Targeting, Screening, and Retention: Evidence from the Supplemental Nutrition Assistance Program in California

Matthew Unrath*

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Abstract

Many households eligible for the Supplemental Nutrition Assistance Program do not enroll. Using enrollment histories for all participants in California between 2005 and 2023, this paper documents how eligibility screens lower retention and contribute to incomplete take-up. Enrollment spells largely coincide with reporting schedules, and the majority of cases that leave are eligible before and after their exit. At the same time, reporting requirements improve targeting, deterring at higher rates recipients who appear more advantaged. The paper concludes that reducing the frequency of these verifications can efficiently improve participation, despite worse targeting, because these ordeals are so costly to administer.

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1 Introduction

The Supplemental Nutrition Assistance Program (SNAP) is a critical part of the American social safety net. In 2023, around 42 million Americans were enrolled in SNAP in any given month and, across the whole year, received over $107 billion in assistance. Although SNAP receipt is associated with reduced food insecurity, reduced poverty, lower criminal recidivism, improved short- and long-term health outcomes, and, for children, greater life expectancy and higher lifetime earnings, roughly one in six eligible individuals do not enroll (Cunnyngham et al., 2018).[1] Incomplete take-up has long concerned policymakers, and significant public and private resources have been expended to increase awareness of the program and encourage eligible households to apply.

Alongside soliciting new applications, policymakers and stakeholders can increase participation by improving program retention. In order to confirm they are still eligible, SNAP recipients must periodically submit information about their income, household composition, and expenses to a state welfare agency, and the burden of these reporting processes induce many participants to leave the program (Kabbani and Wilde, 2003; Ribar, Edelhoch and Liu, 2008; Gray, 2019; Homonoff and Somerville, 2021). Since SNAP is a means-tested program, some degree of ongoing eligibility verification is necessary. Policymakers can only choose the frequency and rigor with which these procedures are administered. When making these choices, they balance two competing objectives: promote efficient redistribution and minimize the costs that these processes impose on enrollees and the government (Kleven and Kopczuk, 2011). Less frequent reporting might allow ineligible households to remain enrolled longer, while more burdensome ordeals can be expensive and risk screening out both eligible and ineligible households.

Despite the importance of this policy decision, there is limited evidence about how current reporting requirements affect the composition of program caseloads or the size of these Type 1 (false rejection or incomplete take-up) and Type 2 (false award) errors. It is similarly unclear how potential efficiency gains from more rigorous screening compare to the costs associated with incomplete take-up and actually administering those ordeals. This evidence is critical for policymakers to judge whether current policy is maximally efficient and equitable.

In this paper, I study how reporting requirements affect SNAP participation in California, the state with the highest SNAP enrollment and one of the lowest take-up rates. I build a new dataset of monthly enrollment histories for 16 million recipients between 2005 and

[1] An incomplete list of the many studies documenting these benefits includes: Almond, Hoynes and Schanzenbach (2011); Ratcliffe, McKernan and Zhang (2011); Gregory and Deb (2015); Mabli and Ohls (2015); Hoynes, Schanzenbach and Almond (2016); Oddo and Mabli (2015); Schmidt, Shore-Sheppard and Watson (2016); Bronchetti, Christensen and Hoynes (2019); Tuttle (2019); East (2020); Morrissey and Miller (2020); Bailey et al. (2020).

2023, to which I merge quarterly earnings data from 2012 onward as well as monthly case-level benefit issuance records from 2010 onward. The breadth of these data allow me to document several new facts about program enrollment and the impacts of administrative burdens.

I show that program retention is low and exits largely coincide with reporting schedules. More than half of new entrants leave the program within one year of enrolling when their first recertification is due. I also show that the large majority of cases that leave appear income eligible in the months before and after their exit. At the same time, I find that reporting requirements improve targeting by screening out seemingly more advantaged recipients at higher rates. Ineligible cases, cases with higher earnings, cases with lower benefit amounts, and cases without children are all more likely to exit in a reporting month. Household characteristics associated with higher food insecurity are negatively associated with likelihood of exit, as well. Quicker rebounds in earned income after enrollment also correspond with earlier exits from the program. I reconcile these seemingly contradictory findings – that the majority of leavers appear income eligible, but average earnings among leavers appears to recover to pre-enrollment levels – by documenting a high rate of ongoing income eligibility among recipients before, during, and after their enrollment.

