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PERSPECTIVES ON
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How Large Would SNAP Be? Simulating the Size of SNAP Based on Changes to the Unemployment Rate

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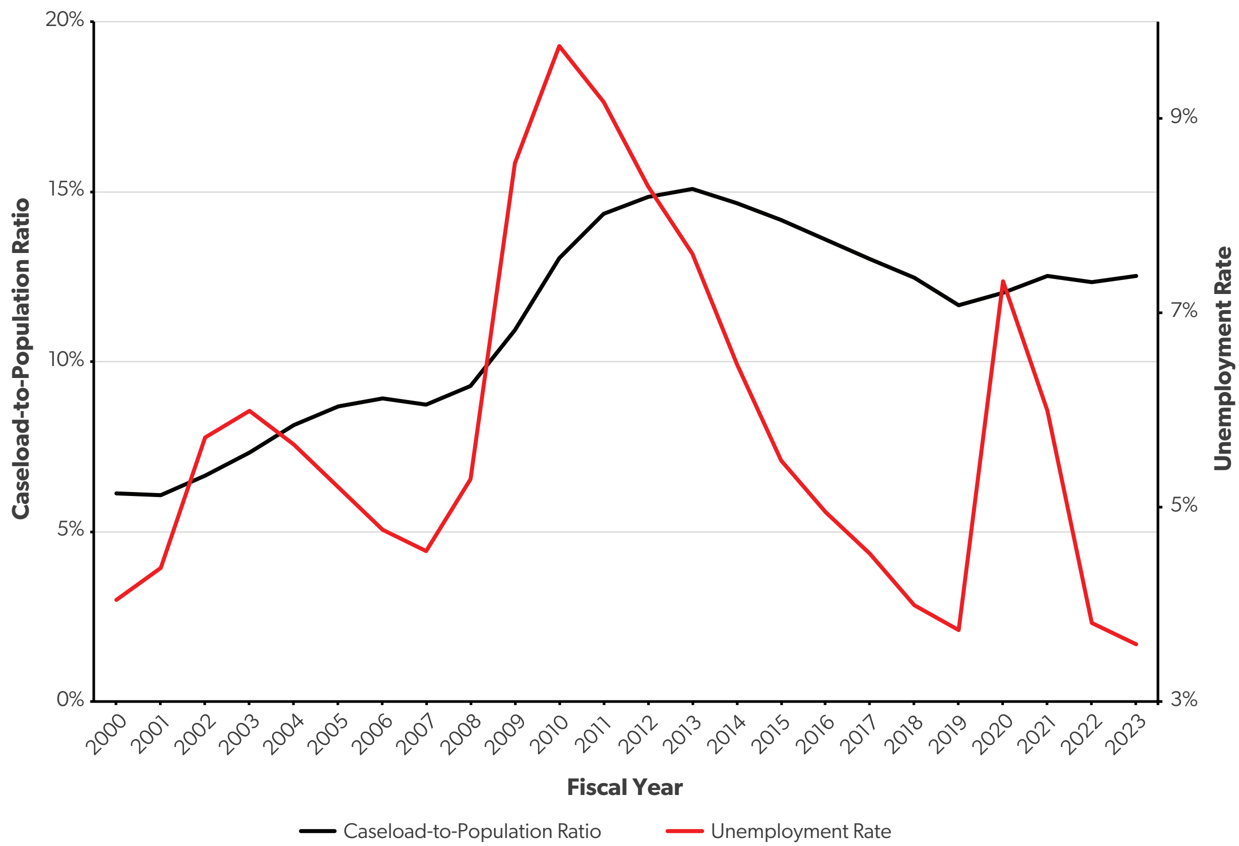
The Supplemental Nutrition Assistance Program (SNAP) is a means-tested transfer program available to all households that meet the eligibility criteria. Therefore, SNAP is also a countercyclical program, meaning that the size of the program increases during recessionary periods and decreases during expansionary periods. A large literature quantifies the magnitude of the relationship between the business cycle and SNAP's caseload. We leverage this literature—as well as data from the US Department of Agriculture and Bureau of Labor Statistics—to simulate how large SNAP would have been in recent decades had the program's size varied over time with respect to only the unemployment rate. Using a base year of 2000, we find that if SNAP's caseload had varied based on the unemployment rate and population growth alone, the program would currently serve between 3 and 6 percent of Americans rather than the 13 percent of Americans it now serves. Moreover, we find that the program's expenditures would range from $18 billion to $34 billion, less than one-third of the $109 billion currently spent on benefits.

The Supplemental Nutrition Assistance Program (SNAP) is a federal food assistance program that provided benefits to approximately 42 million Americans per month in 2024 (FNS 2024b). SNAP provides low-income households with a benefit that can be used at food retailers to purchase groceries, and it is available to all households that meet the program's eligibility criteria. SNAP has a relatively high participation rate—the overwhelming majority of households eligible for SNAP receive benefits (Buttenheim et al. 2023). According to the US Department of Agriculture (USDA), nearly 90 percent of eligible households received SNAP benefits in 2022, and virtually all households below the poverty line received benefits (Vigil and Rahimi 2024).

To receive SNAP benefits, households must meet several federal eligibility criteria. First, their gross income must be below 130 percent of the federal poverty line. For example, in fiscal year 2023, a three-person household must have had a monthly income below $2,495 (i.e., an annual income below $29,940) to be eligible for SNAP (FNS 2022). However, in most states, households are categorically eligible for SNAP if they receive benefits from other safety-net programs such as Temporary Assistance for Needy Families (TANF) and Supplemental Security Income (a policy known as broad-based categorical eligibility, or BBCE). Because states can use BBCE to expand income eligibility limits up to 200 percent of the federal poverty line, many households with gross

Figure 1. SNAP Caseload-to-Population Ratio and National Unemployment Rate, Fiscal Years 2000–23



Source: Authors' calculations from USDA (2024); BLS (2024); and US Census Bureau (2024).
Note: The caseload-to-population rate is calculated by dividing the total number of SNAP recipients by the total population in the given fiscal year and corresponds with the primary y-axis. The unemployment rate is the 12-month average unemployment for the given fiscal year and corresponds with the secondary y-axis. Fiscal years extend from October of the preceding calendar year to September of the current calendar year.

incomes between 130 and 200 percent of the federal poverty line in these states may still be eligible for SNAP (Aussenberg and Falk 2022). In addition to the gross income test, households' net income must be below the federal poverty line. Net income is calculated by subtracting several income deductions—including a standard deduction, medical expense deduction, excess shelter deduction, and earnings deduction, for example—from the households' gross income (Monkovic 2024).[1]

SNAP's caseload and expenditures are countercyclical by design—that is, the size of the program expands during periods of high unemployment and contracts during periods of low unemployment. The intuition is straightforward: As unemployment increases, so too should the share of Americans below the poverty line (or 130 percent of the poverty line) and, consequently, the number of people eligible for and receiving SNAP. This pattern is precisely what we observe over the past several decades—SNAP's caseload and expenditures generally increase as the unemployment rate increases and generally decrease as the unemployment rate decreases (Rachidi 2021). Figure 1 shows the relationship between the unemployment rate and SNAP's caseload-to-population ratio in fiscal years 2000–23.

1 Households with an elderly or disabled member must have net incomes below 100 percent of the federal poverty line to be eligible for SNAP, which in 2024 was $25,820 for a family of three. There is no gross income test for households with an elderly or disabled person.

It is clear, however, that certain factors beyond business cycle fluctuations influence the program's caseload. Although the percentage of people receiving SNAP increased as the unemployment rate increased at the beginning of the Great Recession, the caseload remained elevated after the unemployment rate began to decline (Rachidi 2021). Moreover, in the period following the COVID-19 recession, SNAP caseloads remained elevated well after the national unemployment rate returned to its pre-pandemic level.

Fluctuations in the program's expenditures are largely attributable to changes in the caseload. That is, as SNAP's caseload increases, so do program expenditures. However, policy decisions that raise benefit levels can alter this relationship by increasing the per-person benefit. For instance, throughout the COVID-19 pandemic, Congress and the Biden administration raised SNAP benefits three times, increasing the program's expenditures independent of changes in the caseload. The Families First Coronavirus Response Act of 2020 allowed states to temporarily offer all SNAP households the maximum benefit for their household size, which significantly increased program expenditures during the COVID-19 pandemic. Additionally, Congress temporarily increased SNAP benefits by 15 percent at the end of 2021. Moreover, USDA regulations permanently increased SNAP benefits by approximately 21 percent in 2022 (Aussenberg et al. 2023).

In recent history, the most consequential policy reforms to SNAP have come at the beginning of recessionary periods, during which policymakers have expanded SNAP's benefits and reach in response to economic downturns, and as part of the regular legislative process, such as the 2008 Farm Bill (the Food, Conservation, and Energy Act of 2008). However, because SNAP is an entitlement program—meaning that all eligible households who apply for benefits and meet program requirements receive them—we would expect SNAP caseloads and expenditures to increase during recessionary periods, even if policymakers did not alter the program's eligibility criteria or benefit levels.

In this report, we use estimates from the literature on the responsiveness of SNAP's caseload to local economic changes to simulate how SNAP's caseload and expenditures would have varied if they had been driven solely by changes in the unemployment rate and population growth. We compare these estimates with the program's actual caseload and expenditures over the same period to assess the extent to which the program's growth can be explained by changes to the unemployment rate and population growth alone. Whatever growth is not explained by unemployment rate changes and population growth is attributable to policy reforms or other factors that altered program participation.

We find, based on estimates from the literature, that if the SNAP caseload had changed since 2000 based solely on changes to the unemployment rate and population growth, between 11 million and 20 million individuals would have received SNAP in 2023—less than half of the 42 million individuals the program actually served that year. Additionally, we find that SNAP's total benefit expenditures based on these caseload projections would have been between $18 billion and $34 billion in 2023—between 17 and 31 percent of the $109 billion currently spent on benefits. Additionally, we discuss potential reasons for the divergence between actual and counterfactual SNAP caseloads and expenditures, including changes in participation rates, household demographics, and various policy and programmatic decisions. Together, these factors have increased program caseloads and costs by a factor of between two and three beyond what local unemployment rates alone would have predicted.

The report proceeds as follows: First, we provide a brief background of the recent legislative and regulatory reforms to SNAP. Second, we review the literature on SNAP's cyclicality, which estimates how responsive SNAP caseloads and expenditures are to changes in the unemployment rate. Third, we discuss our data sources and methods for calculating counterfactual caseload and expenditures. Fourth, we present those counterfactuals. Fifth, we discuss several factors that may explain the divergence between the actual and counterfactual caseloads. Finally, we conclude with our most important findings and policy recommendations.

Legislative Background

Many policy reforms over the past several decades have influenced SNAP's caseload and expenditures. Many of the most notable policy reforms in SNAP have increased the program's expenditures and expanded the caseload. Below, we offer a brief legislative history of SNAP since the turn of the century.

To begin, the passage of the Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (PRWORA) significantly altered the United States' welfare system, including SNAP (then called the Food Stamp Program). Most notably, PRWORA imposed work requirements on nondisabled working-age recipients without dependent children (known as ABAWDs for "able-bodied adults without dependents"). The imposition of work requirements in SNAP has been shown to increase program exits and reduce caseloads (Gray et al. 2023; Harris 2021).[2] Additionally, PRWORA disallowed SNAP receipt for US permanent residents not in the country for more than 10 years (later reduced to five years) and modestly reduced the maximum benefit, which likely reduced caseloads and expenditures (FNS 2024a).

SNAP underwent several other programmatic reforms in the early to mid-2000s. For instance, the Farm Security and Rural Investment Act of 2002 restored eligibility to certain noncitizen permanent residents and made modest alterations to various income deductions. By 2004, the program had completed its transition from using physical food stamp coupons to using an Electronic Benefit Transfer (EBT) system, which allowed households to access their benefits through a debit card. As part of the 2008 Farm Bill, Congress made several more changes to the program, such as renaming and refocusing the program on nutrition and reducing administrative burdens on recipients (Rosenbaum 2008).

Following the onset of the Great Recession, Congress passed the American Recovery and Reinvestment Act of 2009 (ARRA), which temporarily increased benefit levels. This temporary benefit increase was designed to remain in place until SNAP's annual inflation adjustments caught up to the increased benefit levels. In other words, following the initial increase in benefits, the Food and Nutrition Service did not make any subsequent annual inflation adjustments to SNAP benefit levels until they returned to where they would have been had the ARRA increases not happened. However, because of low inflation, the annual inflation adjustments were slow to catch up to increased benefit levels. Therefore, Congress ended the ARRA increase in October 2013 (FNS 2024a).

