columns (2) and (6)). Among Black mothers, the birth weight of babies with lower-than-normal weight increased by 5.25 grams, and more importantly, the share of low birth weight births declined by 0.36 percentage points (a 2.48% decline).[31] The event-study graph for Black mothers in Figure 7-(c) shows a sharp and persistent drop in the share of low birth weight births, preceded by flat pre-trends. I further confirm that these findings are not driven by changes in fertility or the composition of mothers (Figure A.4).

My findings align with Almond, Hoynes, and Schanzenbach (2011) in that the introduction of the FSP improved birth outcomes, including the lower share of low birth weight. After adjusting the estimates by SNAP participation rate for the corresponding sample, they find a reduction in low birth weight of 7 to 8 percent for Whites and 5 to 12 percent for Blacks. Although I find statistically significant improvements only among Blacks, the 0.36 percentage point decline corresponds to an 7.1 percent reduction when similarly adjusted using the CPS-ASEC. This supports the continued role of benefit transfers including SNAP

[31] This estimate remains statistically significant even after adjusting for multiple hypothesis testing with the Bonferroni correction (Anderson 2008).

in improving birth outcomes in the modern era.

6.3.2 Adult Health Conditions

In addition to the improvements in the health status of the youngest population—children born to Black mothers—discussed in the previous section (Section 6.3.1), the final group of health outcomes focuses on the health status of the older population.

For health conditions of low-income adults, I investigate the effect of the BBCE expansion on three groups of outcomes using the BRFSS. I first estimate how BBCE affected the incidence of medical diagnoses for certain diseases, including asthma, diabetes, and coronary heart disease. In columns (1)–(3) of Table A.6, the BBCE expansion reduced the share of individuals ever diagnosed with these diseases by 2 to 3 percentage points across all three disease types.[32] Still, these effects are imprecise.

Next, I estimate the effect of the BBCE expansion on self-reported health among adults. In Table A.6, columns (4) and (5) 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.[33] Columns (6) and (7) indicate no significant impacts of BBCE on indicators of poor health in the past 30 days, assessed separately for physical and mental health. Event-study graphs for the outcomes in Table A.6 are presented in Figure A.5.

Table A.7 presents the results on health outcomes discussed above by race. Compared to Whites, non-Whites experienced larger declines in the incidence of medical diagnoses (Panel A) and self-reported poor health (Panel B). Although most effects are imprecisely estimated, the 1.1 percentage point decline in obesity for non-Whites (column (2) of Panel B) is statistically significant at the 5% level and represents a 3.86 percent reduction relative

[32] Since health care utilization for low-income households improved following the BBCE expansion (Section 6.2), the observed reduction in diagnoses is unlikely to reflect underdiagnosis and more likely indicates a decline in disease occurrence.

[33] 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.

to the pre-treatment mean, taken at face value. Since obesity can lead to other conditions—including diabetes, cardiovascular disease, respiratory issues, reproductive health problems, and mental health disorders—this reduction may translate into meaningful health gains among non-Whites.[34]

One potential concern with income transfers is that recipients might use their increased financial resources in ways that ultimately harm their health. To address this, I examine whether BBCE led to any behavioral changes related to smoking or alcohol consumption, as an example of risky behaviors. Table A.6 shows that BBCE did not significantly increase the share of low-income individuals who had smoked in the past 30 days (column (8)) or the number of alcoholic drinks they consumed per occasion in the past 30 days (column (9)). These findings indicate no adverse effects of benefit transfers on vice goods.

To sum up, BBCE did not lead to significant improvements in health conditions for the overall sample of low-income adults, although larger—albeit mostly statistically insignificant—effects are observed among the non-White population. Similar to the results on health care utilization in Section 6.2, my findings on adult health conditions also align with those of Bronchetti, Christensen, and Hoynes (2019), although I focus on health outcomes for adults rather than *children*. They find that the local purchasing power of SNAP is not significantly associated with children's health status—including obesity and self-reported health—except for a reduction in 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 for the overall low-income sample, positive effects may emerge in the long run, reflecting improvements in food security and health care utilization—even among low-income Whites. Previous studies document the long-term impacts of the ini-

[34]In unreported results, I construct separate indices for health conditions based on medical diagnoses, self-reported health, and a combined measure. Each index is calculated as the sum of standardized outcomes, following the approach of Bronchetti, Christensen, and Hoynes (2019) and Bailey et al. (2024). For the overall sample, and for the combined index by race, no significant patterns emerge. However, among non-Whites, the self-reported health index shows an immediate improvement after the reform, gradually returning to zero over time. In contrast, the medical diagnosis index shows no initial response but improves progressively following the reform's implementation.

tial rollout of the FSP, showing that children with access to FSP have a lower incidence of metabolic syndrome (Hoynes, Schanzenbach, and Almond 2016) and have higher life expectancy in adulthood (Bailey et al. 2024).[35] Accounting for long-run impacts, including improvements in health-related outcomes, the Marginal Value of Public Funds (MVPF) for the initial rollout of SNAP increases substantially from 1.04 to 62.25 (Hendren and Sprung-Keyser 2020; Bailey et al. 2024).

7 Results: Moral Hazard

Despite meaningful improvements in several health outcomes, safety net programs may also have the unintended consequence of reducing work incentives. For this reason, this section estimates the effects of BBCE on labor market outcomes to examine potential side effects.

Table 8 presents the results of BBCE'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 8 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 indicates a modest but statistically significant adjustment in labor supply on the intensive margin without notable changes on the extensive margin. The decline in hours worked likely reflects both the income effect of higher non-labor income and the substitution effect associated with the benefit tax on earnings (Bitler, Cook, and Rothbaum 2021). Event-study graphs confirm the absence of confounding pre-trends for both employment status (Figure 8-(a)) and weekly hours of work

[35] The outcomes used to construct the metabolic syndrome index in (Hoynes, Schanzenbach, and Almond 2016) largely overlap with those in my study, including obesity, diabetes, heart disease, heart attack, and high blood pressure.

(Figure 8-(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 A.8, the decline in working hours is concentrated among individuals living with dependents under age 18 (columns (1) and (2)), those who are not the household head (columns (3) and (4))—and thus are more likely to be secondary earners—and 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 to adjust their labor supply. Specifically, those with dependents may reduce their labor supply to spend more time with their children, facilitated by easier access to food. By contrast, SNAP recipients without dependents may find it more difficult to reduce their labor supply because of the ABAWD work requirements, as discussed in Section 2.1.

Hoynes and Schanzenbach (2012) find that the initial introduction of the 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, who were more likely to participate in the program.[36] The implementation of the FSP reduced weekly work hours by 3.5 hours among families headed by an unmarried woman as an Intent-to-Treat (ITT) estimate, which translates to 9.7 hours as a Treatment-on-the-Treated (TOT) estimate. This reduction is substantially larger than my estimate of 0.3 hours per week (ITT) or 1.1 hours per week (TOT). The smaller magnitude of my estimate suggests that the potential adverse effects of transfer programs—such as reduced work incentives, discouraged labor supply, and lower tax revenues—are less pronounced today than in earlier periods of program

[36]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 high-income individuals who are less relevant to the program, with only 3 percent reporting food stamp receipt. As another distinction, I find that the decline is 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 could play a larger role in determining the effects of benefit receipt.

implementation, reflecting the transition to more work-based program designs.

8 Conclusion

This paper examines how recent eligibility expansions in SNAP affected a wide range of outcomes for low-income households, including program take-up, participation in other benefit programs, health outcomes, and labor supply. Using a difference-in-differences (DiD) approach, I leverage variation in the timing of BBCE adoption across states, one of the largest SNAP reforms in the modern era.

Following the BBCE expansion, SNAP participation and benefit amounts among low-income individuals increased sharply, with spillover effects increasing participation in Medicaid and WIC. Additional nutrition benefits and resources led to meaningful improvements in food insecurity and health care utilization, including greater use of prenatal care and primary care providers. While short-term impacts on birth outcomes and adult health status for the overall low-income sample are modest, improvements—particularly in low birth weight and obesity—are more pronounced among non-Whites, suggesting that BBCE helped reduce racial disparities in health. Lastly, BBCE had no significant effect on employment status, but it led to a slight decline in hours worked—about one-tenth of what was observed during the program's early rollout in the 1960s and 1970s. In sum, the modern SNAP expansion appears to have achieved many goals, generating substantial benefits while only producing modest moral hazard.

This paper has several policy implications. First, given the scale and coverage of SNAP, evaluating the effects of its recent large expansion advances our understanding of government program operations. On the cost side, expanding eligibility raises government expenditures by increasing program participation. However, this rise in spending should be weighed against substantial benefits. Evidence highlights that benefit transfers including SNAP function as a public investment with long-term gains—improving health outcomes that reduce future medical costs, enhance labor market productivity, and increase tax revenue—beyond pro-

viding immediate nutritional support. Thus, this paper contributes to measuring the MVPF for SNAP expansion in recent years, which offers an estimate that informs current policy debates and is comparable to the program's introduction in the 1960s and 1970s.

Moreover, the findings suggest that welfare programs have implications for addressing inequality. Health disparities—particularly those linked to race and socioeconomic status—are key drivers of income inequality. The stronger health gains among disadvantaged groups support the role of public programs in both alleviating poverty and advancing equity. Future research should evaluate the long-run effects of the BBCE expansion to better understand its broader implications, assess the value of integrated program design, and conduct a cost-benefit analysis to identify the optimal use of government funds.

References

Aizer, Anna, Shari Eli, Joseph Ferrie, and Adriana Lleras-Muney. 2016. "The long-run impact of cash transfers to poor families." *American Economic Review* 106 (4): 935–971.

Almond, Douglas, Hilary W Hoynes, and Diane Whitmore Schanzenbach. 2011. "Inside the war on poverty: The impact of food stamps on birth outcomes." *Review of Economics and Statistics* 93 (2): 387–403.

Anders, Jenna, and Charlie Rafkin. 2024. "The welfare effects of eligibility expansions: Theory and evidence from SNAP."

Anderson, Michael L. 2008. "Multiple inference and gender differences in the effects of early intervention: A reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects." *Journal of the American Statistical Association* 103 (484): 1481–1495.

Baicker, Katherine, Amy Finkelstein, Jae Song, and Sarah Taubman. 2014. "The impact of Medicaid on labor market activity and program participation: evidence from the Oregon Health Insurance Experiment." *American Economic Review* 104 (5): 322–328.

Bailey, Martha J, Hilary Hoynes, Maya Rossin-Slater, and Reed Walker. 2024. "Is the social safety net a long-term investment? Large-scale evidence from the food stamps program." *Review of Economic Studies* 91 (3): 1291.

Bastian, Jacob, and Katherine Michelmore. 2018. "The long-term impact of the earned income tax credit on children's education and employment outcomes." *Journal of Labor Economics* 36 (4): 1127–1163.

Bitler, Marianne, Jason Cook, and Jonathan Rothbaum. 2021. "Working for your bread: The labor supply effects of SNAP." In *AEA Papers and Proceedings,* 111:496–500. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess. 2024. "Revisiting event-study designs: robust and efficient estimation." *Review of Economic Studies* 91 (6): 3253–3285.

Boudreaux, Michel H, Ezra Golberstein, and Donna D McAlpine. 2016. "The long-term impacts of Medicaid exposure in early childhood: Evidence from the program's origin." *Journal of Health Economics* 45:161–175.

Bronchetti, Erin T, Garret Christensen, and Hilary W Hoynes. 2019. "Local food prices, SNAP purchasing power, and child health." *Journal of Health Economics* 68:102231.

Brown, David W, Amanda E Kowalski, and Ithai Z Lurie. 2020. "Long-term impacts of childhood Medicaid expansions on outcomes in adulthood." *Review of Economic Studies* 87 (2): 792–821.

Callaway, Brantly, and Pedro HC Sant'Anna. 2021. "Difference-in-differences with multiple time periods." *Journal of Econometrics* 225 (2): 200–230.

Cha, Paulette, and José J Escarce. 2022. "The Affordable Care Act Medicaid expansion: A difference-in-differences study of spillover participation in SNAP." *Plos one* 17 (5): e0267244.

Cohodes, Sarah R, Daniel S Grossman, Samuel A Kleiner, and Michael F Lovenheim. 2016. "The effect of child health insurance access on schooling: Evidence from public insurance expansions." *Journal of Human Resources* 51 (3): 727–759.