To identify the marginal effect of reporting requirements on the composition of the program caseload, I study a reform that expanded the reporting window. In 2013, California moved from quarterly reporting (cases reverify every three months) to semi-annual reporting (cases reverify every six months). This reform increased the likelihood that cases remained enrolled for at least six months by more than 11 percent, but most increased retention among households predicted to be the least food insecure. I calculate the marginal value of public funds (MVPF) associated with eliminating the quarterly report. I tally the additional benefits disbursed due to higher retention following that reform and use existing estimates of the fiscal costs associated with these processes and SNAP receipt. I allow for these benefits and costs to vary between recipient types in order to account for the effects on targeting. I conclude that eliminating this particular burden still improved welfare. Even if higher frequency screens most deter higher earners and less needy enrollees, the fiscal benefits of that improved targeting are outweighed by the substantial costs associated with actually administering those verifications.

The paper makes multiple contributions to the study of enrollment dynamics in safety net programs. First, I contribute to the literature on incomplete take-up of means-tested programs (Moffitt, 1983; Currie, 2006; Bhargava and Manoli, 2015; Finkelstein and Notowidigdo, 2019). Of the three commonly cited explanations for incomplete take-up – learning, compliance and stigma costs – this paper underscores the importance of compliance costs. I find that limited retention is an important source of non-participation among eligible households, and the burdens associated with reporting requirements have a significant impact on retention.[2]

Second, I build on the many studies investigating enrollment patterns in SNAP – in particular, those studying trends in total participation, enrollment durations, and factors that predict program entry and exit (Blank and Ruggles, 1996; Jolliffe and Ziliak, 2008; Burstein and Siegel, 2009; Mills et al., 2014; Ganong and Liebman, 2018). A persistent issue plaguing this literature has been limited access to reliable, individual-level, and longitudinal enrollment data. Survey data on enrollment in safety net programs is prone to misreporting (Meyer, Mok and Sullivan, 2009; Meyer and Mittag, 2019; Meyer, Mittag and Goerge, 2022) and rarely follows the same individuals and households over time or with sufficient frequency (Leftin et al., 2014; Ganong and Liebman, 2018). Accordingly, most studies investigating the effect of policies and practices on enrollment and take-up evaluate changes in aggregate enrollment flows into and out of enrollment (Kabbani and Wilde, 2003; Heflin and Mueser, 2010; Schwabish, 2012; Ganong and Liebman, 2018). These studies generally do not measure actual enrollment durations, distinguish between changes in entry or exit, or assess how take-up and enrollment patterns vary across different subgroups.[3] Leveraging unprecedentedly extensive administrative data, I address many of these limitations and document several new facts about program reach, retention, enrollment durations, and reentry rates.

A subset of this literature considers the effect of reporting requirements on enrollment and retention. Using aggregate enrollment data and variation in state policy, Klerman and Danielson (2011), Currie and Grogger (2001), Kabbani and Wilde (2003), McKernan, Ratcliffe and Gibbs (2003), and Hanratty (2006) all show that shorter reporting periods are associated with lower program enrollment. A handful of papers use state- or county-level micro-data to document how reporting policies affect retention (Staveley, Stevens and Wilde, 2002; Ribar, Edelhoch and Liu, 2008; Ribar and Swann, 2014; Hastings and Shapiro, 2018; Gray, 2019; Homonoff and Somerville, 2021; Wu and Meyer, 2021). In addition to confirming the significant impact that eligibility verifications have on retention, this paper adds to prior work in several key respects. By linking administrative data on program enrollment and quarterly earnings, I document an important relationship between earnings changes and program exits. I also identify the likely eligibility status of households that leave SNAP. Similar to Gray (2019), I find that a majority of households that exit appear income eligible, and I show that this finding is robust to using several

[2] Government interactions during reporting months might make stigma costs more salient, which could also discourage retention. Even in that case, compliance issues still play an important role in driving exits.

[3] There are a few notable exceptions, including Mills et al. (2014), who use the SIPP and state program data to document the costs of program "churn", Leftin et al. (2014), who also the SIPP to document a number of facts about SNAP enrollment patterns, and Klerman and Danielson (2011), who use the USDA SNAP Quality Control files to study how composition of SNAP caseloads change during large increase in enrollment surrounding the Great Recession. Neither the SIPP nor the SNAP Quality Control files allow researchers to observe enrollment spells as long as those captured by the administrative data that I use.

definitions of eligibility. Finally, I present the broadest evidence to date about how these processes affect targeting and caseload composition, and how the likelihood of exit relates to earnings, benefit amounts, and other household and demographic characteristics.