Additionally, ARRA imposed a nationwide waiver on SNAP's work requirement from April 2009 to September 2010 and later allowed states to waive the work requirement if they qualified for Emergency Unemployment Compensation—a recession-era expansion to unemployment insurance. Effectively, this allowed the majority of states to implement statewide waivers to the work requirement through the end of 2015 (Burkhauser et al. 2024).

Moreover, an increasing number of states began to use BBCE during this time, meaning an increasing number of households with incomes above SNAP's income eligibility threshold became eligible for SNAP (Aussenberg and Falk 2022). These recession-era policy reforms simplified and relaxed many of SNAP's eligibility criteria, leading to elevated caseloads and expenditures even after the unemployment rate began to decline (FNS 2024a).

Several other consequential reforms to SNAP occurred after the onset of the COVID-19 pandemic (Aussenberg et al. 2023). First, the Families First Coronavirus Response Act of 2020 established Emergency Allotments (EAs). EAs temporarily allowed states to provide all SNAP recipients the maximum benefit for their household size, irrespective of their income.

A later USDA decision further increased maximum SNAP monthly benefits by $95 for those who would have otherwise received the maximum allotment.[3] Typically, SNAP benefits phase out as household income increases, but the EA program allowed states to offer all recipients the maximum benefit (or maximum plus $95) for their household size. Although certain states ended EAs before others, many states continued to offer EAs until the program's federal expiration, in February 2023.

2 There is also a small body of literature on the impacts of ABAWD work requirements on employment outcomes and income. The results are mixed, with some studies finding small positive employment effects associated with the reinstatement of work requirements, such as Harris (2021), and others finding no effects, such as Han (2022) and Gray et al. (2023). Other research examines the effect of SNAP work requirements on consumption and credit, such as Cuffey and Beatty (2022) and Dodini et al. (2024).

3 Because the initial EA program raised benefits for only those who were not already receiving the maximum benefit, the Biden administration reformed this program to ensure that the lowest-income SNAP recipients also received additional benefits. See USDA (2021) for details of this decision.

Furthermore, the Consolidated Appropriations Act of 2021 temporarily increased SNAP benefit amounts by 15 percent (Aussenberg et al. 2023). Though this temporary increase lasted only from January to September 2021, the Biden administration announced a permanent increase in benefits to coincide with the expiration of the temporary increase (effective October 1, 2021) by updating the Thrifty Food Plan (TFP)—the basket of goods used to calculate SNAP benefits according to household size. This policy reform led to a 21 percent average increase in benefits, more than offsetting the expiration of the 15 percent increase. The Biden administration's adjustment of the TFP was a notable departure from precedent; previous reevaluations of the TFP had been cost-neutral and never resulted in a real benefit increase (beyond adjusting for food inflation).[4]

Finally, as part of the Fiscal Responsibility Act of 2023 (FRA), policymakers expanded the upper age limit of SNAP's ABAWD work requirement from 49 to 54. However, the FRA also exempted veterans, homeless individuals, and those age 18–24 who have aged out of the foster care system from work requirements. The Congressional Budget Office estimated that these changes would increase SNAP program costs by $2.1 billion from 2023 to 2033 by increasing the number of SNAP participants exempt from the work requirement (CBO 2023).

Each of these policy reforms likely affected SNAP's caseload and expenditures in small and large ways, causing the program's size to diverge from what would have been expected given only economic and demographic changes. In the following section, we review the literature on SNAP's cyclicality, which estimates the responsiveness of SNAP's caseloads and expenditures to changes in the unemployment rate.

SNAP Cyclicality

A large and growing body of literature examines the cyclicality of safety-net and social insurance programs. In this literature, researchers are interested primarily in estimating the extent to which federal safety-net programs protect low-income Americans from economic downturns. To estimate this relationship, researchers identify the responsiveness of certain programs to changes in economic conditions. Most often, this involves estimating the relationship between a given program's size—measured by caseload or expenditures—and the unemployment rate.

A related literature assesses the effect of specific policy reforms on program participation and expenditures in safety-net programs. Here, researchers estimate a given policy reform's effect on the size of a program compared with a counterfactual in which the reform had never been implemented. To develop that counterfactual, researchers typically estimate the expected changes in program participation given demographic and economic changes independent of the policy change of interest. For example, Ganong and Liebman (2018) estimate the effect of various policy reforms—such as states' adoption of simplified reporting and changing recertification periods—on SNAP caseloads. To do so, they control for macroeconomic changes (e.g., the unemployment rate) and thus estimate the caseload's responsiveness to changes in the unemployment rate.

In both literatures, authors isolate the relationship between changes to the unemployment rate and a given safety-net program's caseload. We identified eight studies that estimated the effect of unemployment rate changes on SNAP caseloads. Table A1 summarizes this literature, highlighting each study's primary finding with respect to the cyclicality of SNAP's caseload or expenditures. We also include additional information on each study's methodological approach, data source, and sample period.

Most studies rely on similar methods to estimate SNAP's responsiveness to changes in the unemployment rate. Specifically, most studies regress SNAP's caseload-to-population ratio on the state- or county-level unemployment rate, typically including both geographic (state or county) and time (year or month) fixed effects. The use of two-way fixed effects effectively controls for national policy changes affecting all geographies at the same time (for example, a reduction in stigma due to

4 In an independent review, the US Government Accountability Office (2022) also noted that this reevaluation of the TFP was not in accordance with federal law and "did not fully meet standards for economic analysis, primarily due to failure to fully disclose the rationale for decisions, insufficient analysis of the effects of decisions, and lack of documentation."

changing the program name) and time-invariant factors unique to each geography, isolating state- or county-level caseload responsiveness to changes in the state or county unemployment rate. Each study in Table A1 isolates the relationship between changes in the unemployment rate and SNAP's caseload.

One integral difference across studies is whether the authors choose to estimate the responsiveness of the SNAP caseload to contemporaneous or lagged changes in the unemployment rate. While certain studies assume that any change to the unemployment rate would affect the SNAP caseload at the same time, other studies assume that it would take time for SNAP caseloads to adjust to changes in the unemployment rate—perhaps because recipients rely on other forms of financial assistance or savings before enrolling in SNAP.

For example, Bitler and Hoynes (2010) estimate the responsiveness of state-level caseload-to-population ratios to contemporaneous changes in the unemployment rate using state-level administrative data, assuming that any change to the unemployment rate would affect the SNAP caseload in the same year. Taking a different approach, Dickert-Conlin et al. (2021) allowed caseloads to lag behind changes in the unemployment rate, implying that changes to the SNAP caseload may come several periods after changes to the unemployment rate.

Additionally, while most studies relied on state-level data to generate their estimates, one study (Ganong and Liebman 2018) relied on county-level data. Ganong and Liebman estimated the SNAP caseload's responsiveness to changes in the unemployment rate at the county level after correcting for attenuation bias in county-level unemployment data. Furthermore, the authors used each county's three-year change in the unemployment rate, because they posit that sustained changes to a given county's unemployment rate are more likely than single-year changes to affect SNAP caseloads. They found that a sustained 1 percentage-point increase in county-level unemployment rate corresponds with a 14.8 percent increase in the caseload.

For each of the eight studies, we identify the estimated effect of a 1 percentage-point change in the state- or county-level unemployment rate on the SNAP caseload (or caseload-to-population ratio). The lowest, or least responsive, estimate suggests that a 1 percentage-point increase in the state-level unemployment rate corresponded with a 3.4 percent increase in the caseload-to-population ratio, while the highest, or most responsive, estimate suggests that a sustained 1 percentage-point increase in the county-level unemployment rate resulted in a 14.8 percent increase in the caseload. Across all eight studies, the average effect size is 6.5 percent.

Relying on this literature, we estimate how SNAP's caseload and expenditures would have varied since the turn of the century had they changed with respect to only state- or county-level unemployment rates. By applying our counterfactual caseload-to-population ratios to the corresponding state- or county-level populations, we estimate the program's total caseload had it varied with respect to only the unemployment rate. Finally, we simulate changes to SNAP's expenditures by multiplying our counterfactual caseloads by the actual per-person expenditures in our base year, after adjusting for several changes to SNAP's caseload over time. This exercise allows us to show how SNAP's caseload and expenditures would have evolved if only for changes in the unemployment rate and population growth.

In the following section, we discuss our data sources and methodological approach for calculating counterfactual caseloads and expenditures. We then show how SNAP caseloads and expenditures would have changed if they fluctuated with respect to only the unemployment rate and population.

Data and Methodology

To calculate counterfactual SNAP caseloads and expenditures, we relied on state-level and SNAP office–level data from the USDA. For each state, USDA provides monthly data on the total number of individuals and households receiving SNAP benefits, total program costs, and total costs per person and household. USDA also provides data for each SNAP office, most of which operate at the county level. For each office, USDA provides the total number of individuals and households receiving benefits, as well as total benefit expenditures (FNS 2024b). We construct state- and office-level datasets separately.

First, we create a state-by-fiscal-year panel dataset by taking the average number of SNAP individuals, number of SNAP households, and SNAP expenditures across all months in the fiscal year.[5] We then merge these data with state-level population estimates from the US Census Bureau and state-level yearly unemployment data from the Bureau of Labor Statistics.[6] Next, we create an office-level dataset including all SNAP offices with available data.[7] Note that most states' SNAP offices operate at the county level, but some states contain just one centralized SNAP office.[8] We include data from all SNAP offices, whether they are at the state or county level. For offices that operate at the county level, we merge county-level population data from the US Census Bureau and unemployment data from the Bureau of Labor Statistics Local Area Unemployment Statistics (BLS LAUS) database. For offices that operate at the state level, we merge state-level population and unemployment data.

After assembling our data, our next step was to choose a base year from which to begin our counterfactual calculation. Choosing a base year is ultimately an arbitrary choice, but we balanced several considerations in doing so. If we chose a base year in the distant past—beginning, for example, in 1969, when SNAP served only 2.8 million households—our counterfactual caseload would diverge sharply from the actual caseload, and the divergence would be attributable to over 50 years of policy reforms and macroeconomic changes. Conversely, if we chose a base year too close to the recent past, we would not be able to parse the effect of recent policy changes from economic and demographic changes. Additionally, we aimed to choose a year that was included in the data sources used to generate the estimates. We found that nearly all the papers that we surveyed—ranging from 2003 to 2023—included data from the early 2000s. (See Table A1.) To meet all the above criteria, we chose fiscal year 2000 to be our base year and extended our analyses to fiscal year 2023.[9]

In Appendix B, we calculate counterfactual caseload-to-population ratios using three different base years and sample periods: 2000–07, 2007–19, and 2019–23, using the first year of the sample period as the base year. We do so for two reasons. First, our primary analysis, which uses a single base year to simulate the caseload over the entire period, does not allow us to observe the extent to which our counterfactuals diverge from actual caseloads in each business cycle. We are interested in observing which recession caused the program's caseload to most notably depart from what we would expect given changes to unemployment rate only. Second, altering our base year provides a useful sensitivity check for our primary results. Additionally, in Appendix B, we calculate counterfactual caseload-to-population ratios using 2023 as our base year, relying on historical changes in the unemployment rate to simulate the SNAP caseload in previous years. This effectively illustrates how large SNAP would have been in previous years if the caseload had varied with respect to only the unemployment rate while its composition remained the same as in 2023.

Relying on the range of estimates from the literature, we calculate a lower and upper bound of the responsiveness of SNAP's caseload to changes in the unemployment rate. According to our survey of the literature, a lower-bound estimate comes from Bitler and Hoynes (2016), who found that a 1 percentage-point increase in the state-level unemployment rate corresponds with a 3.4 percent increase in the caseload-to-population ratio. Bitler and Hoynes use state-level caseload and unemployment data to generate their

5 The fiscal year extends from October of the preceding calendar year to the end of September in the current calendar year. For example, fiscal year 2015 extends from October 1, 2014, to September 30, 2015.

6 Note that state-level yearly population data are available only by calendar year, whereas unemployment data are available monthly. Therefore, we rely on the calendar year for our population data but calculate fiscal year unemployment rates from the monthly unemployment data.

