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RESEARCH ARTICLE

Can access to restaurant meals under the Supplemental Nutrition Assistance Program lead to obesity?

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Abstract
Supplemental Nutrition Assistance Program (SNAP) makes an exception to its rules, which allows elderly and/or disabled individuals, their spouses, as well as homeless beneficiaries, to buy hot prepared food from restaurants if they live in a state that participates in the Restaurant Meals Program (RMP). Using the staggered countywide adoption timeline in California, coupled with a stacked difference-in-differences empirical strategy, I examine the intent-to-treat (ITT) nutritional effects of RMP on the elderly population. Overall, I find no evidence that obesity rates for the elderly are any different in counties with RMP versus those without RMP. I can statistically rule out moderate effects. Additional evidence from some of the early-adopting counties suggests that RMP is associated with a reduction in food insecurity among the elderly.

Keywords: food insecurity; obesity; Restaurant Meals Program; SNAP

JEL Classification: I14; I18; I3

Introduction

The United States adult obesity rate has increased by 10 percentage points over the past two decades. Currently, more than 40% of adults live with obesity (CDC 2022). Obesity is linked with some of the most costly health problems in the United States, including diabetes, cardiovascular disease, stroke, cancer, and asthma. Research also shows a clear link between obesity and lower life expectancy, as well as higher medical care costs, for adults compared to those with normal weight (Cawley et al. 2021). Overall, the epidemic costs the health care system $173 billion annually (CDC 2022).

Obesity is more prevalent among low-income households, which has increased the attention toward food assistance programs that are targeted toward the poor. The largest such program is the US Supplemental Nutrition Assistance Program (SNAP), under which the federal government spends billions of dollars to combat food insecurity. The means-tested program provides monthly benefits to low-income households through an electronic debit card, to purchase food from authorized outlets for consumption at home. Typically, the list of items that can be purchased using SNAP benefits is limited to grocery items and excludes hot prepared meals and restaurant meals meant for immediate consumption. Considering many low-income individuals lack the ability to prepare and store meals at home, SNAP introduced the Restaurant Meals Program (RMP) as a state option in 1978. Under RMP, eligible recipients can buy hot prepared food at a discounted rate from authorized restaurants and retailers. To be eligible for RMP, the SNAP recipient must be age 60 and older, disabled, the spouse of someone age 60 and older, or homeless. Unlike child-focused federal food assistance programs, which must follow the 2010 dietary guidelines for Americans, neither SNAP nor RMP is driven by nutrition standards. Both SNAP and RMP have received criticism for lacking emphasis on nutritional standards and for allowing unhealthy food purchases (Franckle et al. 2017; Paarlberg et al. 2018).

Currently RMP is available in nine states, with the widest availability in California.[1,2] Although adoption of the program has been slow, the program is gaining traction, with Virginia implementing the program in 2021; Michigan, Illinois, and Maryland in 2022; and Massachusetts in 2023.[3] Recently one new state, New York, established the program. As the program becomes more widespread, it is important to understand how RMP may affect the health of the target population. A rich literature has investigated the effect of SNAP on health (Conrad et al. 2017; Ettinger de Cuba et al. 2019; Heflin, Ingram, and Ziliak 2019). However, little is known about the effect of RMP on health.

This paper is the first of its nature to present evidence on the intent-to-treat (ITT) nutritional effects of RMP. I focus on individuals belonging to low-income households in California, where counties have had the option to implement the program since 2003, resulting in a staggered county-level adoption. Specifically, I examine the nutritional ITT effects of RMP based on differences in obesity rates between counties with and without RMP, in a stacked difference-in-differences design, using data from 2000 to 2020. I limit my analysis to the non-homeless population over the age of 60 years. I complement my primary analysis by exploiting the age eligibility cutoff of 60 in a triple difference-in-differences design, where I further compare within-county differences between those above and those below the age of 60.

RMP has drawn criticism for allowing participants to eat at fast food chains,[4] which have been linked to weight gain and obesity (Currie et al. 2010). My results provide no evidence to that effect. For my preferred specification, I do not find significant differences in obesity rates between counties with and without RMP. Depending on the specification and subsample, estimates range from small to moderate, but none are statistically

[1]Other than California, the program is currently available in Arizona, Illinois, Maryland, Massachusetts, Michigan, New York, Rhode Island, and Virginia (USDA 2024b).

[2]The widest availability of the program is in California followed by Arizona. Based on the data on participating restaurants obtained from Food and Nutrition Services (FNS) in 2023, 5,722 out of the 7,461 ever participating restaurants were in California, followed by 1,351 in Arizona.

[3]The year of implementation for each state is based on an analysis of the information obtained from FNS in 2023.

[4]For example, an evaluation of RMP in Los Angeles reported that out of the 1,141 RMP-participating restaurants, 982 were national chains, including multiple locations of restaurants such as Carl's Jr., Jack in the Box, Domino's Pizza, Kentucky Fried Chicken, and Pizza Hut. However, some healthier chains such as El Pollo Loco and Subway were also included (Robertson 2020).

significant. The results are robust to using alternative estimators for staggered difference-in-differences research design.[5]

One limitation of this study is that it focuses on low-income individuals who are more likely to be eligible for RMP rather than program participants, leading to a concern that lack of significant results could simply be due to lack of program participation. There is no data set, to the author's knowledge, that directly captures RMP participation by low-income individuals. Although I cannot directly capture how many people participated in the program, I examine whether the program was associated with a reduction in food insecurity, which is the program's primary goal. The evidence on food insecurity is based on some early-adopting counties (those for which data on food insecurity measures is available). My index of food insecurity, which aggregates all relevant food insecurity variables, decreases by 0.205 standard deviation units, indicating a reduction in food insecurity in counties with RMP relative to those without.

I conclude by examining differences in outcomes based on the intensity of treatment, which I measure using the number of participating restaurants in each county by year. My results are consistent with the findings above. I do not find a statistically significant change in obesity rates but find a two-percentage point reduction in the interviewees who experienced hunger in the last year, as a result of a 1% increase in the number of participating restaurants.

Tying together, my results do not indicate an adverse ITT effect of RMP on obesity rates. Though no prior studies have looked at RMP specifically, the results are consistent with other SNAP studies that have found no link between program participation and obesity rates, after controlling for selection bias (Fan 2010; Kaushal 2007). One possible reason could be that low-income individuals who lack the ability to prepare food at home tend to buy food items like those made available under RMP. This RMP potentially does not change the food basket of the target population. This rationale is consistent with what has been observed about SNAP participants and non-participants but requires further research. For example, although SNAP participants spend 20 cents for every dollar on salty snacks, sugar, candy, and sweetened beverages, the spending patterns are similar for non-SNAP households (Schanzenbach 2017). The additional finding that RMP is associated with a reduction in food insecurity is also consistent with what has been observed in prior studies related to SNAP (CBPP 2022b; Keith-Jennings, Llobrera, and Dean 2019).