Currie, Janet. 2004. "The take up of social benefits." NBER Working Paper 10488.

Dahl, Gordon B, and Lance Lochner. 2012. "The impact of family income on child achievement: Evidence from the earned income tax credit." *American Economic Review* 102 (5): 1927–1956.

De Chaisemartin, Clément, and Xavier d'Haultfoeuille. 2024. "Difference-in-differences estimators of intertemporal treatment effects." *Review of Economics and Statistics,* 1–45.

De Chaisemartin, Clément, and Xavier d'Haultfoeuille. 2020. "Two-way fixed effects estimators with heterogeneous treatment effects." *American Economic Review* 110 (9): 2964–2996.

Dickert-Conlin, Stacy, Katie Fitzpatrick, Brian Stacy, and Laura Tiehen. 2021. "The downs and ups of the SNAP caseload: what matters?" *Applied Economic Perspectives and Policy* 43 (3): 1026–1050.

Dodini, Samuel, Jeff Larrimore, and Anna Tranfaglia. 2024. "Financial repercussions of SNAP work requirements." *Journal of Public Economics* 229:105034.

East, Chloe N. 2020. "The effect of food stamps on children's health: Evidence from immigrants' changing eligibility." *Journal of Human Resources* 55 (2): 387–427.

Eslami, Esa. 2014. "Trends in supplemental nutrition assistance program participation rates: Fiscal Year 2010 to Fiscal Year 2012." Mathematica Policy Research.

Finkelstein, Amy, Anna Chorniy, and Matthew J Notowidigdo. 2025. "Paternalistic social assistance: Evidence and implications from cash vs. in-kind transfers."

Ganong, Peter, and Jeffrey B Liebman. 2018. "The decline, rebound, and further rise in SNAP enrollment: Disentangling business cycle fluctuations and policy changes." *American Economic Journal: Economic Policy* 10 (4): 153–176.

Goodman-Bacon, Andrew. 2021a. "Difference-in-differences with variation in treatment timing." *Journal of Econometrics* 225 (2): 254–277.

———. 2021b. "The long-run effects of childhood insurance coverage: Medicaid implementation, adult health, and labor market outcomes." *American Economic Review* 111 (8): 2550–2593.

Gray, Colin, Adam Leive, Elena Prager, Kelsey Pukelis, and Mary Zaki. 2023. "Employed in a SNAP? The impact of work requirements on program participation and labor supply." *American Economic Journal: Economic Policy* 15 (1): 306–341.

Han, Jeehoon. 2016. "The impact of SNAP on material hardships: evidence from broad-based categorical eligibility expansions." *Southern Economic Journal* 83 (2): 464–486.

———. 2020. "SNAP Expansions and Participation in Government Safety Net Programs." *Economic Inquiry* 58 (4): 1929–1948.

Harris, Timothy F. 2021. "Do SNAP work requirements work?" *Economic Inquiry* 59 (1): 72–94.

Hastings, Justine, and Jesse M Shapiro. 2018. "How are SNAP benefits spent? Evidence from a retail panel." *American Economic Review* 108 (12): 3493–3540.

Hendren, Nathaniel, and Ben Sprung-Keyser. 2020. "A unified welfare analysis of government policies." *Quarterly Journal of Economics* 135 (3): 1209–1318.

Hoynes, Hilary, Doug Miller, and David Simon. 2015. "Income, the earned income tax credit, and infant health." *American Economic Journal: Economic Policy* 7 (1): 172–211.

Hoynes, Hilary, and Diane Whitmore Schanzenbach. 2015. "US food and nutrition programs." *Economics of Means-Tested Transfer Programs in the United States, Volume 1,* 219–301.

———. 2018. "Safety net investments in children." *Brookings Papers on Economic Activity,* 89–132.

Hoynes, Hilary, Diane Whitmore Schanzenbach, and Douglas Almond. 2016. "Long-run impacts of childhood access to the safety net." *American Economic Review* 106 (4): 903–934.

Hoynes, Hilary W, Leslie McGranahan, and Diane Whitmore Schanzenbach. 2015. "SNAP and food consumption." *SNAP Matters: How Food Stamps Affect Health and Well Being,* 107–133.

Hoynes, Hilary W, and Diane Whitmore Schanzenbach. 2009. "Consumption responses to in-kind transfers: Evidence from the introduction of the food stamp program." *American Economic Journal: Applied Economics* 1 (4): 109–139.

Hoynes, Hilary Williamson, and Diane Whitmore Schanzenbach. 2012. "Work incentives and the food stamp program." *Journal of Public Economics* 96 (1-2): 151–162.

Jones, Jordan W, Charles Courtemanche, Augustine Denteh, James Marton, and Rusty Tchernis. 2022. "Do state Supplemental Nutrition Assistance Program policies influence program participation among seniors?" *Applied Economic Perspectives and Policy* 44 (2): 591–608.

Klerman, Jacob Alex, and Caroline Danielson. 2011. "The transformation of the supplemental nutrition assistance program." *Journal of Policy Analysis and Management* 30 (4): 863–888.

Lin, Jou-Chun. 2024. "Essays in public economics and wealth mobility." PhD diss., University of California, Davis.

Meyer, Bruce D, Wallace KC Mok, and James X Sullivan. 2009. "The under-reporting of transfers in household surveys: Its nature and consequences." NBER Working Paper 15181.

Miller, Sarah, and Laura R Wherry. 2019. "The long-term effects of early life Medicaid coverage." *Journal of Human Resources* 54 (3): 785–824.

Moffitt, Robert. 1983. "An economic model of welfare stigma." *American Economic Review* 73 (5): 1023–1035.

Mulligan, Casey B. 2012. "Do welfare policies matter for labor market aggregates? Quantifying safety net work incentives since 2007." NBER Working Paper 18088.

Pew Research Center. 2023. "Federal spending on food stamps." (Accessed: May 2025). https://www.pewresearch.org/short-reads/2023/07/19/what-the-data-says-about-food-stamps-in-the-u-s/.

Randall, Bonnie, Susan Bartlett, Sheela Kennedy, Frederick deFriesse, Don Laliberty, Eileen McEnaney, and Tracy Olcott. 1998. "Study of WIC Participant and Program Characteristics."

Rittenhouse, Katherine. 2023. "Essays on child welfare." PhD diss., University of California, San Diego.

Schmidt, Lucie, Lara Shore-Sheppard, and Tara Watson. 2021. *The Impact of Expanding Public Health Insurance on Safety Net Program Participation: Evidence from the ACA Medicaid Expansion.* Technical report. National Bureau of Economic Research.

———. 2024. "Safety-net program spillovers and administrative burden." *National Tax Journal* 77 (1): 199–221.

Stacy, Brian, Laura Tiehen, and David Marquardt. 2018. "Using a policy index to capture trends and differences in state administration of USDA's Supplemental Nutrition Assistance Program." U.S. Department of Agriculture, Economic Research Service.

Sun, Liyang, and Sarah Abraham. 2021. "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects." *Journal of Econometrics* 225 (2): 175–199.

Thaler, Richard H. 1999. "Mental accounting matters." *Journal of Behavioral Decision Making* 12 (3): 183–206.

U.S. Bureau of Economic Analysis. 2024. "Real GDP Per Capita." (Accessed: Nov 2024). https://fred.stlouisfed.org/series/A939RX0Q048SBEA.

U.S. Department of Agriculture. 2024a. "SNAP Data and Statistics." (Accessed: Nov 2024). https://www.ers.usda.gov/topics/food-nutrition-assistance/supplemental-nutrition-assistance-program-snap/key-statistics-and-research.

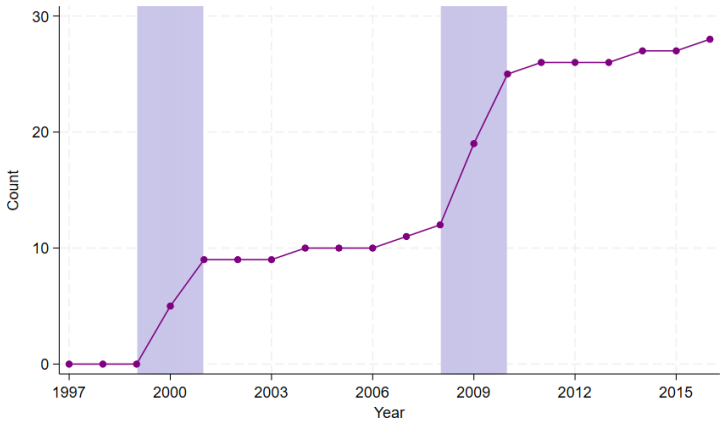
———. 2024b. "SNAP Data Tables." (Accessed: Aug 2025). https://www.fns.usda.gov/pd/supplemental-nutrition-assistance-program-snap.

U.S. Department of Agriculture. 2024c. "SNAP Eligibility." (Accessed: Mar 2025). https://www.fns.usda.gov/snap/recipient/eligibility.

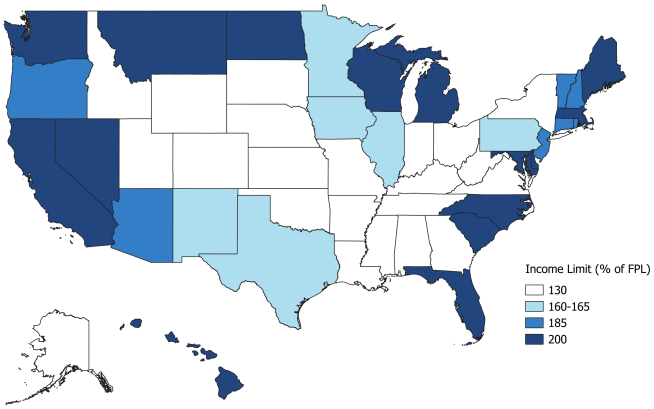
Urban Institute. 2025. "Public Welfare Expenditures." (Accessed: Aug 2025). https://www.urban.org/policy-centers/cross-center-initiatives/state-and-local-finance-initiative/state-and-local-backgrounders/public-welfare-expenditures.

Figures and Tables

Figure 1: States with BBCE Expansion



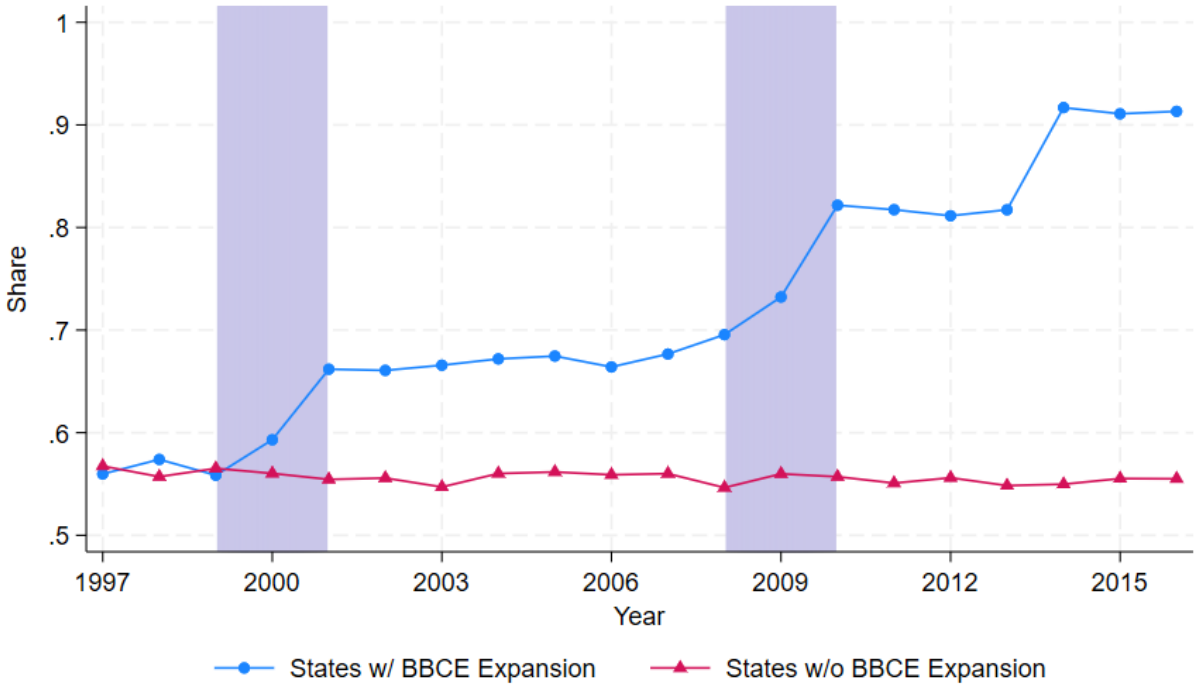
(a) Number of States with BBCE Expansion