7 Data are available in January and July of each calendar year. Following Ganong and Liebman (2018), we use the July data. For 2023, our data include 2,475 SNAP offices.

8 States that report their data at the state level are Alaska, Connecticut, Idaho, Maine, Massachusetts, Nebraska New Hampshire, New York, Oregon, Rhode Island, Utah, Vermont, West Virginia, and Wyoming. Additionally, some states changed from county-level reporting to state-level reporting during our sample period. These are Missouri (after 2006), Montana (after 2001), and Washington (after 2002).

9 Henceforth, when we refer to "year," we mean "fiscal year."

results, and they do not include lagged changes in the unemployment rate.

An upper-bound estimate comes from Ganong and Liebman (2018), who found that a *sustained* 1 percentage-point increase in the county-level unemployment rate corresponds with a 14.8 percent increase in the annual SNAP caseload.[10] Notably, Ganong and Liebman (2018) use county-level data to generate their estimate, and the authors estimate the effect of three-year changes in the county-level unemployment rate on annual SNAP caseloads. They use a three-year change in the unemployment rate rather than a one-year difference because they posit that *sustained* changes in a county's economic circumstances are more predictive of changes in the SNAP caseload than year-to-year fluctuations. Finally, Ganong and Liebman (2018) use a Bartik instrument to correct for attenuation bias in county-level unemployment estimates from BLS LAUS data. They contend that county-level unemployment rates provided by BLS LAUS data suffer from measurement error because county-level unemployment is not directly measured but rather imputed using unemployment insurance claimant data.

We begin by calculating the lower-bound estimate of the caseload's responsiveness to the unemployment rate. We do so by relying on our state-level dataset, spanning from 2000 to 2023. We first calculate the year-to-year change in the unemployment rate for each state. For instance, Alabama's unemployment rate during fiscal year 2000 was 4.64 percent, and its unemployment rate for fiscal year 2001 was 4.90 percent; thus the unemployment rate change for 2001 was 0.26 percentage points.

Next, we calculate a yearly multiplier based on the unemployment rate change and the estimate from Bitler and Hoynes (2016). To calculate the multiplier, we multiply the study's point estimate by the change in the unemployment rate for the given year and add 1. For example, when calculating Alabama's caseload-to-population ratio in 2001—given that its unemployment rate changed by 0.26 percentage points from 2000 to 2001—we multiply 0.034 (from Bitler and Hoynes) by 0.26 and add 1, yielding a final multiplier of 1.009.

Finally, to simulate changes in the caseload-to-population ratio that are attributable to changes in the unemployment rate, we multiply the preceding year's caseload-to-population ratio by the current year's multiplier. For example, to calculate Alabama's caseload-to-population ratio in 2001, we multiply the 2001 multiplier (1.009) by Alabama's caseload-to-population ratio in 2000. Effectively, this calculation implies that Alabama's caseload-to-population ratio would increase by 0.9 percent from 2000 to 2001 given that the unemployment rate increased by 0.26 percentage points (holding all else equal). To calculate the counterfactual yearly total caseload, we multiply the state's caseload-to-population ratio by the state's population in the given year.

To simulate the upper-bound estimate, we turn to Ganong and Liebman (2018) and use the SNAP office-level data. Ganong and Liebman use an instrumental variable approach to correct measurement error in their county-level unemployment data; we adjust our county-level unemployment rates according to the same method. That is, we construct a Bartik instrument using data from the Quarterly Census of Employment and Wages, which provides the total number of those employed in each industry in each county from 1990 to 2023. To create the Bartik instrument, we follow Ganong and Liebman and calculate the product of the three-year national growth rate in each three-digit North American Industry Classification System industry by the share of the county's population employed in the same industry.[11] After creating the instrument, we then estimate the first stage equation provided in Ganong and Liebman and use the predicted outcomes as our

10 Ganong and Liebman (2018) acknowledge that their estimate is higher than in much of the existing literature—such as in Mabli and Ferrerosa (2010) and Bitler and Hoynes (2016)—attributing the difference to their methods: "These prior estimates likely understated the impact of unemployment on SNAP receipt because of attenuation bias due to measurement error. Our IV specification addresses measurement error by instrumenting for changes in the unemployment rate with national industry trends."

11 See Equation 4 in Ganong and Liebman (2018) for further details. Because the Quarterly Census of Employment and Wages extends back to 1990, we are able to generate three-year industry growth rates for all years in our sample period. For example, the three-year growth rate of a given industry in 2000 is calculated using data from 1997 and 2000.

adjusted unemployment rate.[12] In Table A2, we present the results of this regression.

Note, however, that we adjust only the county-level unemployment data; for the state-level data, we rely on unemployment data from BLS. Following Ganong and Liebman (2018), we calculate the three-year average change in the unemployment rate. We then calculate a multiplier similar to that generated for our lower-bound estimate—we multiply the three-year average change in the unemployment rate by the point estimate and add 1. For example, suppose a given county's unemployment rate increased from 5 to 8 percent from 1998 to 2001. We calculate the three-year average change in the unemployment rate (1 percentage point per year) and create a multiplier based on that change. We simulate the caseload in 2001 by multiplying our caseload in 2000 by the 2001 multiplier. Therefore, if the average three-year change in the county's adjusted unemployment rate increases by 1 percentage point, the county's counterfactual annual caseload increases by 14.8 percent. We then calculate the caseload-to-population ratio by dividing the office's counterfactual caseload by the state or county population.[13]

Additionally, we simulate the SNAP caseload using the mean effect size across all studies. Across all eight studies, the mean effect size implies that a 1 percentage-point increase in the unemployment rate corresponds with a 6.5 percent increase in the caseload-to-population ratio. We apply the mean effect size to our state-level data because most estimates are generated using state-level data. Moreover, we assume that changes to the unemployment rate correspond with contemporaneous changes to the SNAP caseload. We generate a multiplier according to the same method as the upper- and lower-bound estimates. We then calculate a counterfactual SNAP caseload-to-population ratio in a given year by multiplying the state-level caseload-to-population ratio in the preceding year by the multiplier in the subsequent year. Just as with our upper- and lower-bound estimates, we then calculate the total number of individuals receiving SNAP by multiplying the counterfactual caseload-to-population ratios by the state population.

Finally, we calculate counterfactual SNAP expenditures using the counterfactual caseloads. To do so, we multiply the real average SNAP benefit per person in our base year by the counterfactual caseload in each year. By anchoring benefits to the base year, we remove the effect of policy changes that increased SNAP benefits per person. However, SNAP benefits per person may also change for reasons unrelated to policy. For instance, smaller households receive larger per-person benefits, and households with lower incomes receive larger benefits. If the average SNAP household has declined in size or income over the sample period, our counterfactuals will understate the increase in SNAP expenditures that are attributable to the unemployment rate. Additionally, changes in the unemployment rate may independently affect per-person benefits through channels other than income and household size. Therefore, we adjust our base year benefit to account for these factors.

We begin by adjusting the base year benefit per person using the Consumer Price Index for All Urban Consumers. After adjusting for inflation, we adjust the base year benefit to account for two changes in the composition of SNAP households and cyclical changes in the average benefit per person. We aggregate the effect of each of these three adjustments in each year and adjust the base year benefit accordingly.

First, we adjust the base year benefit to account for declining sizes of SNAP households. From 2000 to 2022, the average SNAP household size decreased from 2.3 to 1.9 individuals per household (Monkovic 2024). On average, for every household member removed from a household, SNAP benefits per person increase by 4.5 percent.[14]

12 See Equation 3 in Ganong and Liebman (2018) for further details. According to the original BLS LAUS data, the unemployment rates varied from 0.4 to 32.3 percent. After adjusting the unemployment rates, they range from 2.0 to 11.7 percent. In Figure A1, we show our results using the original county-level unemployment data provided by BLS LAUS.

13 Importantly, in our simulation of Ganong and Liebman (2018), we use all SNAP offices, whereas they use only county-level offices. We do so because we are interested in simulating SNAP's total caseload and expenditures, and county-level data are not available for 17 states during our sample period.

14 For example, in 2022, a one-member SNAP household received a (maximum) benefit of $250 per person. Households with two, three, four, five, and six members received (maximum) benefits of $229.50, $219.33, $208.75, $198.40, and $198.33 per person, respectively. Therefore, the average percentage increase in per-person benefits associated with the removal of one person per household is roughly 4.5 percent.

Second, we adjust per-person benefits to account for the increasing share of SNAP households receiving the maximum benefit. From 2000 to 2022, the share of SNAP households with zero net monthly income (i.e., households eligible for the maximum SNAP allotment) increased from 22 to 36 percent (Monkovic 2024). To assess the effect of a 1 percentage-point change in the unemployment rate, we rely on our state-level data and regress the log inflation-adjusted benefit expenditures on the share of households receiving the maximum benefit. To ensure that we do not capture increases in per-person expenditures due to policy changes, we restrict our years to 2000–08, a period in which no major policy reforms significantly increased per-person benefit expenditures. We find that a 1 percentage-point increase in the share of households receiving the maximum benefit corresponds with a 1 percent increase in average SNAP benefit per person.[15]

Third, we adjust our base year benefit to account for cyclical changes in per-person benefits. Although most of the literature estimates the effect of the unemployment rate on program caseloads, certain studies estimate the effect on program expenditures. Specifically, Bitler and Hoynes (2016) estimate that a 1 percentage-point increase in the unemployment rate is associated with a 5.1 percent increase in SNAP expenditures per person. Later, Bitler et al. (2020) found that a 1 percentage-point increase in the unemployment rate is associated with a 5.0 percent increase in real expenditures per person. We adjust our base year benefit using the greater estimate.

To adjust for each of these factors in the same year, we aggregate the effects of all adjustments in a given year. We then use the combined effect to adjust our base year benefit. For example, suppose that a given state (or county) experienced a 0.1 percentage-point decrease in its average household size, a 2 percentage-point increase in the share of households receiving the maximum benefit, and a 1 percentage-point increase in the unemployment rate from 2000 to 2001. Under such circumstances, the base year benefit would increase by 7.55 percent to account for all changes.[16] After combining each of these adjustments, we simulate expenditures by multiplying each state's (or office's) adjusted average per-person benefit by the state's (or office's) counterfactual caseload. We then add together all state (or office) expenditures in each year.

Counterfactual Results

Caseloads

We begin by presenting the results of our counterfactual caseload-to-population ratios. In each of the following analyses, "lower bound" refers to the least responsive estimate from the literature, which suggests that a 1 percentage-point increase in the unemployment rate corresponds with a 3.4 percent increase in the annual caseload-to-population ratio (Bitler and Hoynes 2016). "Upper bound" refers to the most responsive estimate from the literature, which suggests that a sustained 1 percentage-point increase in the unemployment rate corresponded with a 14.8 percent increase in the annual caseload (Ganong and Liebman 2018). Averaging across all eight studies, a 1 percentage-point increase in the unemployment rate corresponds with a 6.5 percent increase in the annual caseload-to-population ratio. We present our counterfactual results for SNAP's caseload-to-population ratio below and illustrate the results in Figure 2.