Literature and background

Literature and contribution

The literature on the relationship between SNAP and weight measures for adults provides varying results (Almada and Tchernis 2018; Fan 2010; Gibson 2003; Kaushal 2007; Kim and Frongillo 2007; Leung and Villamor 2011; Meyerhoefer and Pylypchuk 2008; Ploeg and Ralston 2008). A major challenge in estimation is the fact that characteristics that make a household eligible for SNAP, such as low income, are, on average, associated with poor diet and obesity (French et al. 2019; Levine 2011). This means that correlation studies that do not control for possible selection bias often find a positive correlation between SNAP and obesity (Leung and Villamor 2011; Rigdon et al. 2017).

[5]See Roth et al. (2023) for a recent overview of alternative estimators that address the econometric concerns associated with staggered difference-in-differences design.

Differing techniques have been used to account for selection bias. Gibson (2003) used an individual fixed effects approach and found positive association between SNAP participation and obesity for women, but not for men. Fan (2010) extended on this approach by adding propensity score matching to compare SNAP participants with similar non-participants and did not find a significant effect of SNAP on obesity or BMI. Meyerhoefer and Pylypchuk 2008 used state expenditures on food stamp outreach programs as an instrument for participation and found a significant increase in obesity for women. On the contrary, Kaushal (2007) did not find a significant effect of participation on BMI, though they focused on immigrants, while using legal changes in immigrant eligibility for food stamps as an instrument. Similarly, Alameda and Tchernis (2018) reported no overall effect on obesity levels but found a reduction in BMI for adults with at least one child under 5.

Most of the studies did not find a significant increase in BMI or the likelihood of being overweight or obese for non-elderly men. However, for non-elderly adult women, multiple studies show a link between SNAP and obesity (Gibson 2003; Meyerhoefer and Pylypchuk 2008).

The literature related to the elderly population is limited. Only one prior study examined the relationship between SNAP and weight among the elderly and found some evidence that among food-insecure elders, those who participated in the program were less likely to be overweight than those who did not participate (Kim and Frongillo 2007).

One concern when studying the elderly population has been the low SNAP participation rates among the elderly (Eslami 2015; Giordono et al. 2022). Approximately 55% of eligible elderly did not participate in SNAP in 2022 (USDA 2024c). Several factors have been associated with low participation among the elderly, including lack of information about eligibility (Wu 2009), costs associated with the application and benefit use, and lack of belief that SNAP benefits are worth the effort of going through the application process (Gabor et al. 2002). Across the general population, several programmatic features of SNAP that expand generosity, enhance eligibility, and reduce transactions costs have been shown to increase participation rates. For elderly participation in particular, prior evidence has been limited to policies that expand eligibility (Jones et al. 2022).

While RMP does not expand eligibility, it does increase the generosity of the program. RMP has the potential to increase elderly SNAP participation by improving access, making prepared products available at a cheaper price, and thereby increasing the benefit of using SNAP.

This paper makes two contributions to the literature. First, this is the first paper, to my knowledge, to study the effect of RMP. Second, this paper expands on existing literature related to SNAP by providing further evidence of weight-related outcomes for the elderly.

SNAP background and eligibility

SNAP is a government assistance program designed to combat food insecurity in the United States by providing food assistance to needy families. It is the largest anti-hunger program in the country, currently reaching 42 million Americans (USDA 2023). The program is authorized nationally by the United States Department of Agriculture (USDA) and targets low-income households, low-income older adults, and people with disabilities. Prior to the pandemic, approximately 90% of the participants were in households with children under age 18, an adult age 60 or older, or an individual with a disability (CBPP 2022a). SNAP is federally funded but is administered by state agencies. In California SNAP is known as CalFresh, which is overseen by the California Department of Social

Services (CDSS) and currently serves 4.8 million individuals, belonging to 2.8 million households (CDSS 2023a). CalFresh is a state-supervised and county-administered initiative.

Basic eligibility of CalFresh requires passing two income tests. The gross income test requires that a household's gross income does not exceed 200% of the federal poverty threshold for the household's size, while the net income test requires that net income, which is gross income after standard deductions, should be at or less than 100% of the federal poverty threshold.[6]

Rules of eligibility differ for households containing an individual aged 60 or older or someone with a disability. These households are exempt from the gross income test, whereas the net income test still applies. Additionally, they are required to pass an asset test if their gross income is over 200% of the federal poverty threshold. The asset test requires that assets must fall below certain limits, which are adjusted for inflation each financial year: currently $4,250.

Several aspects of the program make it easier for those aged 60 or older, those with a disability, and their spouses to qualify for benefits. They do not have to satisfy the gross income test, and the definition of SNAP household is more flexible for them.

Typically, a SNAP household is defined as a group of people who live together and purchase and prepare meals together, but people aged 60 or older, people with a disability, and their spouses can be considered a separate household if they live with others who have an income below 165% of the poverty level.

Upon verification of eligibility, the CalFresh office certifies a household to receive benefits for a certain number of months, after which their eligibility is reconfirmed. The certification period can be as short as one month or as long as one year and can be even longer, up to 24 to 36 months, for households with only elderly or disabled members.

Under the program, eligible households receive monthly benefits on an Electronic Benefit Transfer (EBT) card, which is similar to a debit card, that they can then use to buy groceries from USDA-approved stores and retailers.[7] The list of items that can be purchased using the card is limited and only covers food intended for home preparation and consumption.[8] The benefits cannot be used to purchase hot food or prepared food intended for immediate consumption, unless their state participates in SNAP RMP.

RMP background and eligibility

SNAP benefits are designed for individuals and households who have access to a refrigerator and a space to prepare meals. SNAP benefits cannot be used to buy food items from restaurants or items that are hot and/or prepared at the point of sale from grocery stores (e.g., rotisserie chicken, soup bar, deli-prepared foods). However, many SNAP recipients are elderly, disabled, or homeless individuals who lack the ability to store and prepare food safely. California implemented RMP to bridge this gap by allowing more

[6]SNAP eligibility rules differ from state to state. California is one of the states that implements the broad-based categorical eligibility (BBCE) under which households can become categorically eligible for SNAP if they qualify for a non-cash Temporary Assistance for Needy Families (TANF) or state maintenance-of-effort (MOE) funded benefit (USDA 2024a).

[7]The benefits differ by state and are adjusted annually to account for inflation and economic conditions. In 2023 the average monthly benefit per household member under CalFresh was $196 (Hall and Nchako 2023).

[8]Eligible food items include fruits, vegetables, meat, poultry, fish, dairy products, breads, cereals, snack foods, non-alcoholic beverages, and food-producing seeds and plants.

vulnerable individuals another way to use CalFresh benefits – purchasing prepared food at a discounted rate from authorized restaurants and grocery stores.

California began a pilot RMP in San Francisco County in 2003, and it remained as a county option until statewide adoption in September 2021. Between 2003 and 2021, several counties decided to host the program. Currently 37 out of the 58 counties in California have federally approved RMP restaurant vendors, out of which 22 voluntarily opted into the program before statewide adoption.[9]

The program is targeted toward CalFresh benefit recipients who are (i) 60 or older, (ii) disabled, (iii) the spouse of someone above 60 or disabled, or (iv) experiencing homelessness.