(b) Map of States with BBCE Expansion

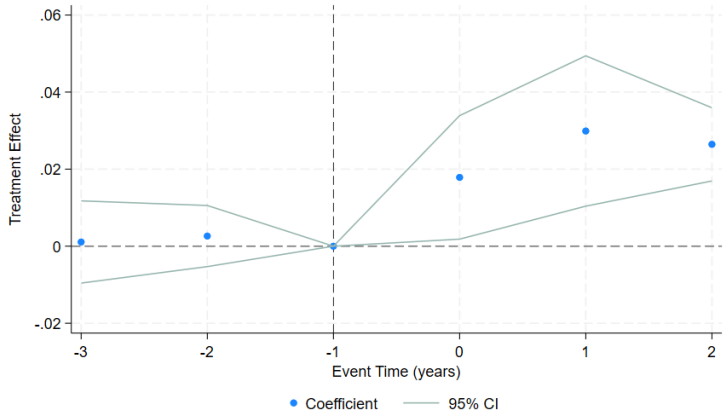
Notes: Figure 1-(a) displays time series graphs of the number of states that adopted the BBCE expansion of the asset test and the gross income rule over time. The x-axis represents calendar years. The light purple areas denote two major expansions: (i) the initial implementation in 2000, and (ii) the period around the Great Recession in 2009. Figure 1-(b) presents a state-level map illustrating the maximum gross income limit under the BBCE expansion up to 2016. States in dark blue implemented the largest expansion by raising the limit to 200% of the FPL, those in blue expanded the limit to 185%, those in light blue to between 160% and 165%, and those in white maintained the gross income limit at 130%, with no expansion.

Figure 2: Time Series Graph of Predicted SNAP-Eligible Population Share

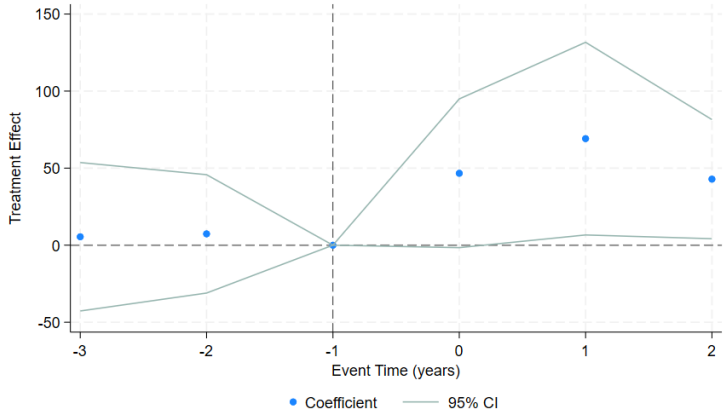


Notes: Figure 2 displays a time series graph of the share of the predicted SNAP-eligible population among the low-income sample of the CPS-ASEC (see Section A.1), separately by each state's BBCE adoption decision. The predicted SNAP-eligible population is defined as individuals whose predicted FPL ratio—family income divided by the FPL—falls below the gross income limit for SNAP eligibility in the pre-treatment period (1997-1999): 130% of the FPL without BBCE, or 160%, 165%, 180%, or 200% of the FPL with BBCE. The x-axis represents calendar years. The blue line shows the average share of predicted 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 predicted SNAP-eligible population for states that have never adopted BBCE (i.e., never-treated). The light purple areas denote two major expansions: (i) the initial implementation in 2000, and (ii) the period around the Great Recession in 2009.

Figure 3: Effect of BBCE Expansion on SNAP Participation and Benefit Amounts



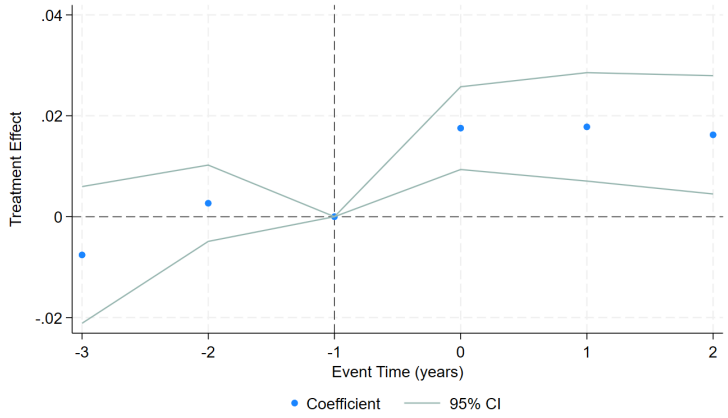
(a) SNAP Participation (binary)



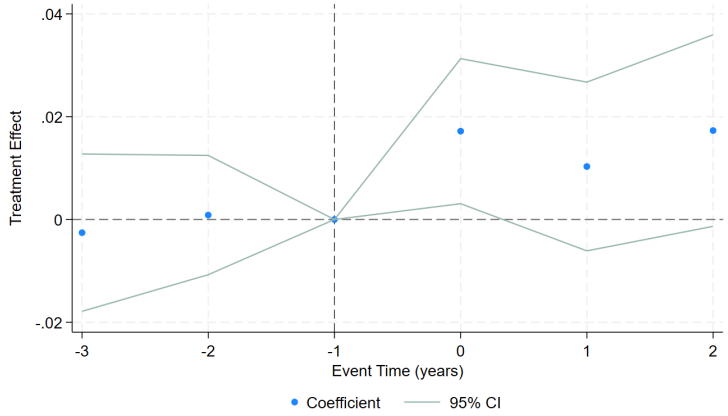
(b) SNAP Benefit Amounts

Notes: Figure 3 displays the estimation results of the impact of the BBCE expansion on SNAP participation and household SNAP benefit amounts (in 2016 dollars) using the event-study framework developed by De Chaisemartin and d'Haultfoeuille (2024) based on Equation 1. Each figure shows the effect on low-income individuals' SNAP participation as a binary outcome (Figure 3-(a)) and reported SNAP benefit amounts per year (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 A.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 2.3.

Figure 4: Effect of BBCE Expansion on Medicaid and WIC Participation



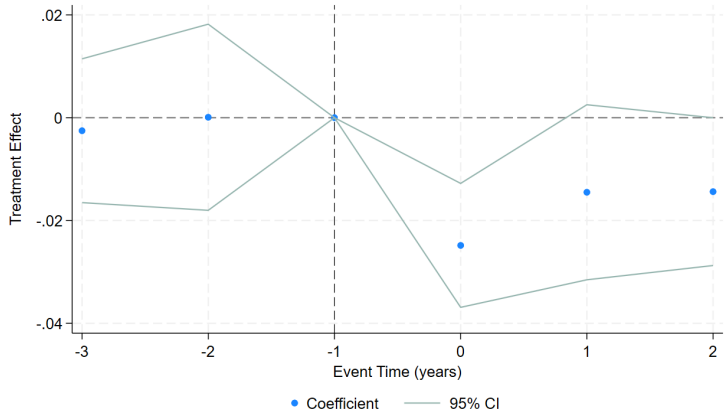
(a) Medicaid Participation (binary)



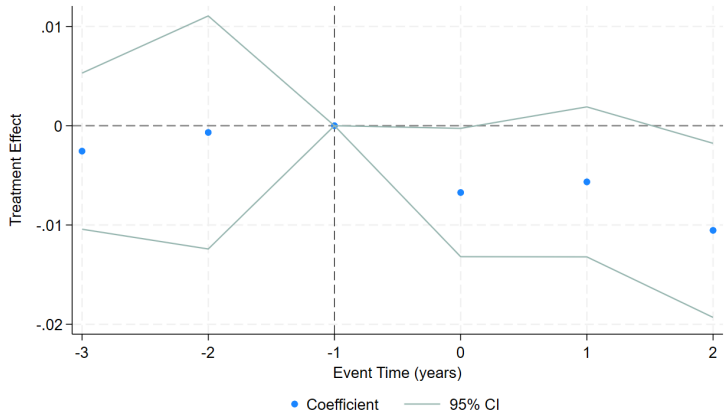
(b) WIC Participation (binary)

Notes: Figure 4 displays the estimation results of the impact of the BBCE expansion on enrollment in other safety net programs using the event-study framework developed by De Chaisemartin and d'Haultfoeuille (2024) based on Equation 1. Each figure shows the effect on Medicaid participation (binary) (Figure 4-(a)) and WIC participation (binary) (Figure 4-(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 A.1, using the CPS-ASEC from 1997 to 2016. In Figure 4-(b), the sample is restricted to females aged 15 to 39 with children in the household. 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, four SNAP policy indices (i.e., eligibility, transaction costs, stigma, and outreach), as defined in Section 2.3, and indicators for Medicaid expansion as part of the Affordable Care Act (ACA).

Figure 5: Effect of BBCE Expansion on Household Food Security



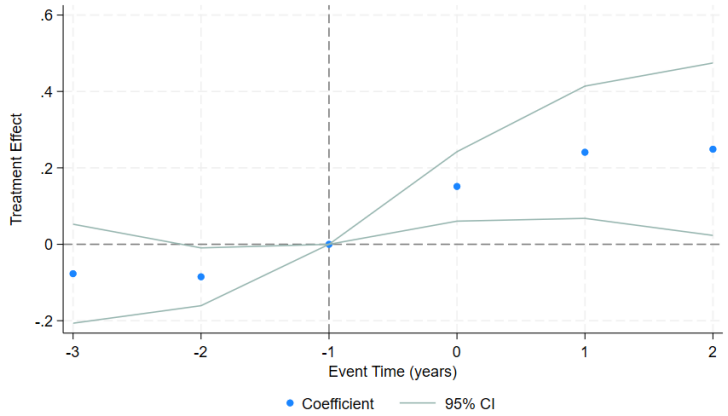
(a) Low Food Security (binary)



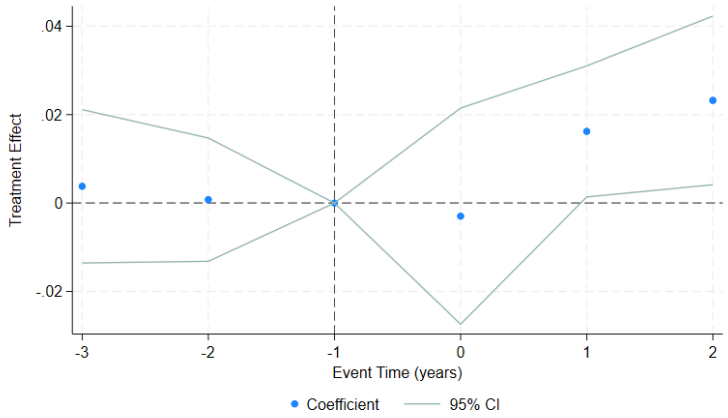
(b) Very Low Food Security (binary)

Notes: Figure 5 displays the estimation results of the impact of the BBCE expansion on household food security 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 very low or low food security (Figure 5-(a)) and very low food security (Figure 5-(b)), as 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 low-income households, as defined in Section A.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 2.3, and indicators for Medicaid expansion as part of the Affordable Care Act (ACA).