Third, this paper contributes to debates about the merits and effects of administrative burdens (Currie, 2006; Kleven and Kopczuk, 2011; Herd and Moynihan, 2019). Early models of the optimal design of safety net programs proposed constructing barriers to enrollment (Akerlof, 1978; Nichols, Smolensky and Tideman, 1971; Nichols and Zeckhauser, 1982; Moffitt, 1983; Besley and Coate, 1992), assuming that these "hassles" screen out potential enrollees with a higher opportunity cost of time and thereby facilitate more efficient redistribution to participants with greater need for assistance. Alternative models contend that ordeals screen out those less able to navigate them, thereby deterring exactly the individuals policymakers most want to help (Bertrand, Mullainathan and Shafir, 2004; Mani et al., 2013; Mullainathan and Shafir, 2013). Empirical evidence supporting either explanation remains relatively limited (Alatas et al., 2016; Deshpande and Li, 2019; Finkelstein and Notowidigdo, 2019; Homonoff and Somerville, 2021; Waldinger, 2021; Wu and Meyer, 2021; Arbogast, Chorniy and Currie, 2022; Shepard and Wagner, 2022; Anders and Rafkin, 2022; Rafkin, Solomon and Soltas, 2023). Indeed, the few studies cited here reach contradictory findings.

I conclude that reporting requirements serve a targeting purpose. Holding an array of other case characteristics constant, income ineligible households are, on average, three times more likely to exit in a reporting month than eligible households. There is also a strong negative relationship between retention and earnings and a positive relationship between retention and benefit amounts. The likelihood of exiting in a reporting month increases by approximately three to four percentage points for each additional $500 in earned income, and households receiving more than $500 in benefits each month are more than 25 percentage points less likely to leave than households receiving less than $50.[4] While earnings are clearly associated with likelihood of exit, other case characteristics that proxy for relative disadvantage appear less predictive. For example, an individual's race, language, and previous enrollment in the Temporary Assistance for Needy Families (TANF) program are only somewhat related to likelihood of exit. I use the combination of these characteristics plus earnings levels to relate each household to similar households in the Current Population Survey (CPS) Food Security Supplement, which asks respondents about their ability to access and afford food. SNAP households most similar to CPS households that report being food insecure are much more likely to reverify and remain enrolled. Reducing the frequency of reporting requirements also worsened targeting, allowing some ineligible and seemingly more food secure households to remain enrolled

[4]The baseline exit rate in reporting months is 11 percent for cases with no earned income and 38 percent for cases with the lowest benefit levels.

for longer than they otherwise would and at higher rates than more food insecure recipients.

Fourth, I contribute to a growing set of studies that evaluate and compare the welfare effects of various public programs (Hendren and Sprung-Keyser, 2020). To my knowledge, I produce the first estimate of the marginal value of public funds (MVPF) associated with higher enrollment due to a longer reporting interval and one of the first MVPF estimates to integrate targeting effects. I find that, in this setting, administering fewer recertifications increases social welfare. The personal and public cost savings from eliminating the quarterly report, plus the limited net welfare costs associated with increased SNAP enrollment, aggregate to an MVPF ratio well above 1. In other words, the costs savings realized by eliminating a complicated screening process exceed the limited fiscal benefits of improved targeting. This result is important because it suggests that compositional changes in program caseloads ought not be the sole measure by which policymakers and the public judge whether administrative burdens are worthwhile. Even if a given ordeal deters more advantaged and ineligible individuals on the margin, lessening the frequency or rigor with which that burden is administered could still improve welfare.

The paper proceeds as follows. In Section 2, I describe the administrative data. In Section 3, I provide background information related to program eligibility and reporting requirements for SNAP in California. In Section 4, I describe my analysis and the corresponding results. In Section 5, I conclude.

2 Data

I use individual-level SNAP enrollment data collected by the California Department of Social Services (CDSS).[5] These data contain monthly enrollment information for over 16 million unique individuals between January 2005 and March 2023. Along with enrollment indicators, these panel data contain basic demographic information about each recipient, including their date of birth, race and ethnicity, language, and sex.[6] I also observe the county in which each individual is enrolled as well as their case number. Table 1 reports summary statistics for key characteristics for a select number of years.