On the retailer side, restaurants that want to participate in RMP must get approval from their state and provide a signed agreement to USDA Food and Nutrition Services (FNS), which then authorizes the restaurant to accept SNAP benefits.

Data and descriptive statistics

Data

The analysis relies on two data sources. The first data source consists of California Behavioral Risk Factor Surveillance System (BRFSS), which includes questions related to weight, and height, along with other demographic details. The second source specifies the dates which restaurants were authorized by FNS to participate in the RMP.

California BRFSS

California BRFSS is a combined effort of the California Department of Public Health (CDPH) and the Centers for Disease Control and Prevention (CDC). Data is compiled using telephone surveys that collect health-related information on California residents aged 18 years and older who are not homeless.[10] Beyond questions about health, the survey also includes demographic characteristics such as age, marital status, income, race/ ethnicity, education, health insurance, employment status, and county identifiers. Data used is from 2000 to 2020.

The primary sample was constructed by restricting the data set to individuals between the ages of 60 and 75, who are more likely to be CalFresh recipients. The data set does not include information on interviewee's household assets or net income, so I use two main criteria to focus on lower income households – if (i) their household income falls below 200% of the federal poverty limit, or if (ii) they are Medi-Cal recipients, as approximately 90% of CalFresh beneficiaries also receive Medi-Cal benefits.[11,12]

[9]For a current list of counties in California with RMP restaurant vendors, see CDSS (2023b).

[10]California BRFSS was obtained by contacting CDPH directly.

[11]Although the data set includes questions related to SNAP/CalFresh participation from 2004 to 2015, I focus on the group with a high likelihood of SNAP participation rather than reported participation for three reasons: (i) approximately 72 percent of the responses to the questions related to SNAP participation were missing values, leading to a very small sample size; (ii) the questions asked between 2004 to 2015 were worded differently in different years, which makes it difficult to compare participation over the years; (iii) approximately 94% of the interviewees who responded positively to SNAP participation were part of the primary sample constructed.

[12]Although 90 percent of CalFresh recipients also receive Medi-Cal benefits, they represent a small share, approximately 30 percent, of Medi-Cal recipients (CDSS 2024). In the results section, I test the robustness of results by excluding interviewees included in the sample solely based on the Medi-Cal participation criteria.

Respondents are asked about their height and weight, and that information is used to calculate their BMI, which is included in the data set as a separate variable. I use BMI to construct a dummy variable for obesity, which takes a value of 1 if an interviewee's BMI is greater than or equal to 30.

Restaurant Authorization Dates Data

The data on participating restaurants and redemptions was obtained from SNAP, Retailer Policy Division (RPD), by contacting FNS. The data set includes all restaurants that have participated in the RMP since 2000, including each retailer's complete address, the date when each restaurant was authorized to participate in RMP by FNS, and the date authorization ended. Table 1, column (1) lists the counties for which data is available in California BRFSS. Column (2) indicates whether the listed county participated in RMP before statewide adoption on September 1, 2021, and for the ones that did, column (3) provides the exact date when the first restaurant was authorized in the county by FNS.[13] Restaurant-level information is aggregated at a county-year level to construct the number of participating restaurants in each county.

My primary treatment variable is an indicator for whether a county has RMP in a particular year. A county is considered treated the year after authorization of the first participating restaurant. A few exceptions should be noted. First, for Riverside County, the first restaurant was authorized in 2011, but there were no participating restaurants between 2012 and 2017. In 2018 the county had 101 participating restaurants, so 2018 is considered as the first year of treatment. Secondly, in some counties, restaurant participation stayed low, and the number of participating restaurants declined to zero after the initial authorization, suggesting that the program was not successful in these counties. Such counties are marked with an asterisk in column (1) of Table 1 and are considered never treated.[14] Column (4) in Table 1 identifies the counties that are considered treated. Table AI in the appendix provides a detailed description of years that are considered treated for the primary treatment variable.

The data provided by FNS also includes information on SNAP redemptions at RMP-participating retailers for each county-year. For some counties the redemption amounts are redacted, for years where the number of authorized restaurants were below the threshold for public release of redemption data.[15] The redacted values are considered as missing for all analyses. Table AI, column (4) in the appendix provides a detailed description of county-years for which redemption data is redacted.

Figure 1 shows trends in CalFresh benefit redemptions by treatment cohort, where treatment cohort is defined as a group of counties that had the same initial year of treatment. Redemption amounts are in millions of dollars per 100,000 CalFresh benefit recipients.[16] Treatment cohorts are as follows: San Francisco had its first RMP restaurant in 2003; Los Angeles in 2005; Sacramento and Santa Clara in 2007; Alameda, San Diego and San Luis Obispo in 2012; Orange and Santa Cruz in 2013; and Riverside in 2018.

[13]Since its statewide adoption, RMP has become more widespread. Currently all the counties listed in column (1) of Table 1 have RMP-participating vendors.

[14]Counties marked with an asterisk in column (1) are assigned a treatment value of zero for all years.

[15]Redemption data was not made available at an individual retailer level, as FNS does not provide records for individual companies. The Supreme Court found that the store-level SNAP data is confidential under Exemption 4. To prevent retailer identification, the redemption information is redacted for years where the number of authorized stores per county was below the threshold for public release of redemption data.

[16]Number of CalFresh benefit recipients by county and year was obtained from the US Census Bureau website: https://www.census.gov/data/datasets/time-series/demo/saipe/model-tables.html.

Table 1. RMP introduction dates

(1) County name	(2) Restaurants meal program	(3) First authorized restaurant	(4) Treated
Alameda	√	6/13/2012	√
Butte			
Contra Costa			
El Dorado			
Fresno			
Humboldt*	√	4/18/2019	
Imperial			
Kern*	√	12/21/2005	
Kings			
Los Angeles	√	6/29/2005	√
Madera*	√	3/25/2021	
Marin			
Merced			
Monterey*	√	7/8/2013	
Napa			
Orange	√	5/7/2013	√
Placer			
Riverside	√	4/22/2011	√
Sacramento	√	6/12/2007	√
San Bernardino*	√	5/1/2014	
San Diego	√	11/27/2012	√
San Francisco	√	2/6/2003	√
San Joaquin			
San Luis Obispo	√	8/3/2012	√
San Mateo*	√	8/25/2014	
Santa Barbara*	√	7/8/2013	
Santa Clara	√	11/29/2007	√
Santa Cruz	√	2/13/2013	√
Shasta			
Solano			
Sonoma			
Stanislaus*	√	6/6/2006	

(*Continued*)

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Table 1. (*Continued*)

(1) County name	(2) Restaurants meal program	(3) First authorized restaurant	(4) Treated
Tulare			
Ventura*	√	8/31/2010	
Yolo			

Notes: Column (1) in the table above provides a list of counties in California that are included in the CA-BRFSS data from 2000 to 2020. Column (2) indicates whether a county had a RMP participating restaurant before the statewide adoption on 9/1/2021, column (3) includes the date when the first restaurant in the county was authorized by FNS, and column (4) identifies whether the county is considered treated in my analysis.
*Indicates counties that are not considered treated for the following reasons – (1) They never had more than five participating restaurants; or (2) Within a few years of initial authorization, the number of participating restaurants decreased to zero.