Figure 6: Effect of BBCE Expansion on Health Care Utilization



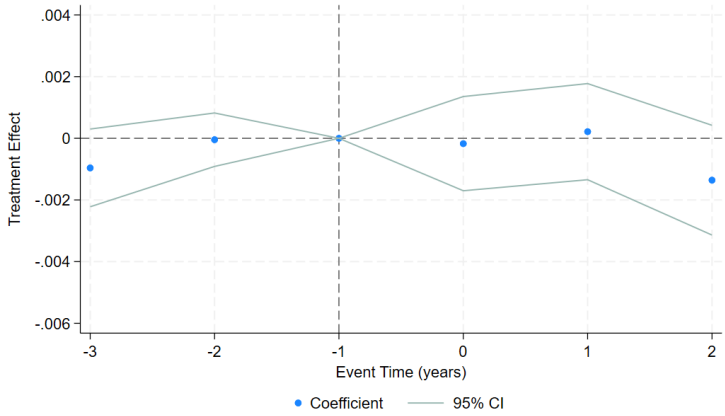
(a) Number of Prenatal Visits



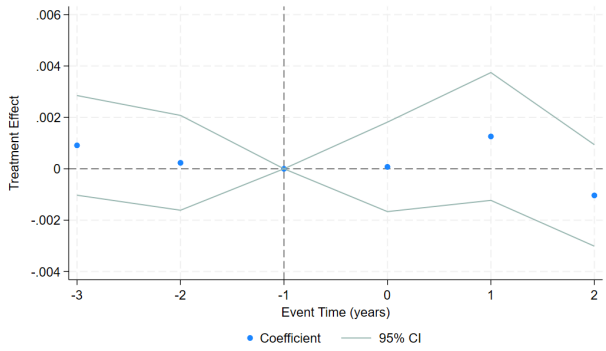
(b) Any Primary Care Provider (binary)

Notes: Figure 6 displays the estimation results of the impact of the BBCE expansion on health care utilization using the event-study framework developed by De Chaisemartin and d'Haultfoeuille (2024). Each figure shows the effect on the number of prenatal visits during pregnancy based on Equation 2 (Figure 6-(a)) and whether having a personal doctor or health care provider (binary) based on Equation 1 (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 A.1, using the restricted-use Vital Statistics Natality Data (Figure 6-(a)) and the BRFSS (Figure 6-(b)) from 1997 to 2016. Standard errors are clustered at the state level. BRFSS person-level weights are applied (Figure 6-(b) only). Individual-level covariates include age, gender, race/ethnicity, marital status, and education level (Figure 6-(b) only). State-level covariates include unemployment rates, four SNAP policy indices (i.e., eligibility, transaction costs, stigma, and outreach), as defined in Section 2.3, and indicators for Medicaid expansion as part of the Affordable Care Act (ACA).

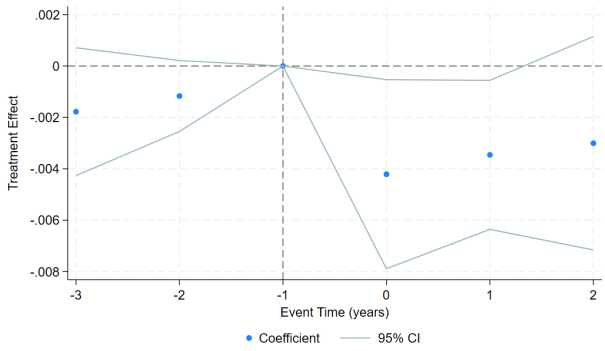
Figure 7: Effect of BBCE Expansion on Low Birth Weight



(a) All



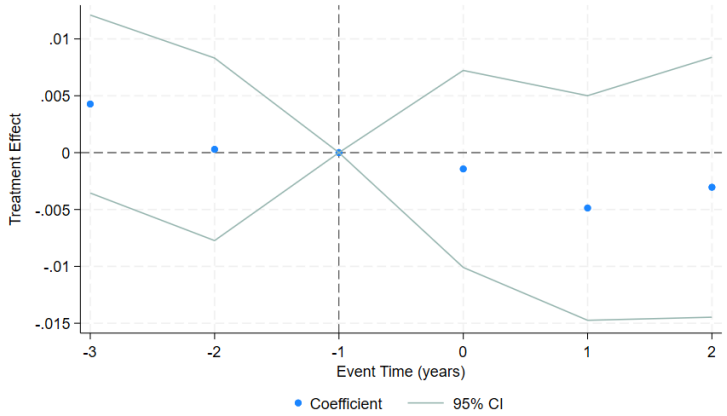
(b) White



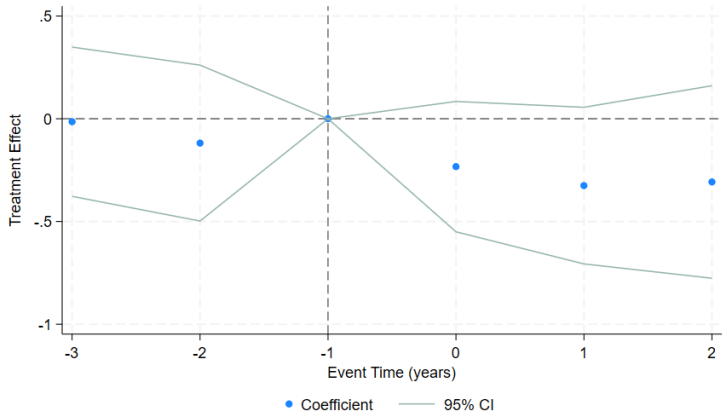
(c) Black

Notes: Figure 7 displays the estimation results of the impact of the BBCE expansion on low birth weight (binary), both for the full sample and by race, using the event-study framework developed by De Chaisemartin and d'Haultfoeuille (2024) based on Equation 1. Each figure shows the effect on the incidence of low birth weight ($<$ 2,500 g $\fallingdotseq$ 5.5 lb) among all mothers (Figure 7-(a)), White mothers (Figure 7-(b)), and Black mothers (Figure 7-(c)). 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 A.1, using the restricted-use Vital Statistics Natality Data from 1997 to 2016. Standard errors are clustered at the state level. Individual-level covariates include age, 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 2.3, and indicators for Medicaid expansion as part of the Affordable Care Act (ACA).

Figure 8: Effect of BBCE Expansion on Labor Market Outcomes



(a) Employment Status (binary)



(b) Hours Worked (per week)

Notes: Figure 8 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 8-(a)) and hours worked (per week) (Figure 8-(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 A.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 2.3.

Table 1: Descriptive Statistics (1997-2016)

Variable	Mean
A. CPS-ASEC	
SNAP participation (binary)	0.231
SNAP benefit amounts (in 2016 dollars)	601.379
Medicaid participation (binary)	0.290
WIC participation (binary)	0.131
Employment status (binary)	0.499
Hours worked (per week)	18.279
Observations	1,317,100
B. CPS-FSS	
Low food security (binary)	0.219
Very low food security (binary)	0.075
Observations	289,237
C. Vital Statistics Natality Data	
Low birth weight (binary)	0.094
Birth weight (in grams)	3,203.208
Number of prenatal visits	10.108
Observations	26,910,878
D. BRFSS	
Ever diagnosed with asthma (binary)	0.138
Ever diagnosed with diabetes (binary)	0.099
Ever diagnosed with coronary heart disease (binary)	0.038
Body mass index (BMI)	27.236
Obesity (BMI $>$ 30) (binary)	0.276
Poor physical health (past 30 days) (binary)	0.373
Poor mental health (past 30 days) (binary)	0.379
Ever smoked (past 30 days) (binary)	0.266
Number of drinks (per occasion; past 30 days)	1.191
Having a primary care provider (binary)	0.726
Observations	2,048,505

Notes: Table 1 reports average characteristics from various data sources between 1997 and 2016. The sample consists of low-income individuals, as defined in Section A.1.

Table 2: Descriptive Statistics: Demographics (CPS-ASEC)

	(1) All	(2) Low-Income
Age	33.671	27.509
Male	0.485	0.439
White	0.643	0.449
Black	0.109	0.162
Hispanic	0.168	0.299
No High School Diploma	0.396	0.602
High School Diploma	0.219	0.235
Some College or Above	0.385	0.163
Married	0.411	0.228
Observations	3,763,147	1,317,100

Notes: Table 2 reports average characteristics for observations in the CPS-ASEC from 1997 to 2016. Averages are reported separately for two groups: all observations (column (1)) and low-income families (column (2)), as defined in Section A.1.

Table 3: Effect of BBCE Expansion on SNAP Participation and Benefit Amounts

	Participation	Amount	
	(1)	(2)	(3)
	Part. = 1	Reported	Winsorized
BBCE	0.025***	52.809**	47.431**
	(0.007)	(21.391)	(19.254)
Baseline Controls	YES	YES	YES
Pre-Period Mean	0.211	541.088	509.164

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 SNAP participation and household SNAP benefit amounts (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 SNAP participation as a binary outcome (column (1)), reported SNAP benefit amounts per year (column (2)), and winsorized benefit amounts where extreme values are replaced at the 2.5th percentile in each tail of the distribution (column (3)). The sample consists of low-income individuals, as defined in Section A.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 2.3.

Table 4: Effect of BBCE Expansion on Medicaid and WIC Participation

	(1) Medicaid	(2) WIC
BBCE	0.017***	0.015**
	(0.004)	(0.007)
Baseline Controls	YES	YES
Pre-Period Mean	0.275	0.149

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 enrollment in other satefy net programs 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 Medicaid participation (column (1)) and WIC participation (column (2)) as a binary outcome. The sample consists of low-income individuals, as defined in Section A.1, using the CPS-ASEC from 1997 to 2016. In column (2), the sample is restricted to females aged 15 to 39 with children in the household. 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 2.3, and indicators for Medicaid expansion as part of the Affordable Care Act (ACA).

Table 5: Effect of BBCE Expansion on Household Food Security

	(1) Low Food Security	(2) Very Low Food Security
BBCE	-0.018***	-0.008**
	(0.006)	(0.003)
Baseline Controls	YES	YES
Pre-Period Mean	0.213	0.072

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

Notes: Table 5 reports the estimation results of the impact of the BBCE expansion on household food security 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 very low or low food security (column (1)) and very low food security (column (2)), which are defined in Section 3.1 as binary outcomes. The sample consists of low-income individuals, as defined in Section A.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 2.3, and indicators for Medicaid expansion as part of the Affordable Care Act (ACA).

Table 6: Effects of BBCE Expansion on Health Care Utilization

	Number of Prenatal Visits			Any Primary Care Provider		
	(1) All	(2) White	(3) Others	(4) All	(5) White	(6) Others
BBCE	0.213***	0.130*	0.240***	0.011	0.008	0.020*
	(0.080)	(0.070)	(0.088)	(0.009)	(0.008)	(0.011)
Baseline Controls	YES	YES	YES	YES	YES	YES
Pre-Period Mean	10.163	10.591	9.950	0.727	0.785	0.668

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

Notes: Table 6 reports the estimation results of the impacts the BBCE expansion on health care utilization, both for the full sample and by race, using the difference-in-differences (DiD) estimator developed by De Chaisemartin and d'Haultfoeuille (2024). Columns (1)-(3) present the DiD estimates for the number of prenatal visits during pregnancy based on Equation 2. Columns (4)-(6) present the DiD estimates for whether having a personal doctor or health care provider (binary) based on Equation 1. The sample consists of low-income individuals, as defined in Section A.1, using the restricted-use Vital Statistics Natality Data (columns (1)-(3)) and the BRFSS (columns (4)-(6)) from 1997 to 2016. Standard errors are clustered at the state level. BRFSS person-level weights are applied (columns (4)-(6) only). Individual-level covariates include age, gender, race/ethnicity, marital status, and education level (columns (4)-(6) only). State-level covariates include unemployment rates, four SNAP policy indices (i.e., eligibility, transaction costs, stigma, and outreach), as defined in Section 2.3, and indicators for Medicaid expansion as part of the Affordable Care Act (ACA).

Table 7: Effect of BBCE Expansion on Birth Weight

	Birth Weight (continuous)				Low Birth Weight (binary)			
	(1) All	(2) White	(3) Black	(4) Hispanic	(5) All	(6) White	(7) Black	(8) Hispanic
BBCE	0.831	0.451	5.249*	-1.258	-0.0004	0.0001	-0.0036**	0.0013
	(1.349)	(2.276)	(2.833)	(2.124)	(0.0007)	(0.0009)	(0.0016)	(0.0010)
Baseline Controls	YES	YES	YES	YES	YES	YES	YES	YES
Pre-Period Mean	2,722	2,729	2,652	2,778	0.095	0.091	0.143	0.066

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

Notes: Table 7 reports the estimation results of the impact of the BBCE expansion on birth weight, both for the full sample and by race and ethnicity, using the difference-in-differences (DiD) estimator developed by De Chaisemartin and d'Haultfoeuille (2024) based on Equation 1. Columns (1)-(4) present the DiD estimates for the continuous measure of birth weight below 3,200 g (≒ 7.1 lb). Columns (5)-(8) present the DiD estimates for the incidence of low birth weight (birth weight < 2,500 g ≒ 5.5 lb) (binary). The sample consists of low-income individuals, as defined in Section A.1, using the restricted-use Vital Statistics Natality Data from 1997 to 2016. Standard errors are clustered at the state level. Individual-level covariates include age, 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 2.3, and indicators for Medicaid expansion as part of the Affordable Care Act (ACA).