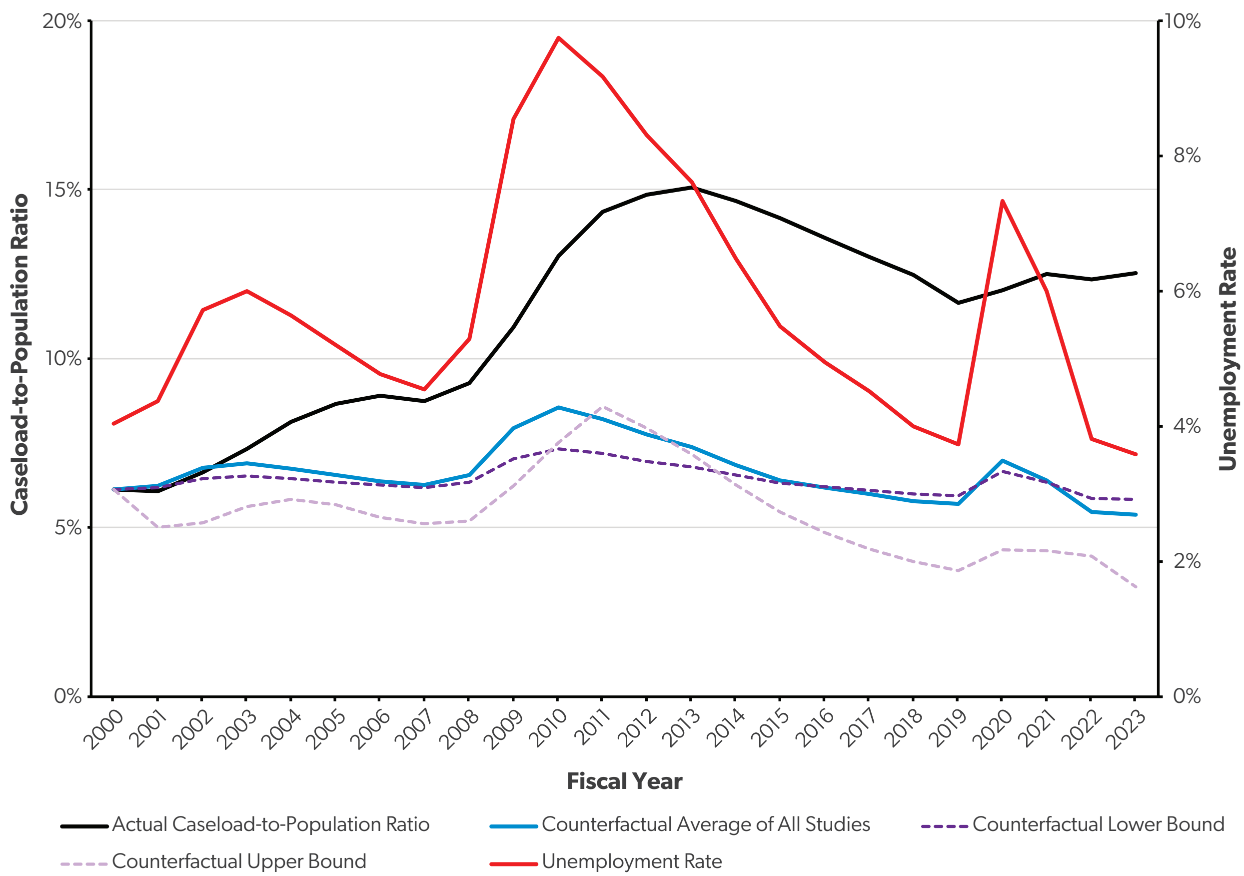
In the early 2000s, the counterfactual and actual caseload-to-population ratios did not substantially differ. This is partly true by construction because counterfactual and actual caseloads in the base year are the same.[17] From 2000 to 2003, the national unemployment rate increased from 4.0 to 6.0 percent. At the same time, SNAP's caseload-to-population ratio

15 We assume that household size and the share receiving the maximum benefit remain at 2022 levels in 2023 because we do not yet have 2023 data.

16 Specifically, the 0.1 percentage-point decrease in average household size corresponds with a 0.45 percent increase in per-person benefits, the 2 percentage-point increase in the share receiving the maximum benefit corresponds with a 2 percent increase in per-person benefits, and the 1 percentage-point increase in the unemployment rate corresponds with a 5.1 percent increase in per-person benefits.

17 Notably, however, small variations in the office- and state-level data resulted in slightly different calculations of the caseload-to-population ratio in the base year between datasets. Our office-level data yielded a caseload-to-population ratio of 5.977 percent, whereas the state-level caseload to population yielded a caseload-to-population ratio of 6.012 percent. Therefore, we adjusted our office-level caseload-to-population ratio by simply adding the difference to all survey years.

Figure 2. SNAP Caseload-to-Population Ratio and National Unemployment Rate, Counterfactual and Actual, 2000–23



Source: Authors' calculations from USDA (2024), BLS (2024), and US Census Bureau (2024).
Note: The caseload-to-population ratio corresponds with the primary y-axis. The "lower bound" implies that a 1 percentage-point increase in the unemployment rate corresponds with a 3.4 percent increase in the caseload-to-population ratio, while the "upper bound" implies that a sustained 1 percentage-point increase in the three-year unemployment rate corresponds with a 14.8 percent increase in the caseload.

increased from 6.1 to 7.3 percent. According to our lower-bound counterfactual, the caseload-to-population ratio would have increased from 6.1 to 6.5 percent had the caseload-to-population ratio changed with respect to only the unemployment rate. Interestingly, our upper-bound estimate would have *decreased* from 6.1 to 5.6 percent.[18]

The counterfactual and actual caseload-to-population ratios begin to diverge when the unemployment rate declined following the 2001 recession. From 2003 to 2007, the actual caseload-to-population ratio increased from 7.3 to 8.7 percent, despite the national unemployment rate falling from 6.0 to 4.5 percent. According to the lower-bound estimate from the literature, the caseload-to-population ratio would have decreased from 6.5 to 6.2 percent during this time if the caseload varied with respect to only the unemployment rate. The upper-bound estimate suggests that the caseload-to-population ratio would have decreased from 5.6 to 5.1 percent. Thus, both our lower- and

18 This decrease is attributable to the three-year lag used to generate unemployment estimates. According to our calculations, the average (adjusted) county-level unemployment rate fell from 5.1 percent in 1998 to 4.8 percent in 2001. Because the 2001 counterfactual result is based on three-year changes in unemployment, we observe declining caseload-to-population ratios at the beginning of the sample period.

upper-bound counterfactuals indicate that the SNAP caseload-to-population ratio should have fallen during the economic expansion following the 2001 recession, whereas in reality, SNAP's caseload-to-population ratio increased over this period.

During and following the Great Recession, counterfactual caseload-to-population ratios diverged even further from the actual caseload-to-population ratio. From 2007 to 2011, the national unemployment rate increased from 4.5 to 9.2 percent. In response to the increase in unemployment, the caseload-to-population ratio increased from 8.7 to 14.4 percent (a 66 percent increase). Our lower-bound estimate indicates that the caseload-to-population ratio would have increased from 6.2 to 7.2 percent (a 16 percent increase), while our upper-bound estimate indicates that the caseload-to-population ratio would have increased from 5.1 to 8.6 percent (a 69 percent increase). Therefore, although the lower-bound estimate predicts a much smaller increase in SNAP's caseload-to-population ratio than the actual increase, our upper-bound estimate was very similar to the actual rate of increase.[19]

This congruence did not last. As the unemployment rate began to decline following the Great Recession, the actual caseload-to-population ratio remained elevated, while each counterfactual caseload-to-population ratio declined. The actual caseload-to-population ratio did not peak until 2013 (15.1 percent), when the national unemployment rate had fallen by more than 2 percentage points since its peak in 2010. That is, from 2010 to 2015, the national unemployment rate fell from 9.7 to 5.5 percent, while the caseload-to-population ratio increased from 13.0 to 14.2 percent. According to our average estimate from the literature, the caseload-to-population ratio would have decreased from 8.5 to 6.4 percent had it changed with respect to only the unemployment rate. Therefore, estimates from the literature suggest that if SNAP's caseload were to vary with respect to only the unemployment rate, the caseload-to-population ratio would have fallen throughout the early 2010s. In reality, however, the caseload-to-population ratio increased during this time.

Finally, during the COVID-19 recession, the national unemployment rate underwent its single largest monthly increase in recent history. From 2019 to 2020, the unemployment rate increased from 3.7 to 7.3 percent. In response, the caseload-to-population ratio increased only modestly, from 11.6 to 12.0 percent (a 3 percent increase).[20] The lower-bound estimate suggests that the caseload-to-population ratio would have increased from 5.9 to 6.7 percent (a 14 percent increase), while the upper-bound estimate suggests that the caseload-to-population ratio would have increased from 3.7 to 4.3 percent (a 16 percent increase). As the unemployment rate declined from 7.3 percent in 2020 to 3.6 percent in 2023, the actual caseload-to-population ratio continued to increase from 12.0 to 12.5 percent. For comparison, the average estimate indicates that the caseload-to-population ratio would have decreased from 7.0 to 5.4 percent.

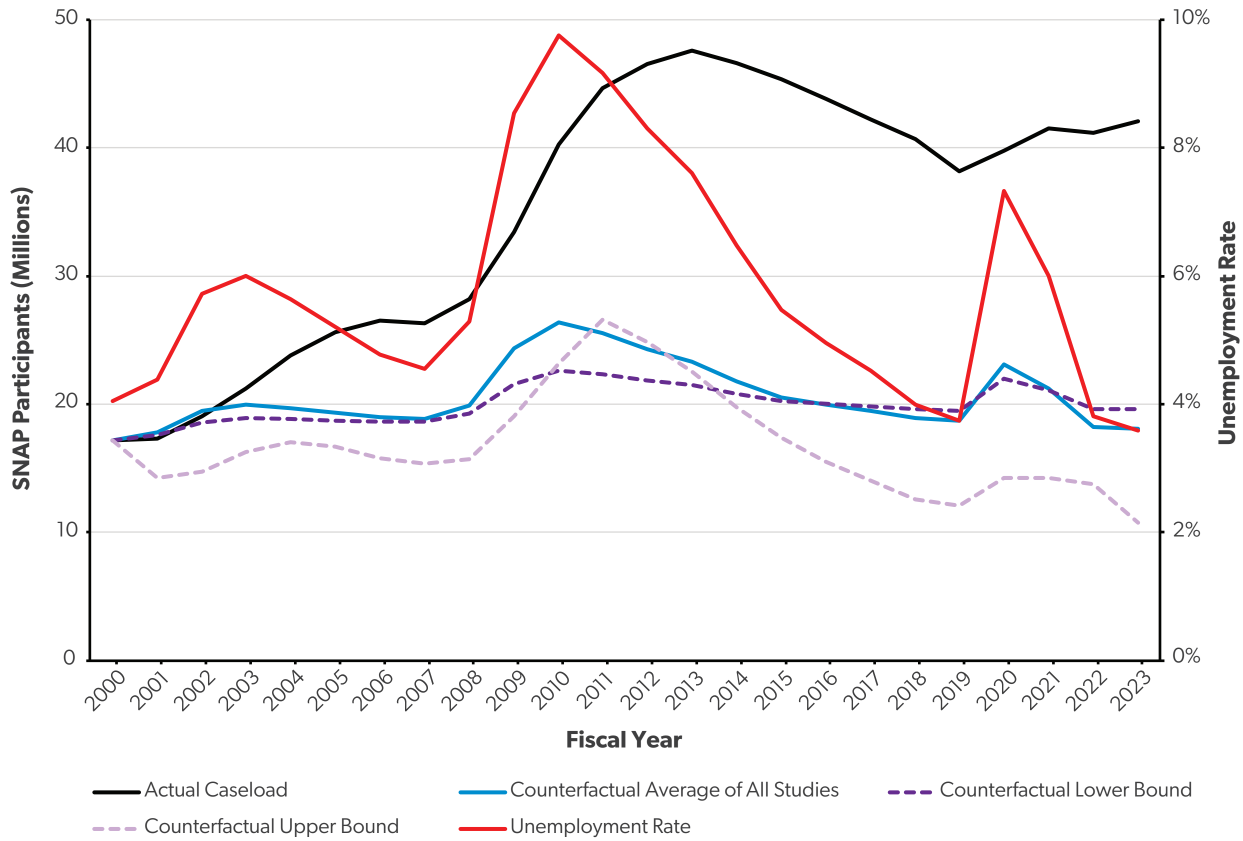
These results suggest that had the SNAP caseload-to-population ratio changed with respect to only the unemployment rate, the caseload-to-population ratio would be significantly lower than its current rate. Much of the divergence between the counterfactual and actual caseload occurs during the recovery periods following recessions, implying that certain factors beyond changes to the unemployment rate explain elevated caseloads following recessions. In the following section, we introduce other explanations for the divergence between actual and counterfactual caseloads based on the unemployment rate alone.

Though these counterfactuals inform us of the share of the population that would receive SNAP benefits if only for changes in the unemployment rate, they do not inform us of how many *total* individuals would receive benefits. By accounting for changes in each state's (or county's) yearly population, we calculate counterfactual changes in the total SNAP caseload. That is, we calculate each state's (or county's) total caseload by multiplying the state's (or county's) counterfactual caseload-to-population ratio by its yearly population. We then add

19 Figure B1 shows how the caseload-to-population ratio would have varied over the Great Recession (base year 2007); our upper-bound estimate increases at a greater rate than the actual caseload-to-population ratio.

20 The limited increase in SNAP enrollment at the onset of the COVID-19 pandemic was likely due to the brief nature of the recession, along with the availability of other safety-net benefits, such as economic impact payments and expanded unemployment insurance benefits.