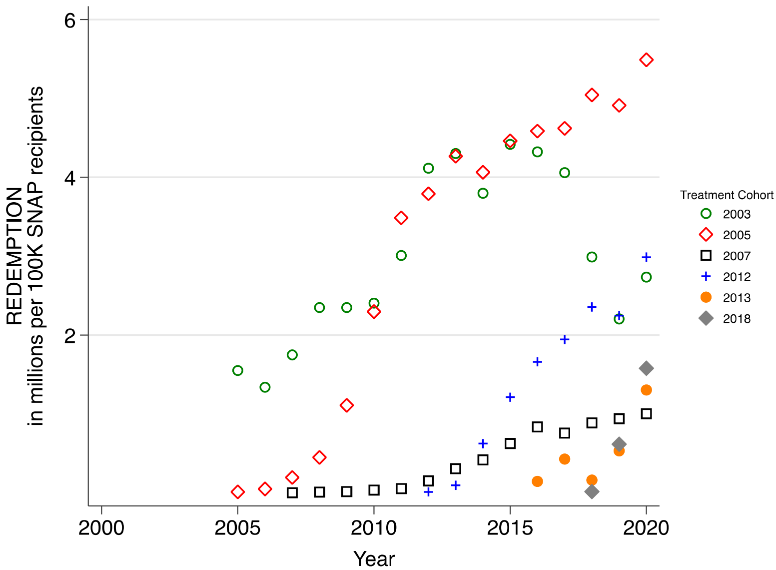

Figure 1. CalFresh benefit redemption at RMP participating restaurants by treatment cohort.
Notes: The plot above shows SNAP/CalFresh benefits that were redeemed at RMP participating restaurants per 100,000 SNAP benefit recipients by treatment cohort. The vertical axis includes dollars in millions. Treatment cohorts are as follows: 2003 includes San Francisco (in green with circle markers), 2005 includes Los Angeles (in red with diamond markers), 2007 includes Sacramento and Santa Clara (in black with square markers), 2012 includes Alameda, San Diego and San Luis Obispo (in blue with cross markers), 2013 includes Orange and Santa Cruz (in orange with circle markers) and 2018 includes Riverside (in gray with diamond markers). Some values were redacted by FNS and are not shown in the plot.

Some values were redacted by FNS and are not shown in the plot. All but one cohort experienced an increase in redemptions over time. The only exception is the 2003 cohort, which represents San Francisco County, which saw a steady increase in redemptions until a sharp decline in 2018 that continued thereafter. Figure A1 shows a similar plot, where

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RMP redemptions are shown as a percentage of total CalFresh benefits issued in each treatment cohort. RMP redemptions have been increasing over time but represent a small proportion of total issued benefits.[17]

Figure A2 explores the relationship between number of participating restaurants and dollars redeemed at participating restaurants per 100,000 SNAP recipients, measured in natural logarithms. The two variables are very highly and positively correlated.

Many of the participating retailers in RMP in California are national chains. A non-exhaustive list of top participating national chains is provided in Appendix Table AII. Restaurants listed in the table make up approximately 71% of all participating retailers. The most common participants are Subway chains (16.71%), followed by Jack in the Box (10.53%), Pizza Hut (6.85%), and KFC (5.88%).

Descriptive statistics

Table 2 presents the characteristics of the primary sample. All values are computed using survey weights. The average age in the sample is 66.68, where 43% of the individuals are male and 47% report being currently married. The average household size is 2.75, and 64% of the individuals report having a household income of less than $20,000. The two county types are comparable in terms of age, proportion male, proportion married, and income groups. The treated counties, however, are more diverse, have higher proportion of college graduates, have a smaller proportion of those who are unable to work, come from slightly larger households, and are less likely to be smokers. Looking at the outcome variable, counties with RMP are less obese than counties without RMP. The differences between the two groups may lead one to wonder about the plausibility of the parallel trends assumption in this setting. I address these concerns in the results section.

Empirical strategy

I estimate the effect of RMP introduction by comparing the before-after difference in obesity rates in counties that opted into RMP relative to counties that either opted later or never opted into RMP, using a stacked difference-in-differences design.

Following Cengiz et al. (2019) and Deshpande and Li (2019), I construct the stacked sample as follows. First, I restrict my primary analysis to treatment cohorts with at least five years of pre-treatment data and seven years of post-treatment data. Next, I create separate data sets for each of the treatment cohorts. In each data set, counties that opted into RMP are labeled as treated, while counties that opted into the program eight years later and counties that never opted into RMP are labeled as control counties.[18] Last, I append all stacks into one data set.

[17]Since the RMP-eligible population is a relatively small subsection of CalFresh participants, it is not surprising that RMP redemptions are a small portion of total benefits issued. For example, in July 2014 only about 5% of total CalFresh beneficiaries in the four treated cohorts (2003, 2005, 2007, and 2012) were 60 or older (CDSS 2023a). For the same treated cohorts, 1.5% of total benefits issued to all CalFresh beneficiaries were redeemed at RMP-participating restaurants in 2014.

[18]The counties marked with an asterisk in column (1) of Table 1 are included in the control group. They are considered never treated (or to have never opted into RMP). In the results section, I test the robustness of my results by excluding these counties from the analysis, as well as by changing the event windows, and by using different control groups.

Table 2. Summary statistics for primary sample and by RMP status

	(1) Primary Sample mean	(2) Counties with RMP mean	(3) Counties without RMP mean	(4) *p*-Values from *t*-tests RMP vs no RMP
County demographics				
Age	66.68	66.63	66.77	0.539
Male	43%	44%	42%	0.153
Education				
Less than high school	31%	31%	30%	0.624
High school graduate	24%	22%	27%	0.002
Some college/ technical scl.	26%	26%	27%	0.405
College grad or higher	19%	21%	16%	0.005
Married	47%	48%	45%	0.126
Race/ethnicity				
White/non-Hispanic	41%	35%	52%	0.000
Black/non-Hispanic	8%	11%	4%	0.000
Hispanic	35%	37%	31%	0.042
Other/non-Hispanic	15%	17%	12%	0.030
Employment				
Employed	20%	21%	19%	0.119
out of work	7%	7%	6%	0.178
Retired	48%	48%	48%	0.794
Unable to work	17%	16%	21%	0.000
Have a health plan	91%	90%	93%	0.027
Income				
Less than $10,000	23%	23%	22%	0.635
10K≤income<20K	41%	40%	42%	0.514
20K≤income<35K	26%	25%	26%	0.742
≥35K	11%	12%	10%	0.417
Household Size	2.75	2.88	2.54	0.000
Smoker	15%	14%	16%	0.045

(*Continued*)

Table 2. (*Continued*)

	(1) Primary Sample mean	(2) Counties with RMP mean	(3) Counties without RMP mean	(4) *p*-Values from *t*-tests RMP vs no RMP
Outcome				
Obese	30%	29%	33%	0.024
Number of counties	35	10	25	
Number of observations	12,908	7,531	5,377	

Notes: This table presents summary statistics for the primary sample and separately by RMP status of counties. The data is obtained by merging the restaurant dates data set with the California BRFSS. Primary sample is obtained by restricting to those who are 60- to 75-year-old and who either have an income below 200% of the federal poverty limit or are Medi-Cal recipients. Counties are classified as treated (with RMP) if counties had a participating RMP restaurant with some exceptions: (i) number of restaurants did not decline to zero after few years; (ii) number of participating restaurants was not below five in every given year. Otherwise, the counties are classified as untreated (without RMP). Means are computed using survey weights provided in California BRFSS. The last column provides *p*-values from *t*-tests.