[5]These data originate from the California Department of Health Care Services' Medi-Cal Eligibility Data System (MEDS) files. This data system is primarily used for the administration of the state's Medicaid program (known as Medi-Cal), but it also captures monthly enrollment information in other safety net programs including CalFresh (California's instantiation of SNAP) and CalWORKs (California's instantiation of the Temporary Assistance for Needy Families [TANF] program). Based on guidance from staff at CDSS, I identify an individual as enrolled in SNAP if s/he is recorded as enrolled in both data systems. The original version of this paper, released in early 2021, did not apply this restriction, leading me to slightly overstate SNAP enrollment and the number of eligible non-claimants in this population.

[6]Refer to Appendix D for more information about how race and ethnicity are recorded in the CDSS data.

I identify the start date, end date, and length of every continuous enrollment spell for all recipients between 2005 and 2023.[7] To account for censoring issues, I exclude from most analyses enrollment spells beginning in January 2005. I use county identifiers and case serial numbers to group enrollees into common households in each enrollment month.[8] All adults are matched to their available quarterly wage earnings records, including all quarters in which the adult was enrolled in SNAP, as well as the six quarters before their enrollment started and six quarters after their enrollment ended. Earnings records are available between January 2012 and December 2022.[9] I also match each individual to their households' SNAP benefit amount from January 2010 through March 2023 and their monthly enrollment records for the Temporary Assistance for Needy Families (TANF) program between January 2005 and March 2023.[10]

California is unique in that its 58 counties, as opposed to a single state agency, separately administer SNAP, and each county office retains their own official enrollment data. These county records are different than the state administrative data on which I rely.[11] Figure 1 plots total monthly enrollment according to the CDSS data and the official aggregate enrollment counts published by the Food and Nutrition Service (FNS) at the US Department of Agriculture, which are based on the county records. The CDSS records appear to overstate enrollment by nearly 100,000 individuals, or two to three percent of the total caseload, each month. This difference is partially explained by the CDSS data capturing participation in a state-run food assistance program.[12]

[7]Other work studying similar enrollment trends "fill in" one month enrollment gaps, assuming these gaps more likely reflect data errors than actual breaks in enrollment (Burstein, 1993; Gleason, Schochet and Moffitt, 1998; Cody et al., 2005, 2007; Mabli et al., 2011; Ratcliffe, 2016; Gray, 2019). Leftin et al. (2014) find that these gaps could be instances of churn, as opposed to misreporting, but still choose to fill them in. I identify enrollment spells both ways, filling in these one-month gaps and not. I choose to use the version in which I do not fill in these gaps, because my measures of churn and total enrollment better align with what the state reports when I do not, but my results are qualitatively similar when using either approach.

[8]I assign each household to one of six types, according to the ages of their case members: children-only, working-age adults with no children, single working-age adults with children, multiple working-age adults with children, seniors, and seniors with children. These different households are subject to different reporting requirements and likely have different levels of need for food assistance. Children-only households are generally households in which adults are not eligible for SNAP due to their immigration status, but their children are. I refer to "cases" and "households" interchangeably throughout the paper. A SNAP case is defined as a group of individuals who prepare and eat meals together.

[9]The division at the state agency responsible for administering unemployment insurance (UI) and which helped to facilitate this match does not retain earnings records for more than seven years, which precluded me from matching earnings records to participants before 2012.

[10]CDSS does not have issuance histories for cases enrolled before 2010. Figure 1 plots total benefits disbursed each month according to the CDSS data from 2010 onward and the official US Department of Agriculture Food and Nutrition Service (USDA FNS) records from 2005 onward. The significant drop in benefits in March 2023 corresponds to the end of emergency allotments that were started at the outbreak of the pandemic in March 2020.

[11]An important limitation of the state records is they do not have information about applications, recertification submissions, or denials.

[12]The California Food Assistance Program is a state program for qualified immigrants who are not eligible

Figure 1 also highlights important trends in total SNAP enrollment in California since 2000. Participation increased significantly in the aftermath of the Great Recession, as it did nationally (Ganong and Liebman, 2018), and enrollment fell between 2015 and 2019 as the economy recovered. It increased again in June 2019 when Supplemental Security Income (SSI) recipients in California became eligible for SNAP; total enrollment increased by 330,000 in the first three months after expansion. Enrollment spiked again in Spring 2020 amidst the Covid-19 crisis. The economic disruption wrought by the pandemic plus subsequent policy expansions resulted in more Californians enrolling in SNAP and receiving more in total benefits than at any other point the program's history (5.28 million recipients and $1.5 billion benefits in March 2023).