Figure 3. SNAP Participants and National Unemployment Rate, Counterfactual and Actual, 2000–23



Source: Authors' calculations from USDA (2024), BLS (2024), and US Census Bureau (2024).
Note: "Actual caseload" corresponds with the primary y-axis and shows the actual SNAP caseload by fiscal year. The "lower bound" implies that a 1 percentage-point increase in the unemployment rate corresponds with a 3.4 percent increase in the caseload to-population ratio, while the "upper bound" implies that a sustained 1 percentage-point increase corresponds with a 14.8 percent increase in the caseload.

the counterfactual caseloads for all states and counties, and we present our results in Figure 3.[21]

In Figure 3, we observe a similar pattern to what we observed in Figure 2. The total number of SNAP recipients is far greater than we would expect given changes to the unemployment rate and increases in the US population. From 2000 to 2006, the number of SNAP recipients increased linearly from 17.2 million to 26.5 million, despite the fact that the unemployment rate increased only from 2000 to 2003 and declined thereafter. For comparison, our average counterfactual suggests that that SNAP caseload would have increased from 17.2 million to 20.0 million from 2000 to 2003, then declined to 19.0 million by 2006.

During the Great Recession, the annual unemployment rate increased to nearly 10 percent, and SNAP caseloads increased dramatically. From 2007 to 2010, the unemployment rate increased from 4.5 to 9.7 percent, and the SNAP caseload increased from 26.3 million to 40.2 million (a 53 percent increase). Our average counterfactual indicates that the SNAP caseload would have increased from 18.8 million to 26.4 million over

21 Importantly, population estimates are released yearly, not monthly, so we assume that populations do not change from month to month but do change from year to year.

the same two years (a 40 percent increase). However, counterfactual caseloads begin to diverge sharply from actual caseloads in the period immediately following the Great Recession, as the unemployment rate began to decline. That is, the actual SNAP caseload did not reach its recession-era peak until 2013, when 47.6 million individuals received benefits. By 2013, however, our counterfactuals indicate that SNAP's caseload would have ranged from 21.5 million to 23.3 million, less than half of the actual caseload during that year.

These differences are even more pronounced during and following the COVID-19 recession. According to our upper-bound counterfactual, the SNAP caseload would have increased from 12.1 million to 14.2 million from 2019 to 2020. And according to our lower-bound counterfactual, the caseload would have increased from 19.5 million to 22.0 million during the same period. In reality, SNAP's caseload increase from 2019 to 2020 was relatively modest, increasing from 38.2 million to 39.8 million. Notably, however, the actual SNAP caseload continued to increase following the COVID-19 pandemic, reaching its highest point in 2023, serving 42.1 million individuals. But according to each of our counterfactuals, the SNAP caseload would have declined following the COVID-19 recession due to the rapid decline in the unemployment rate following 2020. The average effect size implies that the SNAP caseload would have declined from 23.1 million in 2020 to 18.1 million in 2023 if only for changes in the unemployment rate.

Across our range of counterfactuals, SNAP would have experienced much less program growth if the caseload fluctuated with respect to only the unemployment rate and population growth. That is, according to our counterfactuals, SNAP would have served between 23 million and 26 million individuals at the peak of the Great Recession and between 14 million and 23 million people during the COVID-19 pandemic. Much of the discrepancy between the counterfactual and actual caseloads is attributable to increasing SNAP caseloads in periods following recessions, even though changes to the unemployment rate would predict the opposite. Importantly, however, our counterfactuals demonstrate that changes in the unemployment rate account for nearly all the increase in SNAP participation at the onset of recessions. This finding is consistent with Ganong and Liebman (2018), who found that changes to the unemployment rate explained the majority of the SNAP caseload increase during the Great Recession, with state policy decisions explaining a smaller share.

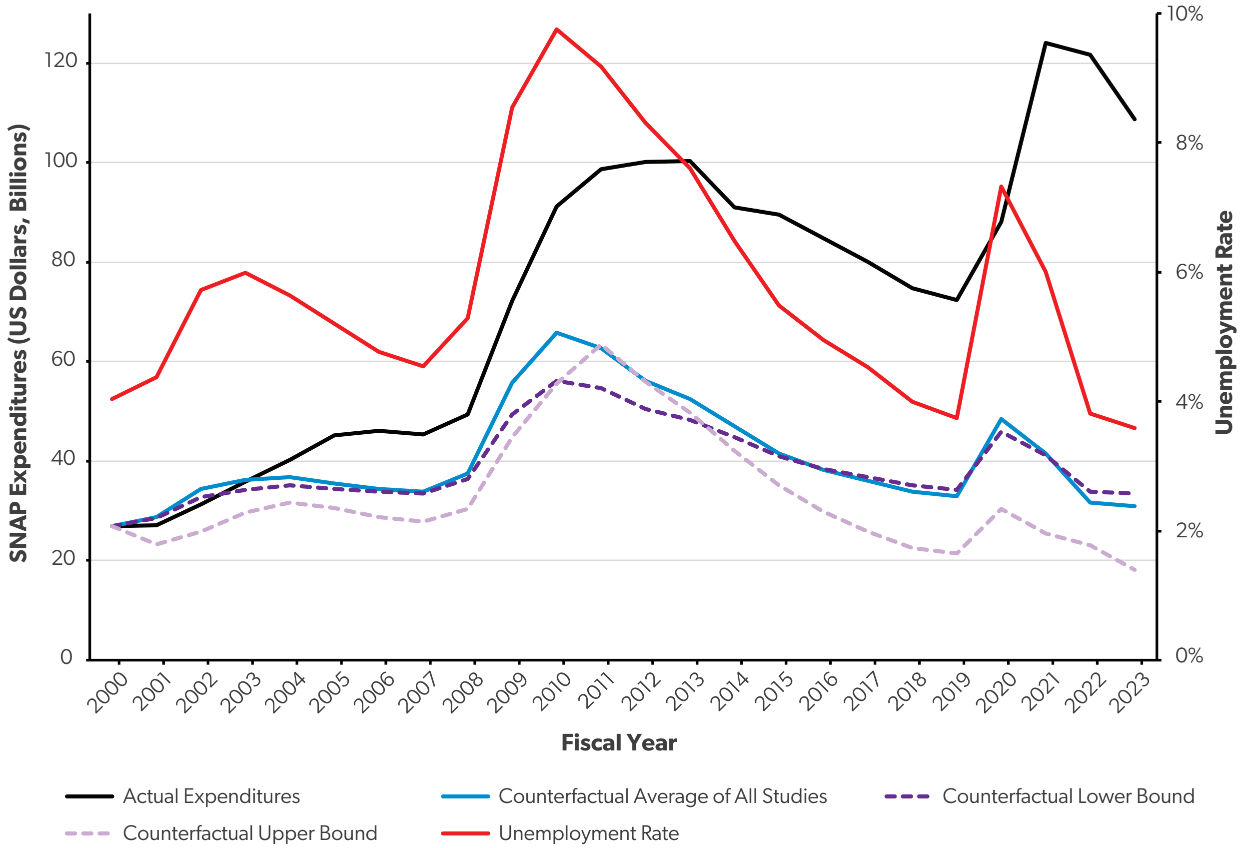
Expenditures

In this section, we calculate counterfactual SNAP benefit expenditures attributable to changes in the unemployment rate and population growth. In Figure 4, we present our counterfactual expenditures according to the same upper- and lower-bound estimates. Our upper- and lower-bound estimates display what SNAP's expenditures would be if the caseload varied with respect to only the unemployment rate (according to Ganong and Liebman [2018] and Bitler and Hoynes [2016], respectively), and per-person SNAP expenditures were unaffected by policy changes made over the past two and a half decades.

In the early 2000s, counterfactual expenditures were roughly equal to actual expenditures. According to the average counterfactual, expenditures would have increased from $26.9 billion in 2000 to $36.3 billion in 2003. Over the same period, actual expenditures increased from $26.9 billion to $35.8 billion. As the unemployment rate began to decline in 2004, counterfactual expenditures departed from actual expenditures. From 2004 to 2007, our average counterfactual suggests that expenditures would have decreased from $36.8 billion to $33.8 billion. In reality, however, SNAP expenditures increased from $40.3 billion to $45.3 billion during this time.

During the Great Recession, our counterfactuals suggest that SNAP expenditures would have increased substantially if the caseload was dictated entirely by changes in the business cycle. From 2008 to 2011, our upper-bound estimate suggests that the program's expenditures would have increased from $30.3 billion to $63.4 billion—an approximately 109 percent increase. In reality, program expenditures increased from $49.5 billion to $98.7 billion—a nearly 100 percent increase. Just as was the case with the caseload counterfactuals, our expenditure counterfactuals begin to diverge sharply from actual expenditures starting in and following the Great Recession. From 2011 to 2015, actual program expenditures decreased only slightly from $98.7 billion to $89.6 billion. However, according

Figure 4. SNAP Expenditures and National Unemployment Rate, Counterfactual and Actual, 2000–23



Source: Authors' calculations from USDA (2024), BLS (2024), and US Census Bureau (2024).

Note: Actual benefit expenditures correspond with the primary y-axis, and the national unemployment rate corresponds with the secondary y-axis. The low estimate implies that a 1 percentage-point increase in the unemployment rate corresponds with a 3.4 percent increase in the caseload-to-population ratio, while the high estimate implies that a sustained 1 percentage-point increase corresponds with a 14.8 percent increase in the caseload. Benefit expenditures are inflated to 2023 dollars using the Consumer Price Index for All Urban Consumers.

to our average counterfactual, program expenditures would have decreased from $62.7 billion to $41.6 billion. Therefore, if SNAP expenditures had fluctuated with respect to only the unemployment rate, population growth, and changes to the program's composition, SNAP would have spent $48 billion less on benefits per year in 2015 than actual expenditures.

The incongruence between our counterfactuals and actual expenditures becomes even more exaggerated in the aftermath of the COVID-19 pandemic. During the public health emergency, the federal government increased per-person spending on SNAP through various legislation and regulation. For the first time, the federal government also permanently increased the per-household SNAP benefit in 2022 through a reevaluation of the TFP. As a result of these policy changes—and the large unemployment shock at the beginning of the pandemic—program expenditures increased from $72.3 billion in 2019 to $124.1 billion in 2021. Expenditures then declined to $108.7 billion in 2023. According to our average counterfactual, which does not account for these per-person benefit increases, program expenditures would have increased from $32.9 billion to $41.6 billion from 2019 to 2021 and then declined to $31.0 billion by 2023.

In sum, we found that SNAP would be significantly smaller had the caseload and expenditures changed with respect to only the business cycle and population growth. In 2023, SNAP would have served between 3.2 and 5.8 percent of the US population rather than the 12.5 percent of the population that it actually served that year. Moreover, SNAP expenditures would have been between $18.1 billion and $33.5 billion, significantly less than the $108.7 billion the program spent on benefits in 2023.

Other Factors Explaining the SNAP Caseload

Changes in economic conditions are not the only factor contributing to SNAP caseload changes. Beyond unemployment, policy changes such as longer recertification periods, adoption of categorical eligibility, and work requirements, as well as factors less directly related to policy, such as shifts in stigma, participation rates, and population aging, can affect caseloads.[22] While we do not quantify the impact of these factors in this report, we identify them and discuss the likely direction of effects on SNAP participation, highlighting areas for future research on how business cycles and policy shape SNAP caseloads.

Participation Rates

Changes in SNAP's participation rate (i.e., the share of eligible households participating in SNAP, also known as the take-up rate) could help explain why SNAP caseloads remain persistently high following economic recessions. If SNAP's participation rate—the share of eligible households receiving benefits—has shifted over time independent of employment conditions, caseloads may remain high even as the unemployment rate declines. In Figure A2, we plot the yearly participation rate during our sample period according to USDA estimates (Vigil and Rahimi 2024). From 2000 to 2022, SNAP's participation rate increased from 57 to 88 percent (Vigil 2022). Moreover, the participation rate increased most during recessionary periods, especially in 2010 and 2021, and remained elevated following each recession. These trends suggest that increasing participation rates may help explain some of the divergence between SNAP's actual caseload and the counterfactual caseload.