To estimate the effects of introduction of RMP in regression form, I estimate the following equation on the sample:

$$Y_{icgst} = \alpha_{cs} + \delta_{ts} + \beta(Treated_{cs} \times Post_{st}) + \kappa(Treated_{cs} \times Zero_{st}) + \gamma \times \mathbf{X}_i + \epsilon_{ict} \quad (1)$$

Where Y_{icgst} is an outcome for interviewee i in year t and county c that belongs to treatment cohort g and stack s. α_{cs} (or sometimes α_{gs}) indicates county-by-stack (or treatment cohort by stack) fixed effects, δ_{ts} indicates calendar-year-by-stack fixed effects. $\mathbf{X}_i$ are vectors of interviewee-level controls, including age, gender, employment status, education level, race/ethnicity, marital status, smoking status, and an indicator for whether the individual has a health plan. $Treted_{cs}$ is an indicator equal to 1 if county c is a treated county for stack s. $Post_{st}$ is an indicator equal to 1 if calendar year t is after the first restaurant was authorized for RMP in stack s, and $Zero_{st}$ is an indicator equal to 1 if calendar year t is the year of authorization of the first restaurant. I dummy the year of adoption because it is unclear whether to group the year of adoption with the "pre" or "post" period. All regressions are weighted using survey weights, and standard errors are clustered at the county level. I report estimates of β in the tables.

The identifying assumption of the difference-in-differences model is that, in the absence of RMP, obesity rates would have evolved similarly in counties that opted into the program relative to later-adopting and never-adopting counties. Though the assumption cannot be explicitly tested, I provide support for the assumption by estimating a fully dynamic version of equation (1) and checking for potential pretends. I also explore the existence of pretends using the two-way fixed effects (TWFE) model and by estimating a fully dynamic version of the alternative estimators introduced in de Chaisemartin and D'Haultfoeuille (2020), Sun and Abraham (2021), and Callaway and Sant'Anna (2021).

Results

ITT effect of RMP on obesity rates

Figure 2 shows the ITT effect of RMP on obesity rates in counties that opted into the program, based on estimates from the dynamic version of equation (1). The figure also

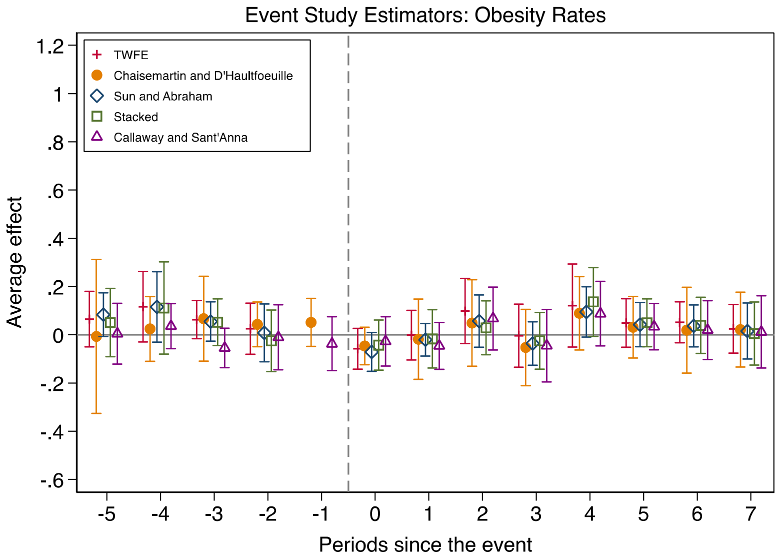

Figure 2. Event study plots for obesity rate.

Notes: The figure above shows event study plots constructed using five different estimators: a dynamic version of stacked DID model given in equation (1) (in green with square markers); a dynamic version of the TWFE model (in red with cross markers); De Chaisemartin and D'Haultfoeuille (2020) (in orange with circle markers); Sun and Abraham (2021) (in blue with diamond markers); and Callaway and Sant'Anna (in purple with triangle markers). The outcome variable is obesity rates, and the time variable is the year relative to the year of authorization of the first participating restaurant in the county. Standard errors are clustered at the county level.

includes dynamic estimates based on TWFE, de Chaisemartin and D'Haultfoeuille (2020), Sun and Abraham (2021), and Callaway and Sant'Anna (2021). None of the specifications include controls, and all standard errors are clustered at the county level. Notice that treated and control counties exhibit parallel trends in obesity rates prior to event year 0. Estimates are similar across specifications and remain insignificant in the after years.

Table 3 presents estimates of β in equation (1). The first column in the table shows results from the simplest specification, which includes cohort-by-stack fixed effects, year-by-stack fixed effects, and an interaction term between indicators for treated and post-RMP. In the second column I include controls. In the third column I replace cohort-by-stack fixed effects with county-by-stack fixed effects. The results are stable across specifications in terms of direction and significance. The point estimates are small, negative, and decrease upon the inclusion of controls, but remain insignificant when county fixed effects are included. Table AIII presents results for BMI as a separate outcome. Estimate for the preferred specification is small, negative, and insignificant.

Robustness

I probe the robustness of my results by using a different stack window, different sample selection criteria, and different control groups. Table 4 presents robustness of the main results by using three-year pre- and two-year post-windows in columns (3) and (4), removing later treated counties from the control group in columns (5) and (6), removing never treated counties from the control group in columns (7) and (8), changing the age

Table 3. Results: obesity rates

	Obesity rates		
	(1)	(2)	(3)
Treated × Post	−0.003 (0.030)	−0.014 (0.027)	−0.018 (0.027)
County by stack FE			√
Cohort by stack FE	√	√	
Year by stack FE	√	√	√
Controls		√	√
Observations	21,146	20,156	20,156

Notes: The table explores the effect of the introduction of Restaurant Meals Program on obesity rates. Specifically, it presents estimates of coefficient β from equation (1) with obesity rates as the outcome variable. Column (1) estimates equation (1) without including controls; column (2) estimates equation (1) including controls; column (3), my preferred specification, replaces treatment cohort by stack fixed effects with county by stack fixed effects. Controls consist of age, gender, marital status, insurance status, smoking status, race/ethnicity, employment status, and education level. Standard errors in parentheses are clustered at the county level.

criteria to all above 60 in columns (9) and (10), and last by removing all those interviewees from the sample that are covered by Medi-Cal but whose income is above 200% of the FPL. Overall, estimates vary in magnitude from small to moderate, but remain negative and insignificant.