Table 8: Effect of BBCE Expansion on Labor Market Outcomes

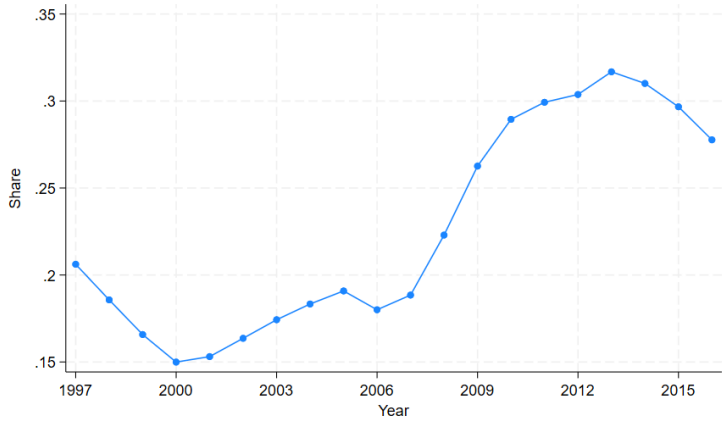
	(1) Employment	(2) Hours Worked
BBCE	-0.003	-0.285*
	(0.004)	(0.158)
Baseline Controls	YES	YES
Pre-Period Mean	0.501	18.455

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

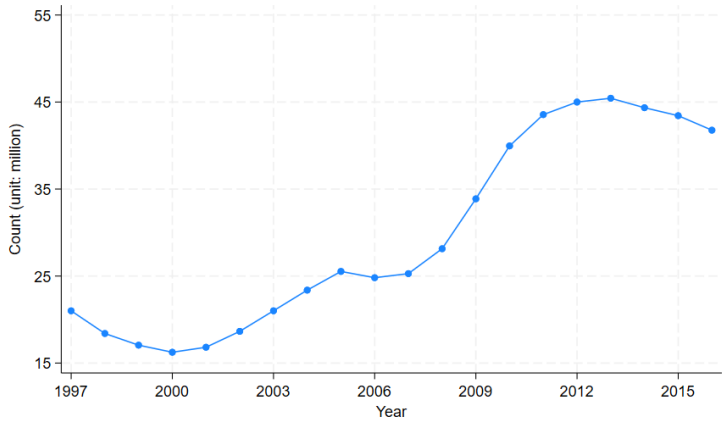
Notes: Table 8 reports the estimation results of the impact of the BBCE expansion on labor market outcomes using the difference-in-differences (DiD) estimator developed by De Chaisemartin and d'Haultfoeuille (2024) based on Equation 1. Each column presents the DiD estimate for employment status (binary) (column (1)) and hours worked (per week) (column (2)). The sample consists of low-income individuals, as defined in Section A.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 2.3.

Appendix

Figure A.1: Time Series Graphs of SNAP Participation



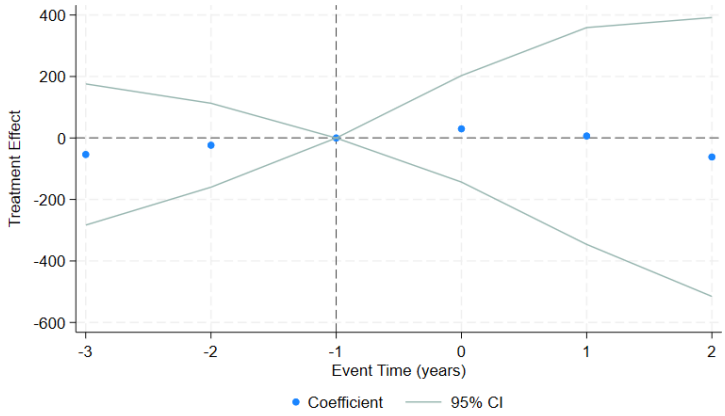
(a) SNAP Participation Rate



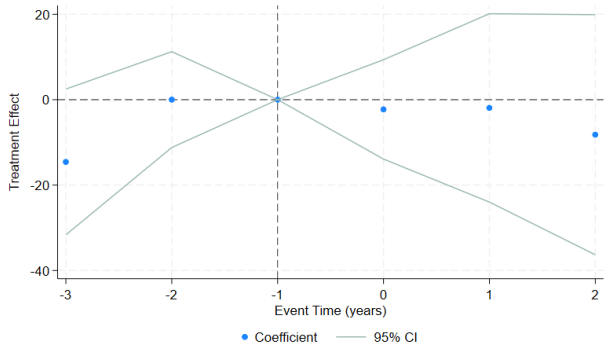
(b) SNAP Participation Count

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

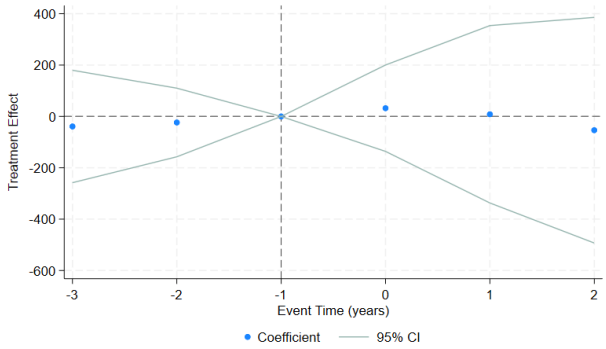
Figure A.2: Effect of BBCE Expansion on SNAP Retailer Participation



(a) All Stores



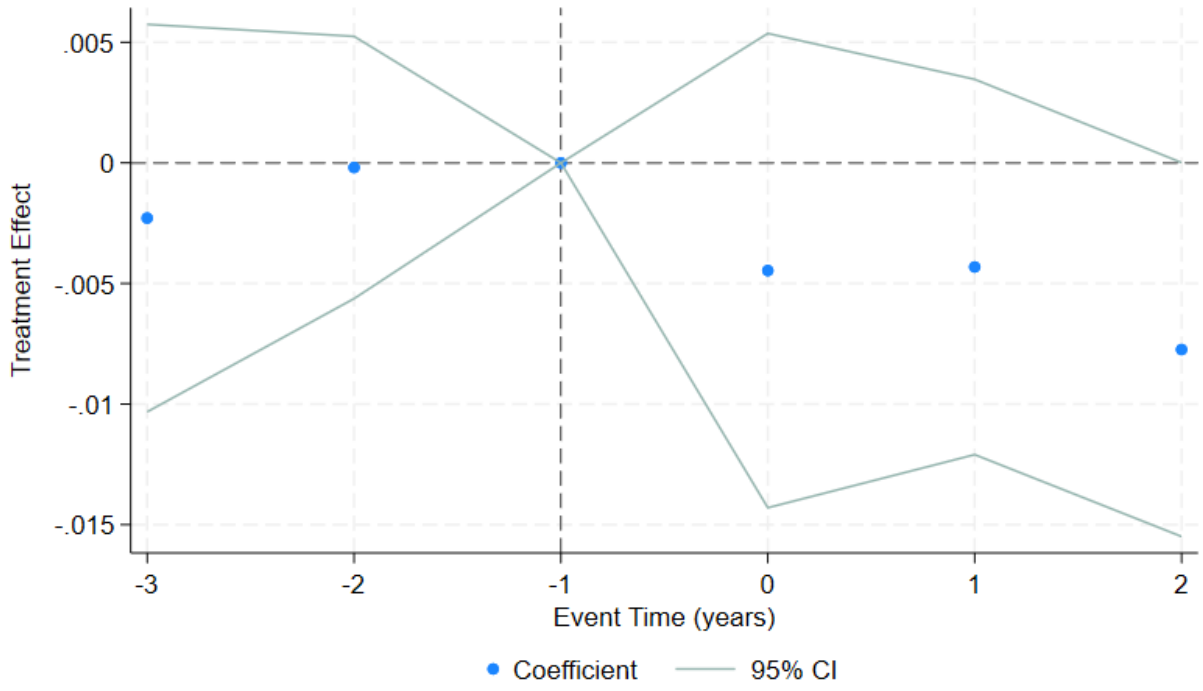
(b) Usual Stores (20%)



(c) Non-Usual Stores (80%)

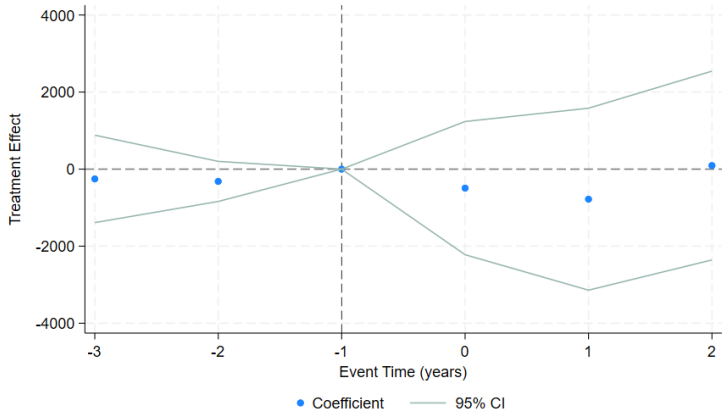
Notes: Figure A.2 displays the estimation results of the impact of the BBCE expansion on SNAP vendor counts using the event-study framework developed by De Chaisemartin and d'Haultfoeuille (2024) based on Equation 2. Each figure shows the effect on the number of all stores (Figure A.2-(a)), usual stores (Figure A.2-(b)), and non-usual stores (Figure A.2-(c)) participating in SNAP, as defined in Section 5.2. 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 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 2.3.

Figure A.3: Effect of BBCE Expansion on Financial Barrier to Medical Care

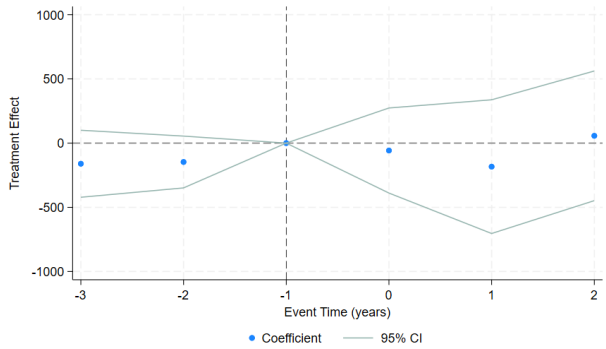


Notes: Figure A.3 displays the estimation results of the impact of the BBCE expansion on cost-related barriers to medical care using the event-study framework developed by De Chaisemartin and d'Haultfoeuille (2024) based on Equation 1. The figure shows the effect on the probability that low-income adults report missing doctor visits due to cost in the past year (binary). 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 A.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 2.3, and indicators for Medicaid expansion as part of the Affordable Care Act (ACA).