To assess whether increasing participation rates explain SNAP's elevated caseload, we simulate SNAP's caseload-to-population ratio assuming a 100 percent participation rate. In Figure A3, we plot our upper-bound, lower-bound, and average counterfactual assuming 100 percent participation. To generate these counterfactuals, we assume that 100 percent of eligible individuals received benefits in our base year and then simulate how the caseload-to-population ratio would vary with respect to the unemployment rate. For comparison, we plot the SNAP caseload-to-population ratio assuming full participation.[23] If changes in the participation rate—along with business cycle fluctuations—explain SNAP's caseload trends, we would expect our counterfactuals to closely track the caseload under full participation. Figure A3 shows that, even after accounting for increasing participation rates, SNAP's caseload remains elevated beyond expectations. This suggests that factors beyond changes in participation rates explain caseload trends.

Household Composition and Demographic Changes

In addition to changes in participation rates, other compositional and demographic trends likely help explain persistently high SNAP caseloads. Over the sample period, SNAP households have grown increasingly older and more likely to be disabled (Rachidi and O'Rourke 2023). From 1996 to 2019, for example, the share of SNAP household heads age 50–64 more than doubled, from 13 to 28 percent. Older and disabled households are more likely to be out of the labor force and will therefore be less responsive to changes in the

22 Ganong and Liebman (2018) estimated the effect of several state-level policy changes on the SNAP caseload and found that policy changes were largely responsible for the increasing caseload during the 2001 recession but less so for the 2008 recession. They also found that much of the SNAP growth unexplained by the business cycle was due to state policy changes. However, the authors restricted their analysis to economic recessions and do not estimate the effect of policy changes on the program's caseload during expansionary periods.

23 To calculate this, we rely on USDA reports of program participation and assume that state-level participation rates are the same as national participation rates. For example, suppose that in a given year, the participation rate was 50 percent. To calculate a given state's caseload under full participation, we double that state's current caseload.

business cycle. Moreover, over the same period, older and disabled households are more likely to require food assistance for longer periods than relatively younger households (Giordono et al. 2022). Together, these demographic shifts in the SNAP caseload are likely to elevate caseloads and make them less responsive to changes in the unemployment rate.

The share of SNAP households consisting of a single member has grown in previous years, which may also be contributing to elevated caseloads. In 2000, the average SNAP household size was 2.3 members; by 2022, the average household size had decreased to 1.9 members (Monkovic 2024). Moreover, the share of SNAP households consisting of a single member increased from 42.8 to 58.5 percent. Notably, SNAP defines a "household" as individuals who live together and purchase and prepare meals together. As a result, multiple SNAP cases can exist within a single household. If this pattern became more common over the sample period—particularly during recessionary periods—caseloads may have remained elevated even without an increase in the number of distinctly participating individuals.[24]

Policy Changes

As Ganong and Liebman (2018) found, programmatic and policy changes at the federal and state level also contributed to SNAP caseload growth beyond what unemployment alone could explain. For example, policies that simplified the application and recertification process, reduced program stigma, extended recertification periods for certain subgroups, and waived work requirements have all likely contributed to higher participation in recent decades, independent of unemployment trends (Hanson and Oliveira 2012; Ganong and Liebman 2018; Rachidi 2021). Some of these policy reforms likely increased program participation among those who were eligible (e.g., reducing program stigma through the adoption of EBT cards), while other reforms increased the duration of time a given household receives benefits (e.g., extending recertification periods or waiving the work requirement). In either case, such policy reforms likely contributed to elevated caseloads beyond what would be predicted by the unemployment rate alone.

Additionally, SNAP reforms that increased benefit levels also likely contribute to elevated caseloads. That is, at various points over the sample period, policymakers and regulators have increased SNAP benefits, incentivizing marginal households to enroll in SNAP and stay on the program for longer periods. This would then elevate caseloads beyond what would be expected based on the unemployment rate alone.

Finally, changes to SNAP's eligibility criteria directly influence program participation. The most notable policy reform expanding eligibility is BBCE. States that have adopted BBCE are permitted to offer SNAP benefits to households with incomes up to 200 percent of the federal poverty line and forgo SNAP's asset test.[25] Importantly, USDA's estimates of program participation rates do not account for households qualifying for SNAP under BBCE. Analysis conducted for the USDA Food and Nutrition Service showed that in fiscal year 2017 approximately four million SNAP recipients qualified due to expanded eligibility rules and were not counted in the participation rate (Vigil 2019). Therefore, states' adoption of BBCE likely contributed to elevated caseloads and perhaps helps explain the divergence of SNAP's caseload from what would be expected given changes to the unemployment rate.

While some research has quantified the effects of specific policy reforms and demographic changes on SNAP's caseload during recessionary periods, future research should explore how policy reforms and other factors affect caseloads during subsequent economic expansions.

Conclusion

This report documents how large SNAP would be—in terms of both caseloads and expenditures—if only

24 For example, suppose a two-person SNAP household split and became two separate SNAP households, each qualifying for benefits independently. If they remained a single assistance unit, a positive income shock for one household member could have disqualified both household members from receiving benefits. However, if they are in separate households, a positive income shock could disqualify only one member.

25 BBCE allows states to confer SNAP eligibility for households when they also receive a benefit from TANF or a TANF-funded benefit. States have increasingly used BBCE to expand SNAP eligibility up to 200 percent of the federal poverty line. When households have large expenses deducted from the SNAP gross income for the purposes of determining eligibility, they can still be eligible for a SNAP benefit at income levels above the federal guideline of 130 percent of the federal poverty line.

for changes to the unemployment rate and population growth since 2000. We found that changes in the unemployment rate almost fully explain increases in the SNAP caseload at the beginning of recessionary periods. However, changes in the unemployment rate are not a good predictor of caseloads during subsequent expansions.

By relying on estimates from the literature, we estimate that SNAP's caseload would be between 26 and 47 percent of the program's current size had the program fluctuated due only to changes in the unemployment rate since 2000. Similarly, we found that if SNAP's expenditures varied with respect only to the unemployment rate, the program would spend between $18 billion and $34 billion on benefits in 2023, between 17 and 31 percent of current expenditures. The fact that SNAP caseloads and expenditures have increased far beyond what is expected given changes to the unemployment rate suggests that other economic and noneconomic factors contributed to SNAP's elevated caseloads, including policy changes at the state and federal level.

Certain policy changes—such as lengthening recertification periods, states' adoption of BBCE, the use of EBT cards, and waiving work requirements—all help explain why SNAP's caseload is greater than what would be predicted based on changes to the unemployment rate alone (Ganong and Liebman 2018). Moreover, factors unrelated or indirectly related to policy—such as the aging of the population, increased rates of disability, and increasing participation rates—can also help explain why SNAP caseloads remain elevated. Future research should evaluate the effects of these policies on SNAP's caseload and expenditures during economic expansions.

These findings have policy relevance. SNAP is traditionally viewed as an automatic stabilizer, meaning caseloads and expenditures increase during economic downturns and decrease when the economy recovers. However, our results indicate that SNAP's growth in recent decades has extended beyond its role as an economic stabilizer; caseloads increase following unemployment rate shocks but remain elevated through economic expansions. These dynamics imply that individuals continue to receive federal financial assistance long after economic conditions have improved, highlighting the need for policymakers to focus on policies that promote economic opportunity and better connect low-income individuals to improved employment conditions.

About the Authors

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Appendix A. Additional Tables and Figures

Table A1. Supplemental Methodological Details on Estimates of the Relationship Between Unemployment Rate and SNAP Caseload-to-Population Ratio

Paper	Caseload-to-Population Estimate*	Data	Methodology	Control Variables	Key Point
Bitler and Hoynes (2010)	4.9 percent	State-level household caseloads and expenditure data by month for 1980–2009 and January–March 2010 provided by USDA. State-level and national unemployment rates annually and by month from the Current Population Survey. National population data from the *Economic Report of the President*, and state population data from the National Cancer Institute.	State-year panel fixed effects model estimating the effect of unemployment rate changes on caseloads per capita at the state-month level.	State fixed effects, year fixed effects, linear time trends, and state-level dummies for various welfare reform policies.	"Interestingly, food stamp caseloads . . . show a similar effect size: the coefficient of 0.17 scaled by the mean of 3.5 implies an effect size of 4.9 percent" (107).
Bitler and Hoynes (2016)	3.4 percent	State-level caseload and expenditure data by month for 1980–2012 provided by USDA. State-level and national unemployment rates annually and by month from BLS LAUS. National population data from the *Economic Report of the President*, and state population data from the National Cancer Institute.	State-year panel fixed effects model estimating the effect of unemployment rate changes on caseloads per capita or real per capita expenditure at the state-month level.	State and month fixed effects.	"The results show that UI [unemployment insurance] is the most responsive of the programs—a 1 percentage point increase in the unemployment rate leads to a 14.3% increase per capita UI beneficiaries, compared to a 5.5% increase in the per capita AFDC [Aid to Families with Dependent Children]/TANF caseload and a 3.4% increase in the per capita Food Stamps caseload" (S418).

(*Continued on the next page*)

Table A1. Supplemental Methodological Details on Estimates of the Relationship Between Unemployment Rate and SNAP Caseload-to-Population Ratio (*continued from previous page*)

Paper	Caseload-to-Population Estimate*	Data	Methodology	Control Variables	Key Point
Bitler et al. (2020)	3.5 percent	State-level caseload and expenditure data by month for 1980–2019 provided by USDA. State-level and national unemployment rates annually and by month from BLS LAUS. State-level population data from the National Cancer Institute.	State-year panel fixed effects model estimating the effect of unemployment rate changes on caseload-to-population ratio.	State and year fixed effects.	Appendix Table 1 shows that a 1 percentage-point increase in the unemployment rate corresponds with a 3.5 percent increase in SNAP.
Dickert-Conlin et al. (2021)	7.3 percent	State-level individual caseloads and expenditure data by month for 1990–2011 provided by USDA. State-level unemployment rates by month from BLS. State-level population data from the Census Bureau.	Static and dynamic model estimating the effect of unemployment rate changes on the SNAP caseload-to-population ratio with different lags (12 or 24 months).	Control variables include state-level SNAP policies affecting eligibility, transaction costs, and outreach, as well as state and time fixed effects.	"Estimates of the long-run effect of unemployment imply a 1% increase in unemployment is associated with a 1.1 to 2.0% caseload increase in the static models and with a 5.2 and 7.3% caseload increase in the dynamic specifications" (14).
Ganong and Liebman (2018)	14.8 percent	County-level individual caseloads data annually for 1993–2015 provided by USDA. County-level unemployment rate annually from the Current Population Survey. County-level population data from the Census Bureau. Additional control variable data from the SNAP Policy Database.	County-year fixed effects model estimating the relationship between the unemployment rate, various SNAP policies, and the caseload-to-population ratio. The authors use three-year unemployment rate change to measure the effect of persistent unemployment rate changes on the SNAP caseload.	Control variable is an index measuring the share of eight distinct policy reforms that could have been adopted at the state level, as well as county and year fixed effects.	"A sustained 1 percentage point increase in the county unemployment rate leads to a 15 percent increase in SNAP enrollment" (154–55).

(*Continued on the next page*)

Table A1. Supplemental Methodological Details on Estimates of the Relationship Between Unemployment Rate and SNAP Caseload-to-Population Ratio (*continued from previous page*)

Paper	Caseload-to-Population Estimate*	Data	Methodology	Control Variables	Key Point
Hembre (2023)	3.8 percent	State-level caseload data by month for January 2014–September 2021 provided by USDA. State-level unemployment rates by month from BLS. Additional control variables data from the Center for American Progress, US Department of Labor, USDA, and the University of Kentucky Center for Poverty Research.	State-year panel fixed effects model estimating the effect of unemployment rate changes on the log of SNAP caseloads per capita at the state-month level.	Control variables include a time interaction for the period during the COVID-19 pandemic, state-level pandemic-era SNAP policies, state and month fixed effects, and linear time trend.	"Turning to the labor market effects on caseloads, for each percentage point increase in the unemployment rate, I find that TANF cases increased between 2.5% and 3.0% while SNAP caseloads are slightly more responsive at 3.5%–3.8%" (272).
Ziliak et al. (2003)	8.2 percent	State-level annual caseload data for 1980–99 provided by USDA. State-level annual unemployment rates from BLS. State-level population data from the Census Bureau. Additional control variables data from Americans for Democratic Action, CQ Almanacs, the Current Population Survey, Crouse (1999), US Department of Health and Human Services, NGA, and the US House Committee on Ways and Means *Green Book*.	Dynamic state-level panel fixed effects model estimating the effect of unemployment rate changes on the log of SNAP caseload-to-population ratio.	Authors control for employment growth per capita, indicators of state-level adoption of various pre–welfare reform policies, state-level inequality, and the political party affiliations of state government. Additionally, the authors include state, year, and linear time trends.	"In the long run, a one-percentage-point increase in the unemployment rate leads to an 8.2% increase in food stamp caseloads when we do not control for AFDC caseloads and a 6.1% increase when we condition on AFDC" (913).