3 Policy Background

3.1 Eligibility

SNAP eligibility rules are largely set at the federal level. Generally, a household is income eligible for SNAP if: (1) its gross income is below 130 percent of the households' federal poverty level (FPL); (2) net income (gross income minus taxes, 20 percent of earned income, a $100 to $200 standard deduction, and a portion of the cost of shelter, utility, medical, and care expenses) is less than 100 percent of its FPL, and (3) its total assets are worth less than $2,250, or $3,500 for a household with seniors or disabled members (CBPP, 2020). Income eligibility limits, and benefit amounts credited to cases based on that income, are applied according to each case's total size, regardless of the members' ages. Nearly all forms of earned and unearned income count towards these income tests, and income received by any member of a household counts towards eligibility.

States have the authority to expand eligibility in certain ways. For example, California allows households with members receiving assistance through a TANF-funded program or eligible for Medicaid to qualify for SNAP even if their gross income is up to 200% of their FPL (LSNC, n.d.*a*; USDA, 2020). Households with seniors or disabled members only need to meet the net income test, meaning they can qualify even if their gross income is above 200% of their FPL. And a household automatically qualifies for SNAP if all its members receive TANF, SSI, or a state-financed general assistance program. Households that qualify for SNAP under broad-based categorical eligibility are also exempt from the asset test, meaning I can infer eligibility for using only income data. This is a particular advantage of my study, since researchers rarely have access to information about household wealth.

for federally-funded SNAP. There were at least 35,000 Legal Permanent Residents enrolled in this program in FY2019-2020, though program costs suggests total enrollment might be substantially higher (Anderson, 2012).

Some individuals are categorically ineligible for SNAP, including: non-citizens, workers on strike, students (except in particular circumstances), and until 2019, Californians receiving SSI. These categorical exemptions are generally not a concern in my setting, as I mainly consider continuing eligibility among individuals who were already deemed eligible.

3.2 Reporting Requirements

Generally, SNAP recipients in California must confirm their eligibility twice a year.[13] Six months after enrolling and every 12 months thereafter, most recipients need to complete a two-page semi-annual report (known as a SAR-7), on which they relist all their household members, income sources, and expenses, and also report how their income might change over the next six months. Twelve months after initial enrollment and every 12 months thereafter, most recipients need to complete a full recertification (known as RRR).[14] The annual recertification resembles the initial application in terms of length and complexity. In addition to completing a four-page form, households must also complete an in-person or phone interview with county staff. If a household fails to meet any of these requirements before the last day of the reporting month, its benefits can be cut off. Households can remain enrolled without reapplying if they submit any missing paperwork or complete their interview within 30 days of their initial reporting deadline. If they do not, and they wish to re-enroll, they must undertake a full re-application. In between these scheduled reporting months, households must also notify their county office if their gross income ever exceeds 130 percent of its FPL, or their household composition changes such that they may no longer be eligible.

The six-month cycle of semi-annual report and full recertification describes the reporting process for most households in California, but some face different timelines. Households with only seniors or individuals with disabilities only need to complete the semi-annual report every 12 months. If anything about their status has changed, they might also have to submit the semi-annual report in the intervening months. Households that contain only seniors or individuals with disabilities and who have no earned income are only required to recertify every 36 months (LSNC, n.d.*b*).[15] Figure 2 illustrates the reporting schedule for these three household types.[16]

[13]The federal government sets minimum intervals within which households must verify their eligibility, but states are permitted to administer more frequent verifications (Benvie et al., 2023).

[14]Images of the paper versions of each form – the SAR-7 and CF-37 – are included in the appendix.

[15]For most of my study period, these households were also required to complete a SAR-7 every year. As of March 2022, these households are no longer required to complete the semi-annual report. This waiver is in place through 2026.

[16]There are a handful of exceptions to this standard schedule. For example, in six counties between 2018 and 2020, working-age adults with no children had to demonstrate that they were working or looking for

While federal policy dictates how often households must report and what information they need to submit, states and counties have some discretion over how these verifications are administered. For example, counties can decide how and when to conduct interviews with recipients, whether and how often they remind enrollees about their reporting deadlines, and whether they use third-party information to verify what enrollees report.