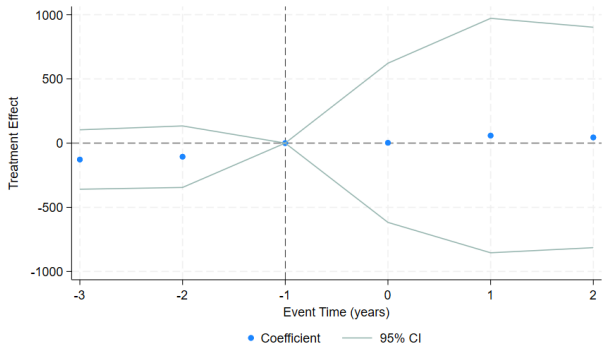
Figure A.4: Effect of BBCE Expansion on Fertility



(a) All



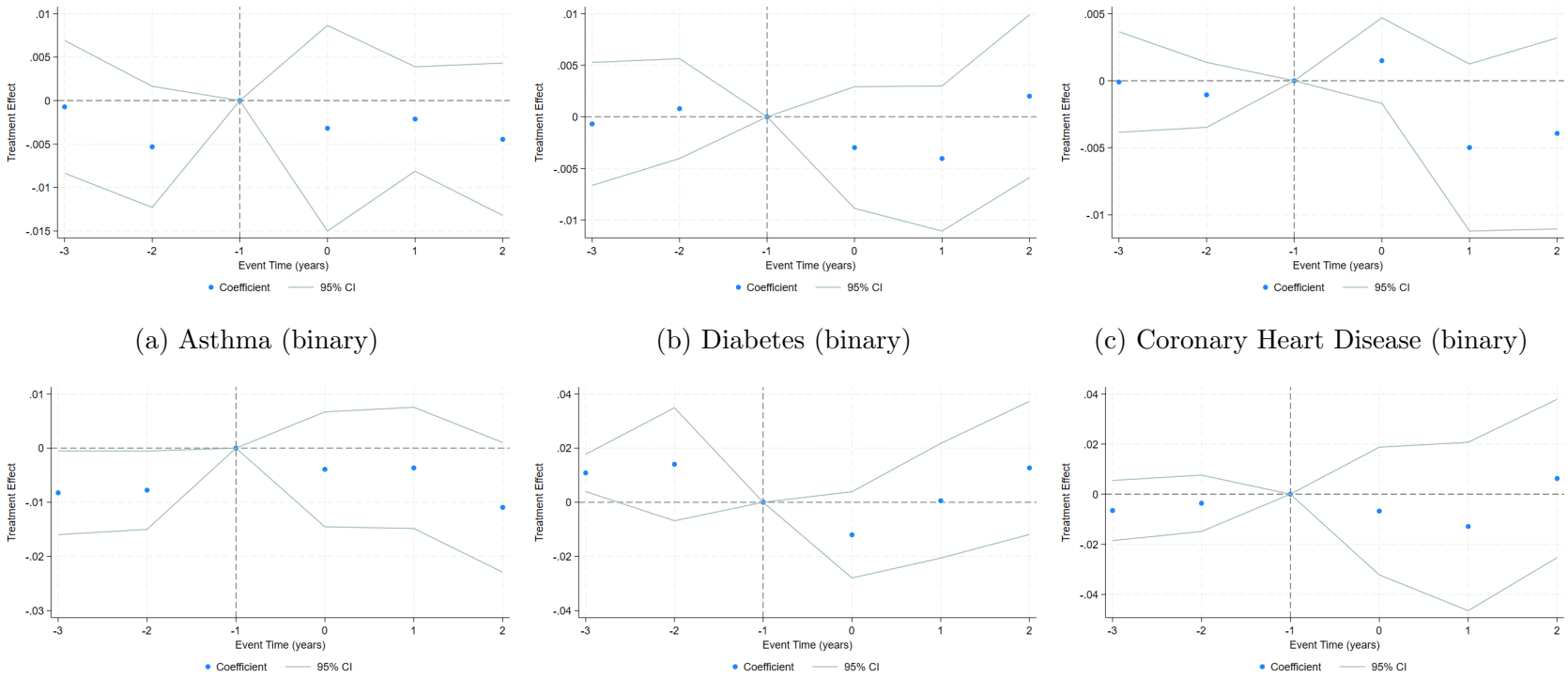
(b) White



(c) Black

Notes: Figure A.4 displays the estimation results of the impact of the BBCE expansion on fertility, both for the full sample and by race, using the event-study framework developed by De Chaisemartin and d'Haultfoeuille (2024) based on Equation 2. Each figure shows the effect on the total number of births among all mothers (Figure 7-(a)), White mothers (Figure 7-(b)), and Black mothers (Figure 7-(c)). 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 A.1, using the restricted-use Vital Statistics Natality Data from 1997 to 2016. Standard errors are clustered at the state level. State-level covariates include unemployment rates, four SNAP policy indices (i.e., eligibility, transaction costs, stigma, and outreach), as defined in Section 2.3, and indicators for Medicaid expansion as part of the Affordable Care Act (ACA).

Figure A.5: Effect of BBCE Expansion on Health Conditions



(a) Asthma (binary) (b) Diabetes (binary) (c) Coronary Heart Disease (binary)

(d) Obesity (binary) (e) Poor Physical Health (30d) (binary) (f) Poor Mental Health (30d) (binary)

Notes: Figure A.5 displays the estimation results of the impact of the BBCE expansion on health conditions 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 ever being diagnosed with the disease (binary) (Figure A.5-(a), (b), (c)), the probability of being obese (binary) (Figure A.5-(d)), and the probability of reporting poor physical or mental health in the past 30 days (binary) (Figure A.5-(e), (f)). 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 A.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 2.3, and indicators for Medicaid expansion as part of the Affordable Care Act (ACA).

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

	(1)	(2)	(3)	(4)	(5)
A. Participation = 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. Benefit Amounts					
BBCE	37.914**	51.175**	51.663**	52.276**	52.809**
	(17.567)	(20.985)	(21.151)	(21.465)	(21.391)
CONTROLS					
Individual	NO	YES	YES	YES	YES
State					
Unemployment	NO	NO	YES	NO	YES
SNAP Policies	NO	NO	NO	YES	YES
Pre-Period Mean			541.088		

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 and household SNAP benefit amounts (in 2016 dollars) with a different combination of covariates using the difference-in-differences (DiD) estimator developed by De Chaisemartin and d'Haultfoeuille (2024) based on Equation 1. Each panel presents the DiD estimates for SNAP participation as a binary outcome (Panel A) and reported SNAP benefit amounts per year (Panel B). The sample consists of low-income individuals, as defined in Section A.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 2.3.

Table A.2: Effect of BBCE Expansion on SNAP Retailer Participation

		Store Type	
	(1)	(2)	(3)
	All	Usual	Non-Usual
BBCE	-8.482	-4.133	-4.349
	(165.353)	(10.299)	(160.897)
Baseline Controls	YES	YES	YES
Pre-Period Mean	3,917.017	802.660	3,114.357

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

Notes: Table A.2 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, as defined in Section 5.2. 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 2.3.

Table A.3: Robustness: Effect of BBCE Expansion on Medicaid Participation

	Post-ACA Period (1997-2016)		Pre-ACA Period (1997-2013)	
	(1)	(2)	(3)	(4)
	All States	All States	All States	w/o CA
BBCE	0.017***	0.021***	0.015***	0.014***
	(0.004)	(0.005)	(0.005)	(0.005)
CONTROLS				
Baseline	YES	YES	YES	YES
ACA Expansion	YES	NO	N/A	N/A
Pre-Period Mean	0.275	0.275	0.275	0.267

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 Medicaid participation 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 Medicaid participation as a binary outcome, using different specifications and data periods. Columns (1) and (2) present estimates from the full sample period (1997–2016), and columns (3) and (4) present estimates from the pre-ACA period (1997–2013). Column (1) presents the estimate from my preferred specification (column (1) of Table 4). Column (2) presents the estimate without controlling for the ACA expansion. Column (3) presents the baseline estimate for the pre-ACA period. Column (4) presents the estimate after excluding California (CA), which adopted BBCE after 2013. The sample consists of low-income individuals, as defined in Section A.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 2.3, and indicators for Medicaid expansion as part of the Affordable Care Act (ACA) (column (1) only).

Table A.4: Effect of BBCE Expansion on Joint Program Participation: SNAP, Medicaid, WIC

	Medicaid			WIC		
	(1) All	(2) w/ SNAP	(3) w/o SNAP	(4) All	(5) w/ SNAP	(6) w/o SNAP
BBCE	0.017***	0.014***	0.003	0.015**	0.011***	0.003
	(0.004)	(0.003)	(0.003)	(0.007)	(0.004)	(0.004)
Baseline Controls	YES	YES	YES	YES	YES	YES
Pre-Period Mean	0.275	0.143	0.133	0.149	0.076	0.072

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 joint program participation 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 Medicaid or WIC participation as a binary outcome, accounting for whether individuals also participate in SNAP. Column (1) presents the baseline estimate for Medicaid participation, without accounting for participation in SNAP (column (1) of Table 4). Column (2) presents the estimate for participation in both Medicaid and SNAP, while column (3) presents the estimate for participation in Medicaid but not in SNAP. Column (4) presents the baseline estimate for WIC participation, without accounting for participation in SNAP (column (2) of Table 4). Column (5) presents the estimate for participation in both WIC and SNAP, while column (6) presents the estimate for participation in WIC but not in SNAP. The sample consists of low-income individuals, as defined in Section A.1, using the CPS-ASEC from 1997 to 2016. In columns (4)-(6), the sample is restricted to females aged 15 to 39 with children in the household. 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 2.3, and indicators for Medicaid expansion as part of the Affordable Care Act (ACA).

Table A.5: Heterogeneous Effects of BBCE Expansion on Medicaid Participation

	Utilization of SNAP Data		Combined Application Portal	
	(1)	(2)	(3)	(4)
	YES	NO	YES	NO
BBCE	0.020**	0.015***	0.019***	0.014
	(0.008)	(0.006)	(0.006)	(0.009)
Baseline Controls	YES	YES	YES	YES
Pre-Period Mean	0.288	0.269	0.267	0.290

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

Notes: Table A.5 reports the estimation results of the heterogeneous impacts of the BBCE expansion on Medicaid participation 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 Medicaid participation as a binary outcome, using different subsamples of states. Columns (1) and (2) present estimates based on whether states use SNAP data to verify Medicaid eligibility, particularly for children, to facilitate enrollment or renewal (e.g., Express Lane Eligibility). Columns (3) and (4) present the estimates based on whether states offer a combined application portal for SNAP and Medicaid. The sample consists of low-income individuals, as defined in Section A.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 2.3, and indicators for Medicaid expansion as part of the Affordable Care Act (ACA)).

Table A.6: Effect of BBCE Expansion on Health Conditions

	Medical Diagnosis			Self-Reported Health				Risky Behavior	
	(1) Asthma	(2) Diabetes	(3) CHD	(4) BMI	(5) Obesity	(6) Physical (−)	(7) Mental (−)	(8) Smoker	(9) # Drinks
BBCE	-0.003	-0.002	-0.002	-0.015	-0.006	-0.001	-0.005	0.003	0.023
	(0.004)	(0.003)	(0.002)	(0.077)	(0.005)	(0.009)	(0.014)	(0.004)	(0.059)
Baseline Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Pre-Period Mean	0.136	0.095	0.038	27.115	0.267	0.371	0.378	0.272	1.188

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

Notes: Table A.6 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 the probability of ever being diagnosed with asthma (column (1)), diabetes (column (2)), or coronary heart disease (CHD) (column (3)), BMI (column (4)), the probability of being obese (column (5)), the probability of reporting poor physical health (column (6)) or mental health (column (7)) in the past 30 days, having ever smoked in the past 30 days (column (8)), and the number of alcoholic drinks per occasion in the past 30 days (column (9)). All outcomes are binary except for columns (4) and (9). The sample consists of low-income individuals, as defined in Section A.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 2.3, and indicators for Medicaid expansion as part of the Affordable Care Act (ACA).

Table A.7: Heterogeneous Effects of BBCE Expansion on Health Conditions

A. Medical Diagnosis of Diseases

	Asthma		Diabetes		Coronary Heart Disease	
	(1) White	(2) Others	(3) White	(4) Others	(5) White	(6) Others
BBCE	-0.002	-0.008	0.002	-0.004	0.001	-0.002
	(0.005)	(0.006)	(0.002)	(0.005)	(0.011)	(0.003)
Baseline Controls	YES	YES	YES	YES	YES	YES
Pre-Period Mean	0.144	0.129	0.080	0.110	0.042	0.034

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

B. Self-Reported Health

	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
	(0.006)	(0.006)	(0.008)	(0.010)	(0.011)	(0.013)
Baseline Controls	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 A.7 reports the estimation results of the heterogeneous impacts of the BBCE expansion on health conditions by race, using the difference-in-differences (DiD) estimator developed by De Chaisemartin and d'Haultfoeuille (2024) based on Equation 1. In Panel A, each column presents the DiD estimate for the probability of ever being diagnosed with asthma (columns (1) and (2)), diabetes (columns (3) and (4)), and coronary heart disease (columns (5) and (6)). In Panel B, each column presents the DiD estimate for the probability of being obese (columns (1) and (2)) and the probability of reporting poor physical health (columns (3) and (4)) or mental health (columns (5) and (6)) in the past 30 days. All outcomes are binary. The sample consists of low-income individuals, as defined in Section A.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 2.3, and indicators for Medicaid expansion as part of the Affordable Care Act (ACA).