In the main specification, counties where the program was unsuccessful are treated as never-treated counties. These never-treated counties are smaller in terms of population, more rural, and have lower average income compared to those where the program was successful. Given that BMI obesity rates are higher in more rural areas, the estimates provided in the main specification are potentially downward-biased. When treated counties are compared only to later-adopting counties in Table 4 columns (7) and (8), the estimates turn positive but remain small and statistically insignificant.

I further probe the estimates by focusing on the age eligibility criteria of RMP in a triple difference-in-differences design. I modify equation (1) to include differences in outcomes between those above the age of 60 and those below the age of 60. More specifically, I estimate the following equation:

$$Y_{icgst} = \alpha_{cs} + \delta_{ts} + \varsigma_{as} + \alpha_{cs}\delta_{ts} + \delta_{ts}\varsigma_{as} + \alpha_{cs}\varsigma_{as} + \beta(Treated_{cs} \times Post_{st} \times Above_{is}) \\ + \kappa(Treated_{cs} \times Zero_{st} \times Above_{ist}) + \gamma \times \mathbf{X_i} + \epsilon_{ict} \quad (2)$$

Where ς_{as} represents the age-group-by-stack fixed effects and $Above_{is}$ is an indicator that equals 1 if interviewee i in stack s is above the age of 60. All other variables are the same as defined under equation 1. I focus on all interviewees between the ages of 45 and 75. Results from the triple difference-in-differences design are provided in Table 5. Columns (1) and (2) provide estimates of β with and without controls. Column (3) presents estimates after replacing cohort-by-stack fixed effects with county-by-stack fixed effects. Since those below the age of 60 may be eligible based on a disability or by virtue of being married to someone above 60 or with a disability, I remove those with any reported disability in columns (4) through (6) and subsequently remove all those who are currently unmarried in columns (7) through (9). Controls consist of age, gender, marital status, insurance status, smoking status, race/ethnicity, employment, and education level.

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Table 4. Robustness checks

	Main specification		3 years pre- and 2 years post-treatment window		Excluding later adopting counties from the control group		Excluding never adopting counties from the control group		Age ≥ 60 years	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treated × Post	−0.014 (0.027)	−0.018 (0.027)	−0.017 (0.034)	−0.026 (0.036)	−0.018 (0.027)	−0.020 (0.028)	0.004 (0.029)	0.001 (0.029)	−0.020 (0.022)	−0.020 (0.022)
County by stack FE		√		√		√		√		√
Cohort by stack FE	√		√		√		√		√	
Year by stack FE	√	√	√	√	√	√	√	√	√	√
Controls	√	√	√	√	√	√	√	√	√	√
Observations	20,156	20,156	12,768	12,768	18,480	18,480	12,677	12,677	31,372	31,372

	Excluding Medi-Cal recipients with income above 200% FPL	
	(11)	(12)
Treated × Post	−0.017 (0.030)	−0.020 (0.031)
County by stack FE		√
Cohort by stack FE	√	
Year by stack FE	√	√
Controls	√	√
Observations	18,389	18,389

Notes: The table explores the robustness of primary results to varying window, control groups, and inclusion criteria. Columns (1) and (2) replicate the estimates of coefficient β from equation (1) with obesity rates as the outcome variable. Columns (3) and (4) provide estimates for a smaller window (3 years pre- and 2 years post-treatment) that allows all treated cohorts to be included in the sample. Columns (5) and (6) provide estimates after excluding all later adopting counties from the control group. Columns (7) and (8) provide estimates after removing all those counties from the control group that didn't adopt RMP voluntarily before the statewide adoption. Columns (9) and (10) provide estimates for all above the age of 60 and the last two columns, (11) and (12), provide estimates after excluding MediCal recipients whose income is above 200% FPL. Controls consist of age, gender, marital status, insurance status, smoking status, race/ethnicity, employment status, and education level. Standard errors are clustered at the county level.

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Table 5. Results: triple difference-in-differences

	All 45- to 75-year-old			45- to 75-year-old No reported disability			45- to 75-year-old Neither married nor have a disability		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treated × Post × Above	0.006 (0.028)	−0.012 (0.025)	−0.019 (0.025)	−0.000 (0.052)	0.001 (0.050)	0.039 (0.053)	−0.009 (0.050)	−0.014 (0.056)	−0.017 (0.053)
County by stack FE			√			√			√
Cohort by stack FE	√	√		√	√		√	√	
Age group by stack FE	√	√	√	√	√	√	√	√	√
Year by stack FE	√	√	√	√	√	√	√	√	√
County by year by stack FE			√			√			√
County by age group by stack FE			√			√			√
Cohort by year by stack FE	√	√		√	√		√	√	
Cohort by age group by stack FE	√	√		√	√		√	√	
Year by age group by stack FE	√	√	√	√	√	√	√	√	√
Controls		√	√		√	√		√	√
Observations	44,722	42,881	42,871	24,881	22,954	23,897	13,217	12,739	12,594

Notes: The table explores the effect of the introduction of Restaurant Meals Program on obesity rates using a triple difference in differences design. Specifically, it presents estimates of coefficient β from equation (2) with obesity rates as the outcome variable. Column (1) estimates equation (2) without including controls; column (2) estimates equation (2) including controls; column (3), my preferred specification, replaces treatment cohort by stack fixed effects with county by stack fixed effects. Estimates are reported separately for those without any reported disability in columns (4) through (6) and for those who are currently unmarried and do not have a disability in columns (7) through (9). Controls consist of age, gender, marital status, insurance status, smoking status, race/ethnicity, employment, and education level. Standard errors in parentheses are clustered at the county level.

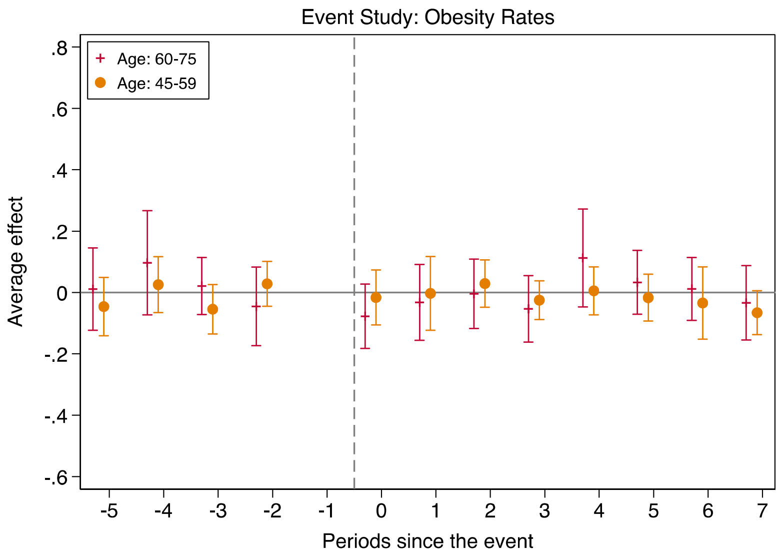


Figure 3. Event study plot for obesity rate by age group.