Before October 2013, households were required to submit eligiblity reports every quarter.[17] These quarterly reports required cases to report an estimated income amount for each month in the quarter; the semi-annual report only asks for current earnings and potential future changes in earnings. In Section 4.4.3, I document the impact this 2013 reform had on program enrollment.

4 Analysis

This section summarizes results from multiple analyses. In Section 4.1, I present facts about enrollment patterns in SNAP, the program's reach in California, and the impact of reporting requirements on retention. In Section 4.2, I calculate the share of households that exit the program despite appearing eligible. In Section 4.3, I document how households' earned income evolves before, during, and after enrollment. In Section 4.4, I identify how individual and household characteristics predict likelihood of exiting SNAP in reporting and non-reporting months. In Section 4.5, I calculate the marginal value of public funds associated with extending the reporting interval.

4.1 Enrollment Durations and Program Reach

The CDSS data are unique both in their detail (monthly enrollment at the person-level) and their scope (spanning more than eighteen years in the country's largest state). These features allow me to identify new facts about SNAP enrollment patterns. First, and most relevant to the paper's main topic, I measure recipients' continuous enrollment spells. Figure 3 summarizes the frequency distribution of these person-level enrollment durations.

work at least 20 hours a week; otherwise, these individuals were limited to receiving benefits for only three months over the course of three years. The Trump Administration planned to institute these benefit limits and work requirements on so-called Able-Bodied Adults without Dependents (ABAWDs) nationwide starting in March 2020, but implementation was postponed indefinitely due to the Covid-19 pandemic. California received a waiver from implementing this rule in any county through October 2024.

[17] This reform was permitted by a series of regulatory changes dating back to 1999, which also permitted states to decrease not only the frequency of these reports, but also the amount of information that families had to provide (Danielson et al., 2011). Between 2003 and 2011, USDA FNS authorized a series of waiver requests from California to continue administering quarterly reporting, all the while urging the state to move to semi-annual reporting. State policymakers insisted the transition was complicated by legislative, political, and technological obstacles (CDSS, 2010). Finally, the California legislature passed AB6 in 2011, directing CDSS and the counties to adopt semi-annual reporting by October 2013.

Panel A includes spells that began at least two years before October 2013, when reporting requirements shifted from every three months to every six. Panel B includes spells that began between October 2013 and March 2021.[18] In both, it is clear that enrollment spells are commonly in intervals that coincide with when households must verify eligibility. More than one-fifth of enrollment spells that started after October 2013 lasted exactly six months. Over 40 percent of enrollment spells were exactly 6, 12, 18, or 24 months.[19] I set the maximum spell length in Figure 3 to be three years, but a small share remain continuously enrolled for longer. Appendix Table 4 summarizes the share of enrollees that stay enrolled in SNAP for one to 17 years by the calendar year their enrollment started. Low retention is a chronic issue: Each year, almost half of new entrants will exit within 12 months after enrolling. And multi-year enrollment spells are rare: Only five percent stay continuously enrolled for six or more years and, among recipients who initially enrolled in 2006, less than one percent remained enrolled throughout the rest of my study period. The comparable survival rates in subsequent years suggests that long-term enrollment is likely to be as rare among recipients who enrolled after 2006.

Conditioning on continuous enrollment means understating the total months that participants are ever enrolled in SNAP during the study period. Figure 4 plots the distribution of months enrolled for all recipients whose enrollment started between February 2005 and March 2021.[20] Even in this figure, one can clearly see spikes at enrollment durations that coincide with reporting intervals, suggesting that for many recipients who enrolled and exited at one of their first reporting months, those spells were their only instances of enrollment over these nearly two decades.[21]

Finally, the nearly two-decade coverage of these data allow me to measure SNAP's reach in another novel way. I can count the number of unique Californians who have ever interacted with the program over this period. The program has a much wider reach than cross-sectional counts might suggest. SNAP has assisted over 15 million unique Californians since 2010, over 12.8 million since 2015, and 8.8 million since the onset of

[18] I exclude recipients whose enrollment started within two years of October 2013 and March 2023 in order to account for right censoring.