Table A.8: 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)
Baseline Controls	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 A.8 reports the estimation results of the heterogeneous impacts of the BBCE expansion on hours worked (per week) across different subsamples, using the difference-in-differences (DiD) estimator developed by De Chaisemartin and d'Haultfoeuille (2024) based on Equation 1. 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. The sample consists of low-income individuals, as defined in Section A.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 2.3.

A.1 Sample Construction

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).[37]

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.[38] 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 corresponds to the proportion of individuals whose family income was below 200% of the poverty level before BBCE. The same procedure is applied to all analyses using different data, except when using USDA administrative data on statewide SNAP participation counts for individuals and vendors.

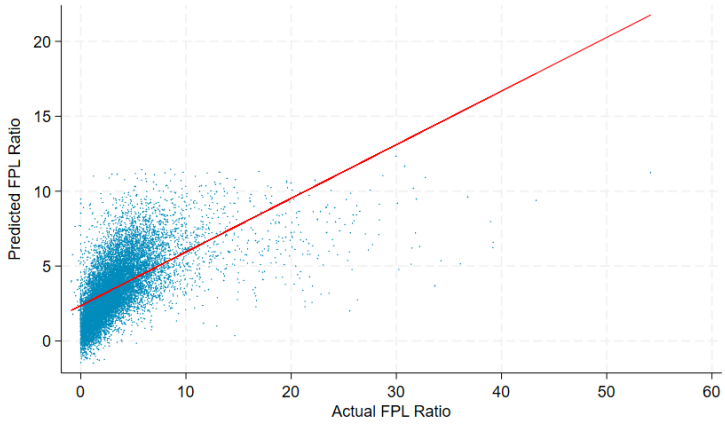
The scatter plots in Figure A.6 compare predicted and actual FPL ratios in the validation sample (25%) of the CPS-ASEC. Each blue dot in Figure A.6-(a) corresponds to an

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

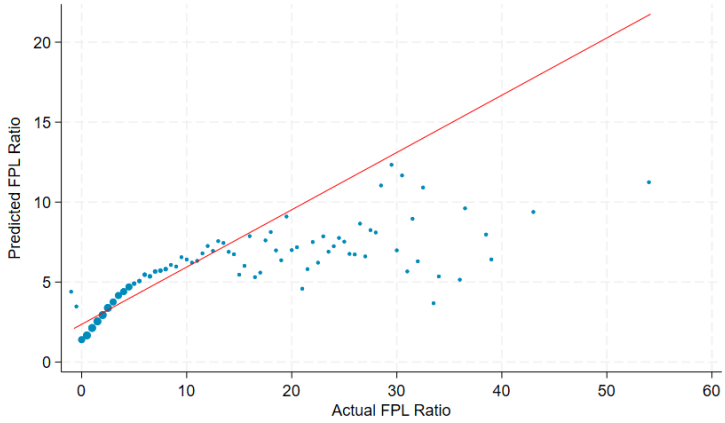
[38] This is because SNAP benefits may be limited to three months within a three-year period for households without a child under age 18, unless they meet work requirements or qualify for an exemption.

observation, while Figure A.6-(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.

Figure A.6: Out-of-Sample CPS-ASEC Predictions



(a) Scatter Plot of Raw Data



(b) Binned Scatter Plot

Notes: Figure A.6 compares predicted and actual FPL ratios in the validation sample (25%) of the CPS-ASEC from 1997 to 1999. 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.6-(a), each blue dot represents an individual observation. In Figure A.6-(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.

A.2 Robustness Checks

A.2.1 Testing for Confounds

My 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. One concern is that the second major BBCE expansion occurred around the Great Recession, potentially confounding the relationship between policy adoption and my outcomes. To address this, I estimate an event-study version of the main specification based on Equation 2 without controls, using the unemployment rate as the dependent variable. Figure A.7 shows no strong evidence that state unemployment rates follow different trends depending on the timing of BBCE adoption, both over the entire data period (Figure A.7-(a)) and in the restricted period from 2007 onward (Figure A.7-(b)). Notably, there are no positive pre-trends, even when I restrict the sample to later years. This suggests that unemployment rates—representing a key measure of state economic conditions—were not a primary driver of BBCE adoption, consistent with the findings of Anders and Rafkin (2024).

A.2.2 Comparison with U.S. Department of Agriculture (USDA) Data

As robustness checks on the first stage effects of the reform using the CPS-ASEC in Section 5.1, I rely on administrative data from the USDA covering the period from 1997 to 2016. The data on SNAP participation counts are aggregated at the level of month and participant's state of residence. In the administrative data, a participant in a given month is defined as an individual who has been issued SNAP food instruments (i.e., paper vouchers or EBT cards) for that month. I use the yearly level data to ensure consistency with other results from different data sources. I also draw on the average benefit amount for SNAP-participating households in each state and year to validate the treatment effects on the reported value of SNAP benefits.

Table A.9 shows the DiD estimates for the natural log of the number of individuals (Panel

A) and households (Panel B) participating in SNAP (i.e., participation counts) with different covariates, estimated using Equation 2. In my preferred specification with full controls in column (4), BBCE increased SNAP participation by 7.2 to 7.5 percent on average, with both estimates statistically significant at the 1% level. Compared to the estimate using the CPS-ASEC in column (1) of Table 3 as a binary outcome (i.e., an 11.7% increase relative to the baseline mean), these estimates are somewhat smaller but lie within the 95% confidence interval. The corresponding event-study figures, which show flat pre-trends and sharp dynamic increases, are presented in Figure A.8.

Next, the effect of BBCE on SNAP benefit amounts from the CPS-ASEC ranges from $47.4 to $52.8 per year (a 9-10% increase across specifications), as shown in columns (2) and (3) of Table 3. 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 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 21.1 percent. Following the policy adoption, SNAP participation rates increased by 7.2 percent for households as discussed above. Adjusting the average benefit amount using the sample mean and the treatment effect yields an increase of $48.1 in household SNAP benefits. This suggests that the effect sizes of reported benefits from the CPS-ASEC align with those from the administrative data.

A.2.3 Underreporting of SNAP participation

Underreporting of program participation variables in survey data, including the CPS, is well documented in the literature (Meyer, Mok, and Sullivan 2009). Although the CPS-ASEC complements USDA administrative data with detailed demographic variables, my estimates of SNAP participation could be biased if the degree of underreporting responds to the BBCE expansion.

Therefore, I directly test whether this measurement error is significantly affected by

BBCE, using the administrative data that are not subject to this issue. In particular, I measure the degree of underreporting of SNAP participation as the ratio of SNAP participation between the CPS-ASEC and the administrative data (multiplied by 1,000 as a scaling factor). The numerator is the reported SNAP participation count of low-income individuals from the CPS-ASEC, and the denominator is the statewide SNAP participation count from the administrative data.

Table A.10 shows that the SNAP participation ratio does not change significantly following BBCE, under different combinations of controls. This holds both in terms of statistical significance and the magnitudes of the coefficients. These findings suggest that, even with the well-established underreporting of SNAP participation in the CPS, this measurement error is not correlated with the BBCE expansion and therefore does not bias my estimates.

A.2.4 Falsification Tests

To ensure that my results capture true policy effects, I conduct two types of falsification tests to evaluate the impact of BBCE expansion on SNAP participation.

I first perform a permutation test using two data sources: the CPS-ASEC and USDA administrative data. In this test, I randomly reassign states to 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.9, separately for each data source.

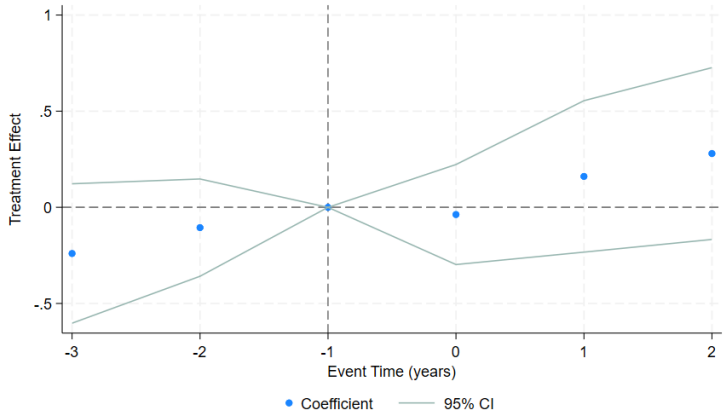
Figure A.9-(a) presents the results from the CPS-ASEC, where the distribution is bell-shaped with a mean of -0.001 and a standard deviation of 0.008. The vertical red line represents the original DiD estimate of 0.025 for the effect of the BBCE expansion on low-income individuals' SNAP participation rates as a binary outcome (column (1) of Table 3). Figure A.9-(b) presents the results from USDA administrative data, showing the coefficients on the natural log of the number of individuals participating in SNAP (i.e., participation counts).

The distribution closely resembles that in Figure A.9-(a), with a mean of 0 and a standard deviation of 0.021. Again, the original DiD estimate of 0.075 (column (4) of Table A.9-A), represented by the vertical red line, also falls in the right tail of the distribution. The p-values from the two permutation tests are 0.003 and 0.001, respectively.

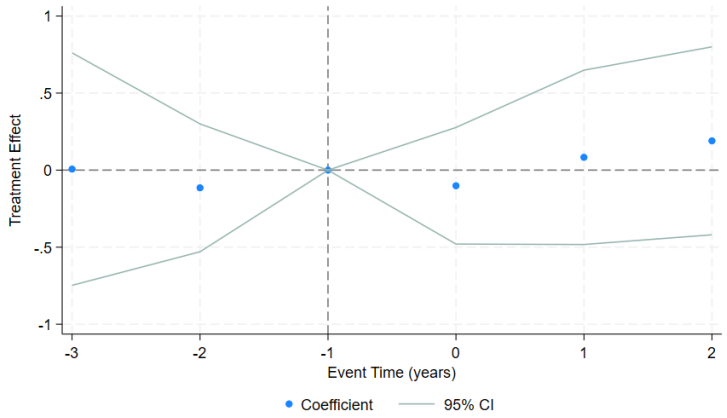
As another type of falsification test, I estimate the effects of BBCE on SNAP participation among *high*-income individuals as placebo groups and report the event-study graphs in Figure A.10. I use the same specification as in Figure 3-(a) and column (1) of Table 3, using a binary outcome in the CPS-ASEC. However, the sample now consists of high-income individuals, defined as the top 10% (Figure A.10-(a)), top 20% (Figure A.10-(b)), and top 35% (Figure A.10-(c)) of individuals based on the predicted FPL ratio, as discussed in Section A.1.

Using the same y-axis scale as in Figure 3-(a) for low-income individuals, Figure A.10 shows that there is no sharp increase in SNAP participation for any subsample of high-income individuals across different thresholds. Together with the permutation test, these results support the validity of my research design and estimates, indicating that they reflect actual policy effects rather than patterns driven by chance.

Figure A.7: Effect of BBCE Expansion on Unemployment Rates



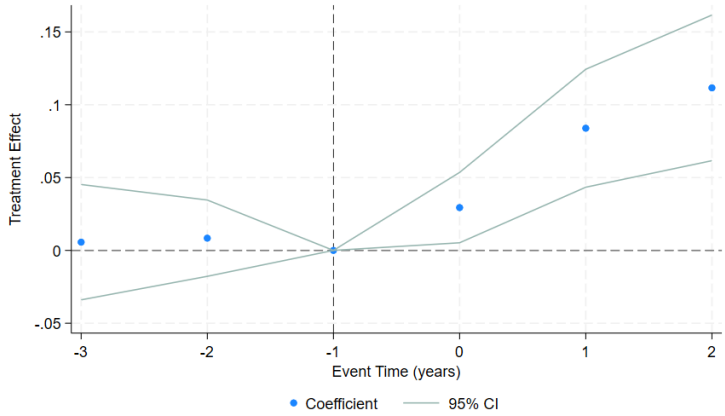
(a) Unemployment Rates (1997-2016)



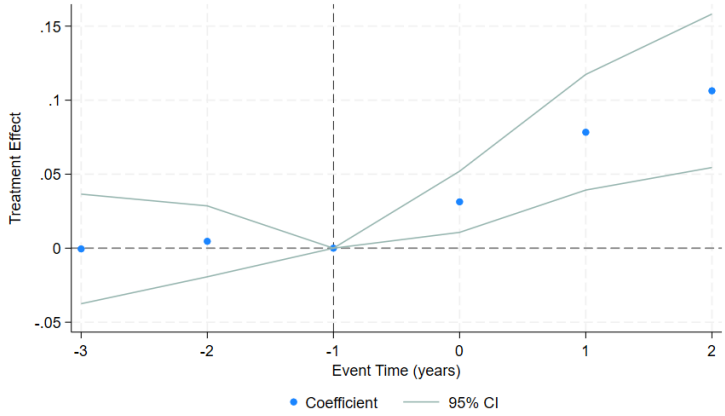
(b) Unemployment Rates (2007-2016)

Notes: Figure A.7 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.7-(a)) and in the restricted period from 2007 onward (Figure A.7-(b)). Standard errors are clustered at the state level.