(*Continued on the next page*)

Table A1. Supplemental Methodological Details on Estimates of the Relationship Between Unemployment Rate and SNAP Caseload-to-Population Ratio (*continued from previous page*)

Paper	Caseload-to-Population Estimate*	Data	Methodology	Control Variables	Key Point
Mabli and Ferrerosa (2010)	6.3 percent	State-level SNAP caseload data from 2000–08 state administrative records. Unemployment data from the 2000–08 Current Population Surveys.	State-year panel fixed effects model estimating the effect of unemployment rate changes (including a one-year lag) on the log of SNAP caseloads per capita at the state-year level.	Authors include controls for state-level policies and demographics, including whether the state offers short recertification periods and has positive outreach expenditures and BBCE, as well as the share of the state population that are noncitizens.	"We find that a rise in the unemployment rate of 1 percentage point increases the per capita participant count by 6.3 percent" (31).

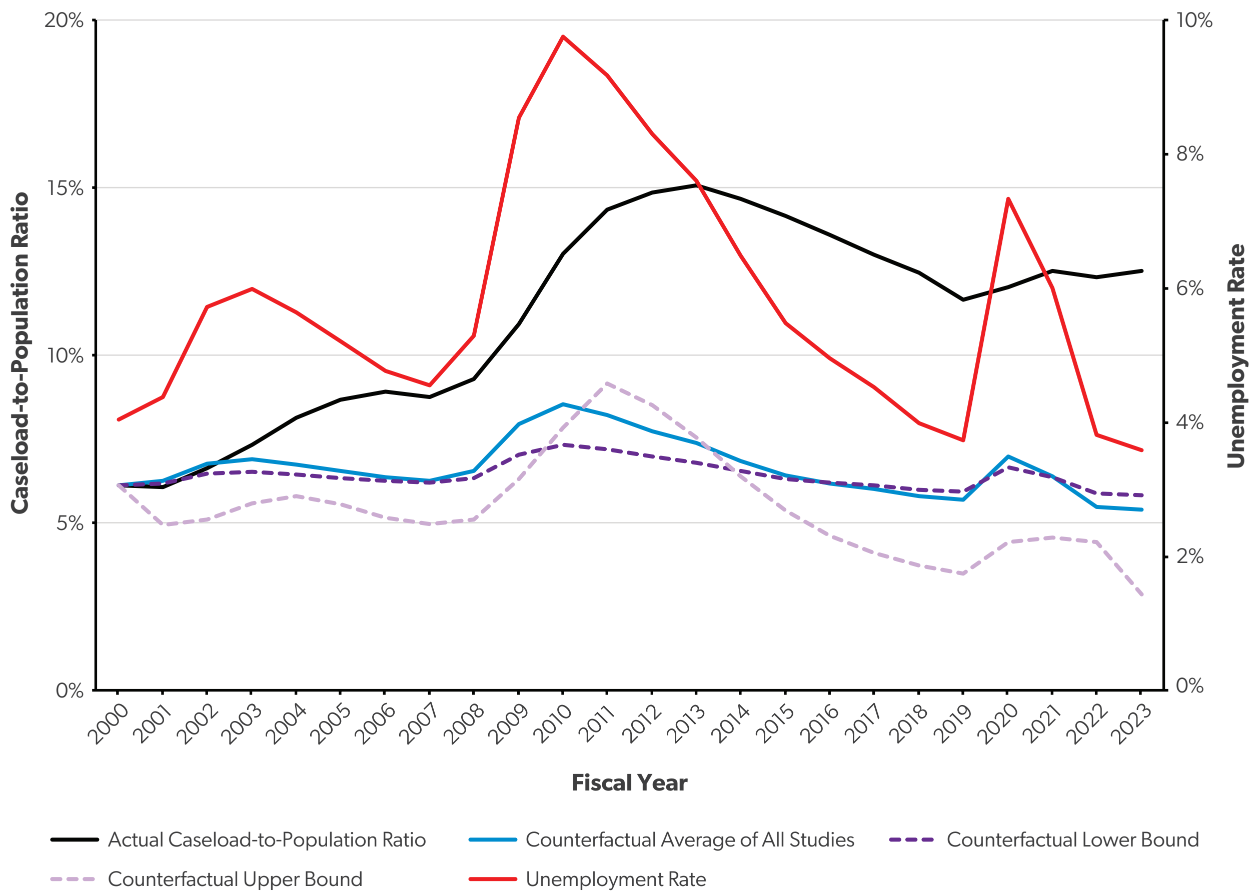
Note: * The caseload-to-population estimate is based on a 1 percentage-point unemployment rate change.

Table A2. County-Level Association Between the Unemployment Rate and Bartik Instrument, 1994–2023

	Bartik Instrument
Unemployment Rate	−11.0815
	(0.3140)
Number of Observations	78,852

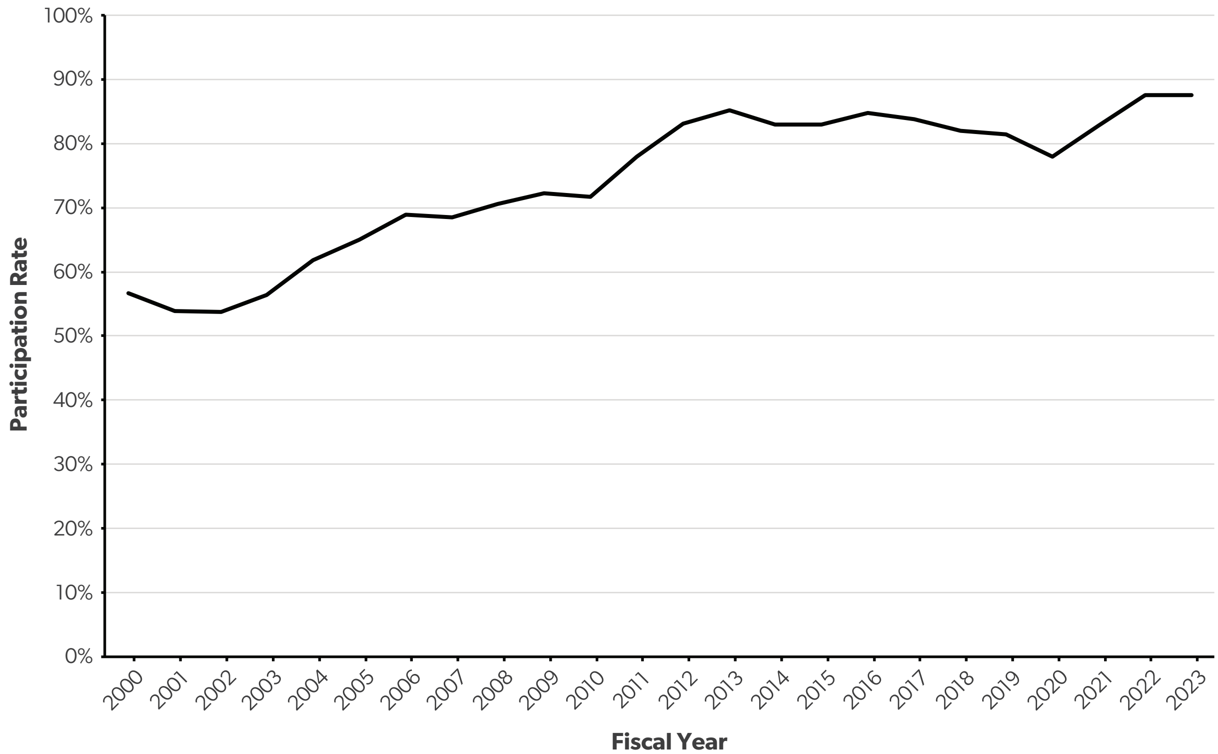
Note: Table A2 reports regression coefficients of our regression of county-level unemployment rates on the adjusted unemployment rate, including county and year fixed effects. We use all available years of data, from 1994 to 2023. We use the predicted values as our county-level unemployment value in all counterfactual calculations.

Figure A1. SNAP Caseload-to-Population Ratio and National Unemployment Rate, Counterfactual and Actual, Using BLS LAUS Data, 2000–23



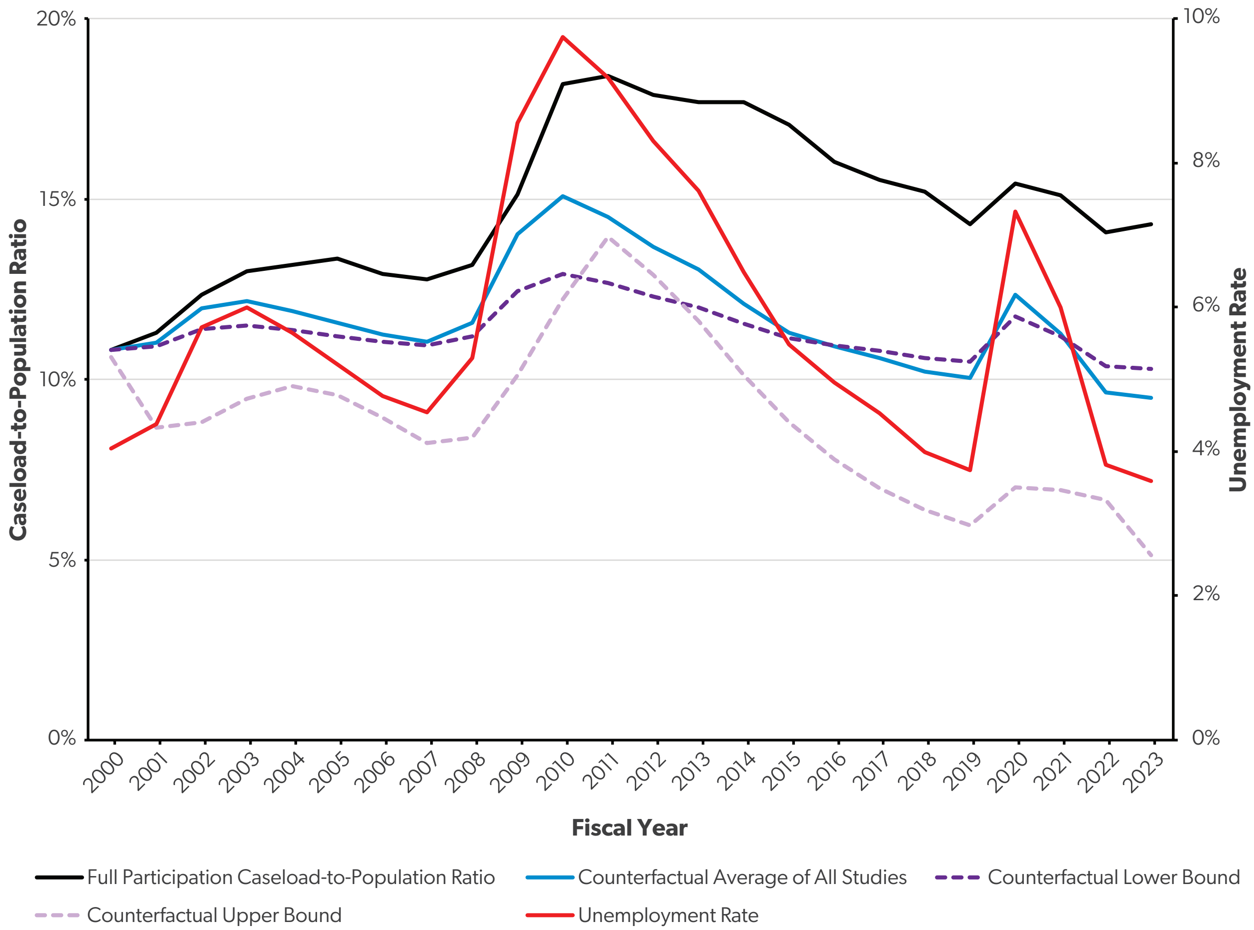
Source: Authors' calculations from USDA (2024), BLS (2024), and US Census Bureau (2024).
Note: The caseload-to-population ratio corresponds with the primary y-axis. The "lower bound" implies that a 1 percentage-point increase in the unemployment rate corresponds with a 3.4 percent increase in the caseload-to-population ratio, while the "upper bound" implies that a sustained 1 percentage-point increase in the three-year unemployment rate corresponds with a 14.8 percent increase in the caseload. County-level unemployment rates come from BLS LAUS and are not corrected for attenuation bias.