[19] In the appendix, I also provide additional evidence that individuals exit SNAP in the month a report is due, including a survival plot (Appendix Figure 3) and estimates of per-month hazard rates (Appendix Figure 4) that mirror the enrollment durations shown in Figure 3. I also show that the average hazard rate in the highest drop-off months as well as the churn rates are fairly constant over time (Appendix Figure 5 and Appendix Figure 6).

[20] This distribution risks understating longer enrollment counts due to both left and right censoring. I account for this in two ways. First, I identify the distribution of enrollment spells among the roughly two million Californians enrolled on January 2005, whom I exclude from Figure 4 to be consistent with prior analysis. Slightly more than half were enrolled for 18 months over the next 18 years. Only five percent were enrolled for more than a total of 12 years, a similar rates as those who enrolled after January 2005. Second, in Appendix Figure 7, I report, by enrollees' age as of 2022, the share enrolled for less than a year up to 15 years.

[21] It's also possible that recipients reenrolled and then again exited in a reporting month, such that their total months enrolled are still a multiple of the reporting interval. The general point still holds.

the Covid-19 pandemic. Of the nearly nine million Californians who enrolled since March 2020, nearly one-third had never enrolled before then, at least back to 2005.

4.2 Measuring Eligibility Among Leavers

The preceding evidence indicates that individuals typically remain enrolled in SNAP until they are required to recertify. Then, because they are deemed ineligible, believe they were no longer eligible, are deterred by a paperwork issue, or decide the costs of proving eligibility exceed the benefits of remaining enrolled, many exit. I distinguish between some of these competing explanations in the following section.

CDSS infers the degree to which eligibility verifications burden eligible households by tracking the share of cases that exit SNAP in a reporting month, but reapply to the program within one to three months. The assumption is that households who leave but quickly re-enroll were never actually ineligible, but simply failed to complete their semi-annual report or recertification on time. Counties report these "churn" rates to CDSS, and CDSS publishes them every quarter. In any given quarter, about 10 percent of cases reapply for benefits within one month after failing to complete their recertification, and 15 percent reapply within three months.[22]

I replicate and extend these estimates using my administrative data. Table 2 reports the share of individuals who exited SNAP at some point between 2014 and 2021, but returned to the program within six different timelines. From 2014 onward, 10 and 18 percent of individuals who exited SNAP re-enrolled within one and three months, respectively.[23] Roughly 40 percent who exit re-enroll within one year, and about half re-enroll within two years. These rates are similar to those reported by Leftin et al. (2014).[24] That nearly one-in-six individuals return to the program within three months after exiting suggests that a significant share of exits were not due to ineligibility. However, this measure potentially understates the share of leavers who are eligible, because it does not count eligible individuals who exit the program and never return or return after three months.

I address this concern by measuring income eligibility directly using the linked administrative earnings data. Specifically, I identify each households's total wage earnings in the quarter before and after their exit, and then count the number of exiting households whose

[22]These rates are fairly constant over time (Appendix Figure 6) and are similar to national estimates reported by Mills et al. (2014).

[23]This estimate is slightly below counties' reports. This discrepancy is possibly due to county SNAP case files capturing more brief enrollment interruptions than the Medicaid records. This issue might also contribute to the my administrative data slightly overstating total enrollment.

[24]Appendix Figure 6 reports the shares by each individuals' exit date going back to 2005. It is clear that the 2013 reform also reduced the churn rate. Fewer eligibility verifications reduced not only the number of leavers in each month, but also the share of those leavers who would quickly re-enroll.

total income is above or below their respective eligibility threshold.[25] I also account for concurrent enrollment in TANF, since cases with only TANF recipients remain categorically eligible for SNAP.

Determining eligibility for SNAP is complicated. It's a challenging process even for the government agencies that administer the program and have more information than I observe. My approach, which relies mainly on wage earnings, is likewise imperfect. Below, I discuss how my limited information about alternative sources of income and household expenses might bias my estimates and how I address these challenges. At the end of the section, I present estimates of eligibility using multiple, alternative definitions.