Figure A.8: Robustness: Effect of BBCE Expansion on SNAP Participation (USDA Data)



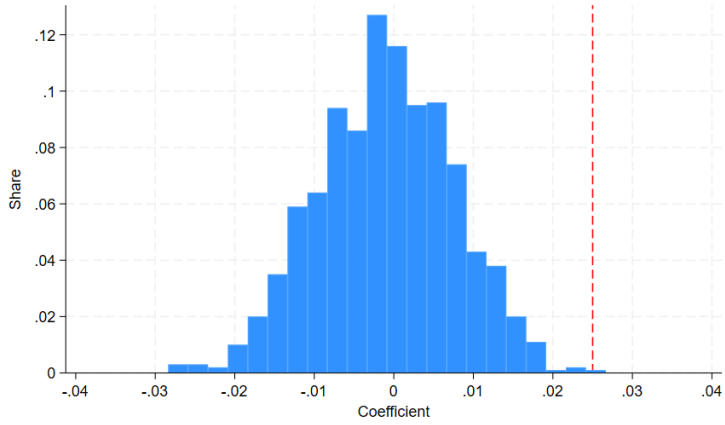
(a) Individuals



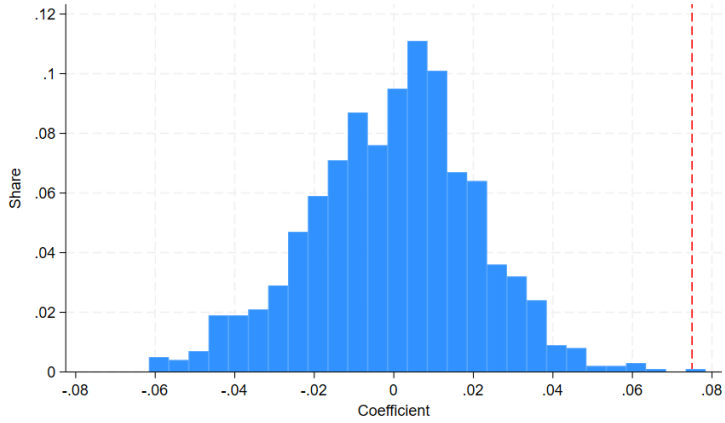
(b) Households

Notes: Figure A.8 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 the natural log of the number of individuals (Figure A.8-(a)) and households (Figure A.8-(b)) participating in SNAP based on Equation 2, using USDA administrative data from 1997 to 2016. 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. 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 2.3.

Figure A.9: Permutation Test: Effect of BBCE Expansion on SNAP Participation



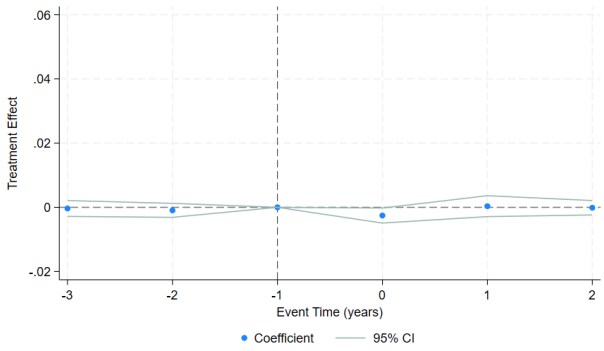
(a) SNAP Participation Rate (binary)



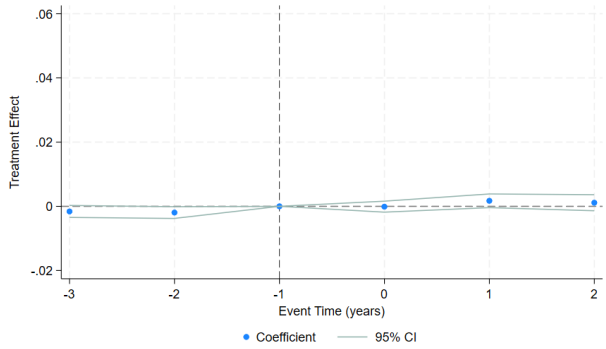
(b) log(SNAP Participation Counts)

Notes: Figure A.9 displays the distribution of the average effect of the BBCE expansion on SNAP participation, using the CPS-ASEC (Figure A.9-(a)) and USDA administrative data (Figure A.9-(b)). This is done by randomizing the treated states 1,000 times with the adoption dates fixed, using the difference-in-differences (DiD) estimator developed by De Chaisemartin and d'Haultfoeuille (2024) based on Equation 1 (Figure A.9-(a)) and Equation 2 (Figure A.9-(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 estimates for the effect of BBCE on SNAP participation: 0.025 (column (1) of Table 3) and 0.075 (column (4) of Table A.9-A). The p-values of the permutation tests are 0.003 and 0.001, respectively.

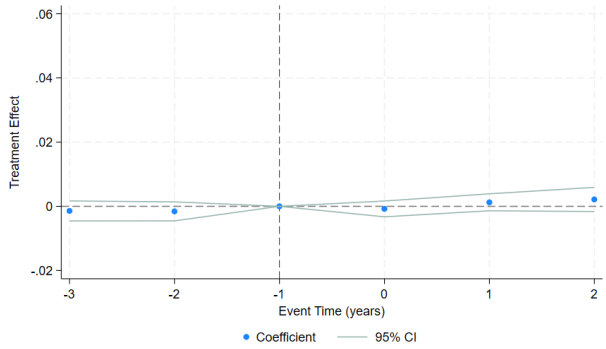
Figure A.10: Falsification Test: Effect of BBCE Expansion on SNAP Participation



(a) Top 10%



(b) Top 20%



(c) Top 35%

Notes: Figure A.10 displays the estimation results of the impact of the BBCE expansion on SNAP participation among high-income individuals using the event-study framework developed by De Chaisemartin and d'Haultfoeuille (2024). Each figure shows the effect on high-income individuals' program participation as a binary outcome based on Equation 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 of high-income individuals is defined as the top 10% (Figure A.10-(a)), top 20% (Figure A.10-(b)), and top 35% (Figure A.10-(c)) of individuals based on the predicted FPL ratio, as discussed in Section A.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 2.3.

Table A.9: Robustness: Effect of BBCE Expansion on SNAP Participation (USDA Data)

	(1)	(2)	(3)	(4)
A. Individuals (in %)				
BBCE	0.081***	0.076***	0.081***	0.075***
	(0.019)	(0.018)	(0.019)	(0.018)
CONTROLS				
Individual	N/A	N/A	N/A	N/A
State				
Unemployment	NO	YES	NO	YES
SNAP Policies	NO	NO	YES	YES
Pre-Period Mean	522,613			
B. Households (in %)				
BBCE	0.078***	0.072***	0.078***	0.072***
	(0.019)	(0.018)	(0.019)	(0.018)
CONTROLS				
Individual	N/A	N/A	N/A	N/A
State				
Unemployment	NO	YES	NO	YES
SNAP Policies	NO	NO	YES	YES
Pre-Period Mean	235,064			

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

Notes: Table A.9 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. Each Panel presents the DiD estimates for the natural log of the number of individuals (Panel A) and households (Panel B) participating in SNAP based on Equation 2, using USDA administrative 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 2.3.

Table A.10: Effect of BBCE Expansion on Underreporting of SNAP Participation

	(1)	(2)	(3)	(4)
BBCE	-0.010	-0.008	-0.010	-0.009
	(0.023)	(0.022)	(0.022)	(0.022)
CONTROLS				
Unemployment	NO	YES	NO	YES
SNAP Policies	NO	NO	YES	YES
Pre-Period Mean	0.941			

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

Notes: Table A.10 reports the estimation results of the impact of the BBCE expansion on the degree of underreporting of SNAP participation 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 SNAP participation ratio between CPS-ASEC and USDA administrative data (multiplied by 1,000 as a scaling factor), using a different combination of covariates. The numerator is the reported SNAP participation count of low-income individuals, as defined in Section A.1, using the CPS-ASEC from 1997 to 2016, with CPS-ASEC person-level weights applied when aggregating to the state-year level. The denominator is the statewide SNAP participation count from USDA administrative 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 2.3.

A.3 Continuous Treatment

I estimate the same specification using two measures of continuous treatment, rather than a binary indicator, to better capture differences in treatment intensity given variation in income thresholds across BBCE states. The average coefficients from USDA administrative data (column (1)) and the CPS-ASEC (columns (2)-(4)) are presented in Table A.11.

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 1.3 percent and 0.4 percentage points (a 2.03% increase), respectively for each data source. With the maximum increase in the income threshold from 130% to 200% of the FPL, the estimates indicate 8.82 and 14.04 percent increases in SNAP participation.

In Panel B, the other continuous treatment measure is based on the share of the predicted SNAP-eligible population as determined by the gross income limit.[39] For example, 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 population share.

Panel B shows that a 1 percentage-point increase in the share of the predicted SNAP-eligible population (i.e., from the bottom 20% of the income distribution to 21%) increased SNAP participation by 0.06 percent (column (1)) and 0.2 percentage points (a 0.93% in-

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

crease) (column (2)). Again, when the eligible population share rises from 130% to 200% of the FPL, SNAP participation increases by 8.72 and 14 percent, which are very similar in magnitude to those in Panel A.

Assuming the maximum increase in all BBCE states, the estimates are slightly larger than those in Table 3 and Table A.9 from the binary treatment: 11.7 percent from the CPS-ASEC and 7.2 to 7.5 percent from the USDA data. Since 16 of the 28 BBCE states in my sample adopted the 200% limit, however, the effects across treatment measures remain highly consistent. Applying the same approach to Medicaid and WIC participation in columns (3)–(4) yields estimates from the continuous treatment that similarly align with those from the binary treatment.

Table A.11: Continuous Treatment: Effect of BBCE Expansion on Program Participation

	log(Part. Count)	Binary Outcomes		
	(1) SNAP	(2) SNAP	(3) Medicaid	(4) WIC
A. Gross Income Limit				
$BBCE_{Inc\ Limit}$	0.013***	0.004***	0.003***	0.003***
	(0.003)	(0.001)	(0.001)	(0.001)
Baseline Controls	YES	YES	YES	YES
Pre-Period Mean	522,613	0.211	0.275	0.149
B. Eligible Population Share				
$BBCE_{Pop\ Share}$	0.006***	0.002***	0.001***	0.001***
	(0.001)	(0.0005)	(0.0003)	(0.0004)
Baseline Controls	YES	YES	YES	YES
Pre-Period Mean	522,613	0.211	0.275	0.149

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

Notes: Table A.11 reports the estimation results of the impact of the BBCE expansion on program 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 predicted 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 the natural log of the number of individuals participating in SNAP based on Equation 2, while columns (2)-(4) present the DiD estimates for low-income individuals' program participation as a binary outcome based on Equation 1. The sample consists of all SNAP participants using USDA administrative data (column (1)) and low-income individuals, as defined in Section A.1, using the CPS-ASEC (columns (2)-(4)) from 1997 to 2016. In column (4), the sample is restricted to females aged 15 to 39 with children in the household. Standard errors are clustered at the state level. CPS-ASEC person-level weights are applied (columns (2)-(4)). Individual-level covariates include age, gender, race/ethnicity, marital status, and education level (columns (2)-(4)). State-level covariates include unemployment rates, four SNAP policy indices (i.e., eligibility, transaction costs, stigma, and outreach), as defined in Section 2.3, and indicators for Medicaid expansion as part of the Affordable Care Act (ACA) (columns (3)-(4)).