Figure A2. SNAP Participation Rate, 2000–23



Source: Vigil and Rahimi (2024); Vigil (2019; 2022).
Note: Participation rates reflect the share of eligible households that receive SNAP benefits in a given year. Participation rates are estimated by USDA and do not account for households that are eligible under only BBCE.

Figure A3. Counterfactual and Actual Caseload-to-Population Ratio Under Full Participation, 2000–23



Source: Authors' calculations from USDA (2024), BLS (2024), and US Census Bureau (2024).
Note: The caseload-to-population ratio corresponds with the primary y-axis. The "low estimate" implies that a 1 percentage-point increase in the unemployment rate corresponds with a 3.4 percent increase in the caseload-to-population ratio, while the "high estimate" implies that a sustained 1 percentage-point increase in the three-year unemployment rate corresponds with a 14.8 percent increase in the caseload. Each counterfactual assumes 100 percent take-up. "Full participation caseload-to-population ratio" displays what the caseload-to-population ratio would be under 100 percent take-up.

Appendix B. Simulating the Size of SNAP Using Different Base Years and Sample Periods

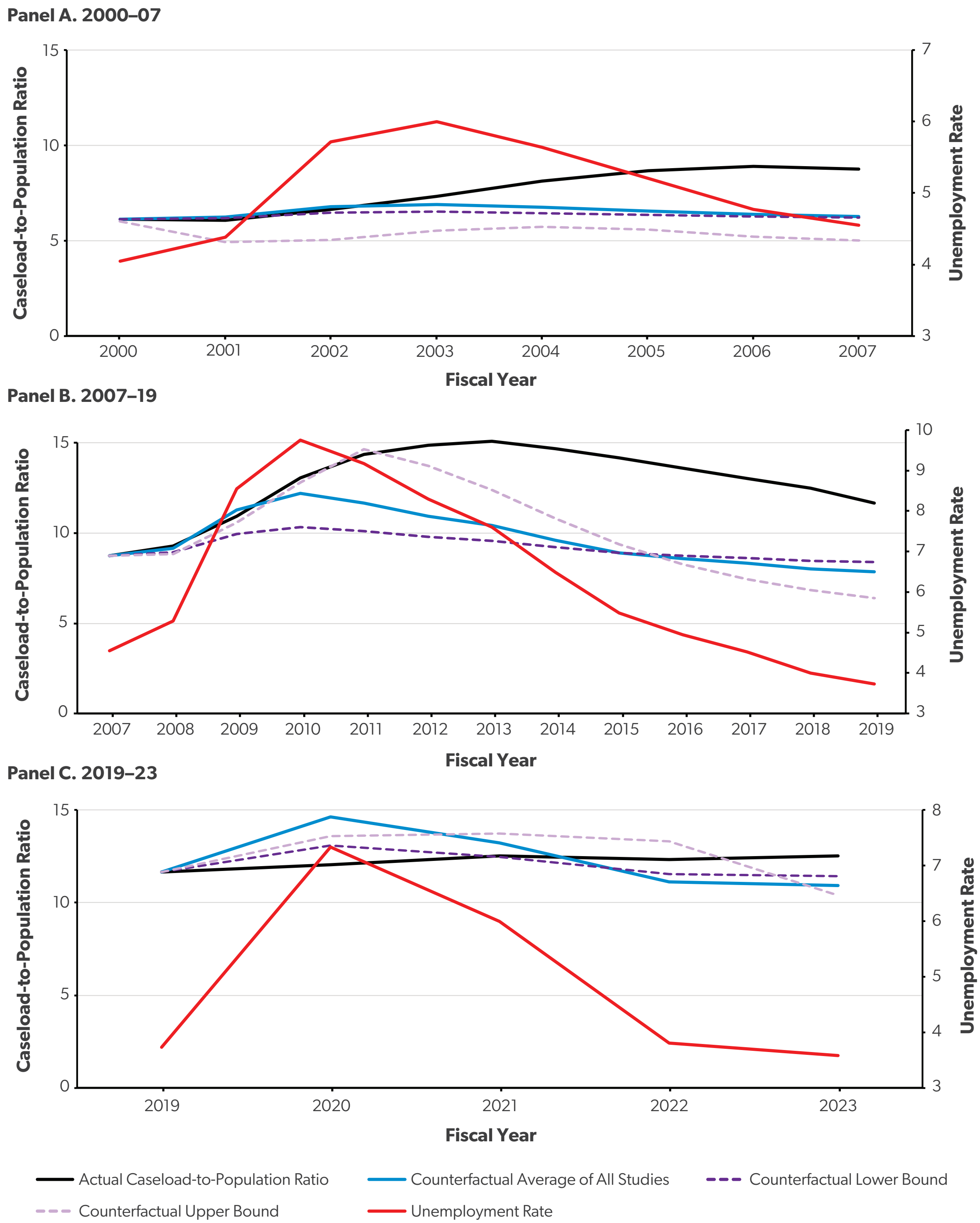
Our long-run counterfactuals show how large SNAP would be if only for changes in the unemployment rate and national population since 2000. However, such analyses do not allow us to observe the extent to which our counterfactuals diverge from actual caseloads across each business cycle. Therefore, in this section, we simulate the SNAP caseload-to-population ratio for three distinct periods—2000–07, 2007–19, and 2019–23—in which we reset the base year to match the beginning of each recession. For example, we start with the actual caseload-to-population ratio in 2007 and use estimates from the literature to simulate the caseload-to-population ratio up to 2019. We similarly use 2019 as our base year and use the same estimates from the literature to project forward until 2023. Based on each new base year, we can observe the responsiveness of SNAP's caseload-to-population ratio following the onset of that recession. Figure B1 presents the results of each counterfactual.

In Panel A, we see that each of our counterfactuals closely tracks the growth in the caseload-to-population ratio, with the exception of Ganong and Liebman (2018). Following 2003, the unemployment rate began to decline, and the counterfactual and actual caseloads began to diverge. In Panel B, we observe a very similar trend: From 2007 to 2010, our average and upper-bound counterfactuals closely track the actual caseload-to-population ratio. However, when the unemployment rate began to decline beginning in 2011, our counterfactuals diverge from the actual caseload-to-population ratio. Finally, in Panel C, we see that all three of our counterfactuals exhibit greater responsiveness to changes in unemployment than the actual caseload. However, from 2020 to 2023, the actual caseload increased linearly, while the counterfactual caseload-to-population ratios declined.

Together, these results suggest that SNAP is a countercyclical program, even in the absence of recession-era policy reforms. In each of the past three recessions, increases in unemployment can explain almost all the increase in SNAP's caseload-to-population ratio. However, SNAP's caseload remains higher than the unemployment rate would predict following each recession.

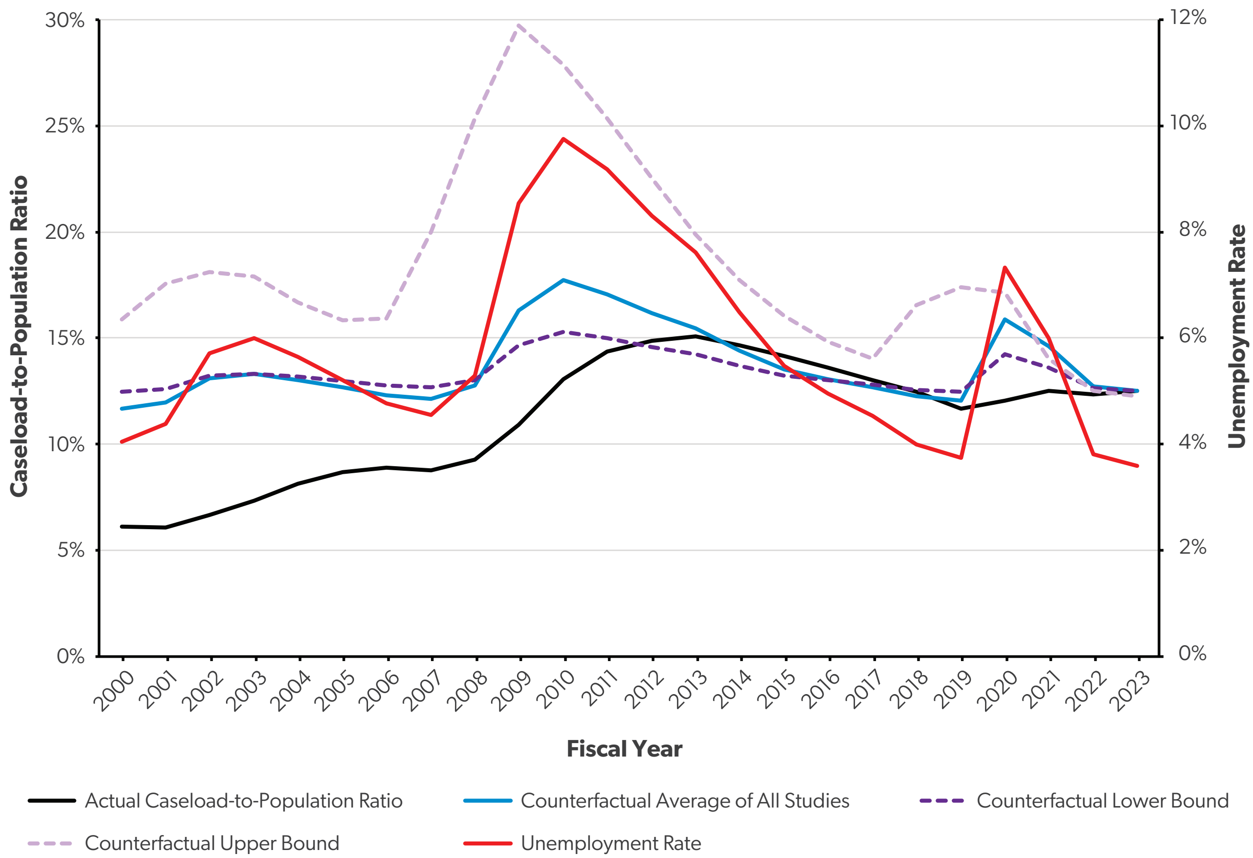
In Figure B2, we present counterfactual trends in SNAP's caseload-to-population using 2023 as our base year and relying on past changes in the unemployment rate to simulate the caseload-to-population ratio. Effectively, this counterfactual shows how large SNAP receipt would have been if the caseload-to-population had historically varied with respect to only the unemployment rate. Note that to simulate the caseload-to-population ratio according to Ganong and Liebman (2018), we continue to use the three-year average change in the unemployment rate. However, because we are not able to observe future unemployment rates, we rely on one- and two-year changes to simulate the caseload-to-population ratio in 2022 and 2021 respectively. By using 2023 as the base year, we observe that historical SNAP caseloads would have been far greater than they were in reality. Specifically, if the caseload-to-population ratio had historically varied with the unemployment rate, the caseload-to-population ratio would have been between 15 and 30 percent at the peak of the Great Recession and roughly double its actual level in 2000.

Figure B1. Counterfactual Caseload-to-Population Ratio Using Different Base Years and Sample Periods



Source: Authors' calculations from USDA (2024), BLS (2024), and US Census Bureau (2024).
Note: The caseload-to-population ratio corresponds with the primary y-axis. The "low estimate" implies that a 1 percentage-point increase in the unemployment rate corresponds with a 3.4 percent increase in the caseload-to-population ratio, while the "high estimate" implies that a 1 percentage-point increase in the caseload-to-population ratio corresponds with a 14.8 percent increase in the caseload.

Figure B2. Counterfactual Caseload-to-Population Ratio Using Base Year 2023, 2000–23



Source: Authors' calculations from USDA (2024), BLS (2024), and US Census Bureau (2024).
Note: The caseload-to-population ratio corresponds with the primary y-axis. The "lower bound" implies that a 1 percentage-point increase in the unemployment rate corresponds with a 3.4 percent increase in the caseload-to-population ratio, while the "upper bound" implies that a 1 percentage-point increase in the caseload-to-population ratio corresponds with a 14.8 percent increase in the caseload.

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