Notes: The figure above shows event study estimates from stacked difference-in-differences for those 60 to 75 years of age (in red with cross markers) and those 45–59 years of age (in orange with circle markers. The outcome variable is obesity rates, and the time variable is the year relative to the year of authorization of the first participating restaurant in the county. Standard errors are clustered at the county level.

Standard errors are clustered at the county level. Consistent with the findings above, all estimates remain statistically insignificant.

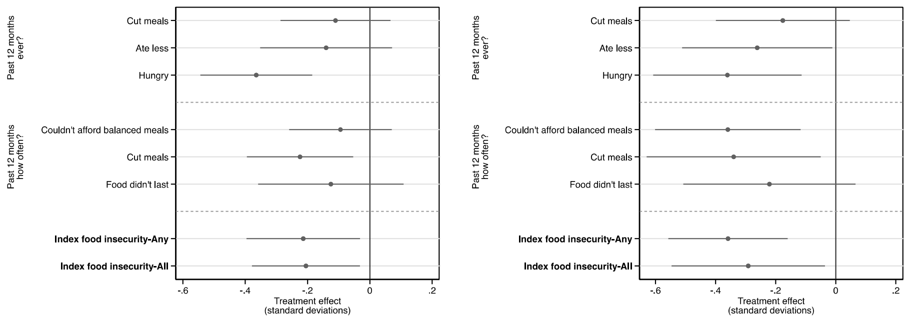
I also estimate the dynamic version of equation (1) separately for each age group and provide the results in Fig. 3. Estimates are similar across the two groups and remain statistically insignificant in the after period.

I conduct additional robustness tests by excluding counties belonging to each treatment cohort in turn in Table AIV (see appendix). I present estimates separately, using difference-in-differences and triple difference-in-differences. The largest change in magnitude is upon the exclusion of the 2005 cohort, but estimates remain consistently insignificant.

ITT effect of RMP on food insecurity

One consideration while interpreting the estimates from equation (1) is that the lack of significant effects on obesity rates could simply be due to lack of participation into the program. While data limitations do not allow me to test the effect of RMP on the eligible population's participation in the program, I provide supporting evidence from some early-adopting counties by assessing the program's ITT effect on food insecurity, the program's primary target.

California BRFSS includes several questions related to food insecurity, but while questions related to BMI were asked in each survey year, questions related to food insecurity were only asked from 2003 to 2013. Specifically, the California BRFSS survey



Panel A-DID **Panel B-Triple DID**

Figure 4. Intent-to-treat effect of the introduction of RMP on food insecurity.
Notes: The figure explores the ITT effect of the introduction of RMP on all outcomes related to food insecurity and on related indices. Specifically, it presents estimates of β from equation (1) in panel A and from equation (2) in panel B from my preferred specification. All outcomes are standardized so that for never treated counties, they have a mean of zero and a standard deviation of one. Controls consist of age, gender, marital status, insurance status, smoking status, race/ethnicity, employment, and education level. Standard errors are clustered at the county level.

asked six questions about food insecurity experienced by interviewees in the past twelve months: (i) how often someone could not afford to eat balanced meals, (ii) whether the person or a household member cut the size of their meal due to limited food or money, (iii) how often did they cut their meal size, (iv) whether they ate less than they wanted to or felt like they should eat less because there was not enough money, (v) were they ever hungry but did not eat because they could not afford enough food, and (vi) how often did the food they buy not last and they could not afford to get more. I consider all six questions and create an index of food insecurity, where all observations with any missing components are excluded (referred to as "FI Index-All"). The index was created as follows: first, all variables that compose the index were oriented in such a way that higher values indicate greater food insecurity; second, means and standard deviations for never-treated counties were used to standardize each variable; third, an equally weighted average of the index components was created, where all observations with any missing components were excluded. Last, the final index was standardized using the mean and standard deviation for never-treated counties. Another index was created in a similar fashion, in which all observations with even a single non-missing component were included (referred to as "FI Index-Any").

Estimates of β from equations (1) and (2) are presented in Fig. 4, where all outcomes are in standard deviation units. Due to limited years of data on food insecurity outcomes, I am only able to examine 2005 and 2007 stacks. I use full years of data for each stack without any window restriction and later test the robustness of my results by changing window length and including the 2012 stack in the sample. All estimates for outcomes related to food insecurity are negative, including the estimates for indices. The overall index of food insecurity, FI Index-All, decreased by 0.205 standard deviation units and is statistically significant at a 5% significance level.

Results are similar for the two indices, though the magnitude of decrease is slightly larger when all observations with even a single non-missing component are included. The decrease in index is primarily driven by a 0.365 unit (or 11% point) decrease in people

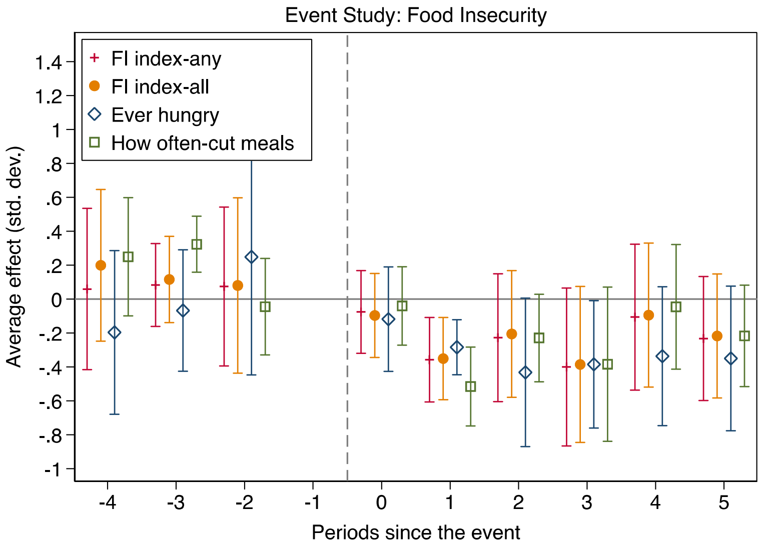


Figure 5. Event study plots for outcomes related to food insecurity.

Notes: The figure above shows event study estimates from stacked difference-in-differences for various outcomes related to food insecurity. Outcomes include an index for food insecurity where none of the components are missing (in orange with circle markers), an index of food insecurity where at least one of the components is non-missing (in red with cross markers), a standardized variable for ever felt hungry in the past twelve months (in blue with diamond markers), and a standardized variable for how often did you cut meals in the past twelve months (in green with square markers). Standard errors are clustered at the county level.

reporting ever feeling hungry in the past twelve months, which is statistically significant at 0.1% significance level. Additionally, there is a decrease in how often people cut their meal size due to limited food or money by 0.224 standard deviation units. All estimates are more negative once those below the age of 60 are included as a control group within each county.

Results from the dynamic version of equation (1) for the two indices and selected outcomes are presented in Fig. 5. Event studies for all outcomes are included in the appendix, Figure A3. There is a visible decrease in interviewees reporting ever feeling hungry in the past twelve months, a year after the introduction of RMP. The decrease is persistent over time.

I conduct a series of robustness checks using different window sizes, different control groups, and different primary sample selection criteria in Table AV (see Appendix). Additional results from the triple DID are provided in Figure A3.

Link between number of restaurants, redemptions, and outcomes

I examine the relationship between the number of participating restaurants, redemptions, and subsequent outcomes by replacing the interaction term between *Treated* and *Post* in equation (1) with a natural logarithm of the number of participating restaurants per 100,000 SNAP benefit recipients.

Column (1) of Table 6 provides results for redemptions (per 100K SNAP benefit recipients measured in natural logarithms), column (2) provides estimates for obesity

Table 6. Results: intensity of treatment

	(1) Log-redemptions	(2) Obesity	(3) Ever hungry
Log-restaurants	3.131*** (0.057)	−0.007 (0.006)	−0.020** (0.008)
County by stack FE	√	√	√
Year by stack FE	√	√	√
Controls	√	√	√
Observations	17,451	17,187	3,733

[a] $p \leq 0.10$.
*$p \leq 0.05$.
**$p \leq 0.01$.
***$p \leq 0.001$.
Notes: the tables above present estimates of β from equation (1) where Treated × Post is replaced with natural log of number of restaurants per 100K SNAP recipients. Each column represents a separate outcome. Column (1) includes natural log of redemptions per 100K SNAP recipients, column (2) includes obesity rates, and column (3) includes an indicator for whether an interviewee felt hungry but didn't eat because they couldn't afford to. Controls include gender, marital status, level of education, race/ethnicity, and indicators for disability, health insurance and smoking. Standard errors are clustered at the county level.

rates, and column (3) includes the estimate for a binary variable for ever-felt-hungry during the last year.[19]

Consistent with the findings above, an increase in the number of restaurants does not have a significant effect on obesity rates but reduces food insecurity, as measured by using an indicator for ever-hungry. More specifically, a 1% increase in the number of restaurants decreases the percentage of people who experienced hunger in the past 12 months by two percentage points. When I relax the age restriction to include all of those above the age of 60 instead of 60-to-75-year-olds, the estimate drops to a one percentage-point decrease, but remains significant. I look at non-elderly, disabled interviewees separately and do not find a statistically significant change in food insecurity for this subgroup.

Additionally, a 1% increase in the number of participating restaurants leads to a 313% increase (or $370,198) in redemptions per 100,000 SNAP recipients. Using a monthly national average of $120 for food benefits of elderly in 2019, the increase in redemptions translates to an additional 257 elderly beneficiaries per 100,000 SNAP recipients using all of their annual benefits at RMP-participating retailers.[20] In California, approximately 16,000 out of every 100,000 SNAP recipients were elderly in 2019. Assuming the benefits are used entirely by the elderly, a 1% increase in restaurants is associated with a 1.6 percentage point increase in elderly SNAP recipients using all their benefits at participating

[19]Number of participating restaurants is based on the authorization dates included in the FNS data set. It should be noted that date of authorization is not necessarily the date when a restaurant becomes operational for the purposes of RMP. After FNS approval, restaurants have to get the point of sale (POS) equipment ready to accept EBT transactions. There is likely a lag between FNS authorization and when a restaurant can accept EBT cards. Given the lag, it is possible that actual number of participating restaurants are less than the ones used for the estimates provided in Table 6. Consequently, the estimates shown in Table 6 are likely smaller (in absolute terms) than they should be.

[20]$120 estimate is obtained from the USDA report available at "https://fns-prod.azureedge.us/sites/default/files/resource-files/Characteristics2019.pdf"

restaurants, or a 19-percentage point increase in elderly SNAP recipients making one $10 transaction at a participating restaurant daily.

Limitations

I examine the ITT effect of RMP on obesity rates among the elderly in California. I do not find a statistically significant difference in obesity rates between counties that did and those that did not implement the program. The null estimate for the ITT effect of the RMP on obesity must be interpreted cautiously, under a set of limitations.

First, there is no existing data set, to my knowledge, that captures the take-up of the RMP among the eligible population in California. It is a possibility that the take-up has been low in participating counties and leads to negligible impact on obesity rates simply due to lack of participation. While the possibility cannot be completely ruled out, supporting evidence from some early-adopting counties suggests a significant reduction in food insecurity in counties that implemented the program, where, on average, 60- to 75-year-olds from low-income households in counties with RMP were 11-percentage point less likely to report ever feeling hungry over the last year than those in counties without the program.

Secondly, research indicates that self-reported weight and height are often misreported in US surveys (Flegal et al. 2019). Under the assumption that the measurement error is constant over time for each county, the estimate provided will remain unbiased. The assumption, however, is less likely to be satisfied given that the pattern of misreporting is complex and varies by many factors including age, sex, time, and socioeconomic status (Ljungvall, Gerdtham, and Lindblad 2015; Ng 2019; Yannakoulia et al. 2006). Given the complexity of misreporting, it is not possible to determine how mismeasurement may influence the estimates provided and thus should be noted as a limitation of this study.

Conclusions

One of the important aspects of the SNAP is that it only covers food meant for at-home consumption. The program does not allow food items that are hot at the point-of-sale, even if purchased from a grocery store. Many states, including California, make an exception to this policy by allowing elderly, disabled, and/or homeless individuals to buy hot prepared food from eligible restaurants and grocery stores under SNAP's RMP. To be eligible for RMP, a SNAP recipient must be 60 and older, disabled, married to someone disabled or elderly, or homeless.

This study is the first of its nature to examine the ITT effect of RMP on obesity rates. I use a stacked difference-in-differences design to study the effect of the staggered countywide adoption of RMP in California. I find no evidence that obesity rates for the elderly are any different in counties with RMP compared to those without RMP. The magnitude of change points toward a decrease in rates of obese population in counties with the program, relative to those without. The small to moderate effects, however, are ruled out at a 5% significance level. My results hold for various robustness checks and for varying control groups and samples.

A limitation of my analysis is that it focuses on low-income individuals who are more likely to be eligible for RMP rather than program participants. While data limitations do not allow me to capture the number of participants in RMP, I look for supporting evidence by examining the effect of RMP on food insecurity, which is the program's primary focus. The results from some early-adopting counties suggest a reduction in food insecurity among the elderly. For a more precise analysis, further progress on this question will require data sets that capture RMP participation. Nonetheless, my analysis provides an important benchmark for future research on RMP.

The results are of direct importance for policy makers interested in the effect of expanding SNAP to include hot prepared meals. One concern among policy makers has been that RMP may drive participants to fast food and unhealthy restaurants, which may lead to obesity. I find no evidence to this effect.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/age.2025.4

Data availability statement. "CA-BRFSS" can be obtained upon request from the California Department of Public Health (Email: BRFSShelp@cdph.ca.gov). "FNS dates data" can be obtained by contacting the author directly.

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Competing interests. None.

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