First, eligibility for SNAP is determined monthly, but I observe quarterly earnings. In order to not misassign income earned while on or off the program, I restrict my analysis to individuals who exited SNAP at the end of a calendar quarter. I assume that each person's monthly earned income is equal to one-third of their quarterly earnings. In an alternative definition, I assume that households receive all their quarterly earnings in the month they must verify their eligibility (or the month directly after), meaning I compare each case's total quarterly earnings to their respective monthly income eligibility threshold. Second, I do not observe all forms of earned and unearned income.[26] To test the relevance of unearned income, I assign each household in the CDSS data the average level of unearned income reported among similar households in San Francisco county records and the SNAP Quality Control files.[27] I then recalculate the share of households who appear eligible assuming that they each receive this simulated level of unearned income, in addition to their actual earned income.[28] Third, I do not observe each household's deductible expenses, like housing, child care, and medical costs, which determine the

[25]Since I am unable to match children-only households (i.e., mixed immigration status families) to their parent's earned income, I exclude these households from this analysis. I also only consider cases whose exit lasts for at least two months, meaning my estimates tend to be lower bounds on the true share of eligible leavers.

[26]EDD data captures the sum of three-months' worth of each individual's in-state wage earnings from all jobs that are covered by the unemployment insurance program. Self-employment income, military and the federal government salaries, and under-the-table wages are not covered by the state's unemployment insurance program, and so are not captured in these records. Kornfeld and Bloom (1999) conclude that UI records cover roughly 90 percent of workers and their earnings. See also Czajka, Patnaik and Negoita (2018). BDT (2020) report that less than five percent of SNAP recipients receive self-employment income. In contrast, Iselin, Mackay and Unrath (2023) find that around one-sixth of California tax returns that included a SNAP enrollee also reported positive self-employment income. Similarly, Giannella, Sutherland and Paredes (2019) find that around one-fifth of employed SNAP recipients involved in an experiment administered by Code for America in California reported positive self-employment income.

[27]Refer to Appendix C for more information about this procedure.

[28]Large increases in unearned income after a household exits SNAP could result in my overstating eligibility after exit. Neither the San Francisco case records nor the Quality Control files capture changes in unearned income after a household leaves the program. To account for this concern, I use the Survey of Income and Program Participation (SIPP) to track SNAP households before, during, and after SNAP enrollment. I find no evidence of any significant change in unearned income around program exits. Refer to Appendix B for a summary of this analysis.

net income test against which their income is compared. I account for this concern by estimating the share whose income is below 200 percent of FPL and 130 percent of FPL – the gross income thresholds that roughly correspond to the binding net income thresholds for households high and low levels of deductions, respectively. Fourth, I do not observe household composition after a household exits the program. For example, if a household loses a member after exiting, then their earnings would be applied to a different eligibility threshold. I partially account for this concern by identifying the share of households whose total earnings are below 130 percent of their FPL, assuming their last-observed household size was reduced by one person.[29]

I count the number of cases that leave SNAP at the end of each calendar quarter between December 2013 and December 2021 and the number of these cases that appear eligible under each of the above definitions in either the month they exit or the month after.[30] Figure 5 reports the ratio of these counts – the share of exiting cases that appear income eligible according to each definition. That the churn rate severely underestimates the rate of unwanted exit is robust to using any of these alternative measures. The share of cases with zero earned income in the quarter following exit (around 50 percent) is more than three times higher than the 90-day churn rate (15 percent). Over 70 percent of cases have earnings that would still qualify them for SNAP, assuming their household size remains the same, which is almost five times higher than the 90-day churn rate. Neither removing a household member nor adding in households' average unearned income amounts have a meaningful effect on estimated eligibility rates. Assigning all quarterly earnings to just one month and using the 130 percent threshold matters more, but it remains the case that the majority of exiting cases appear eligible. These eligibility rates among leavers are nearly the same for every quarter over the last six years and whether testing for eligibility in the month they exit or the subsequent month.

4.3 Earnings Trends

In the preceding section, I showed that most households that exit SNAP do so despite appearing income eligible. In the next two sections, I investigate potential explanations for exits in reporting months.

First, I consider whether households exit because their earnings have changed since they enrolled. Even if households are still eligible, their earnings might have recovered enough that the stigma and compliance costs of remaining enrolled exceed the value of their SNAP benefits. Similar to Hastings and Shapiro (2018), I identify these earnings

[29] A household might also exit because a new member with substantial earnings whom I do not observe joins the household. If this person does not enroll in SNAP, I do not observe their earnings.

[30] I limit to these cases because I have earnings data for all of these quarters and all of these quarters occur after the 2013 reform.

trends by regressing case-level earnings on a vector of lead and lagged indicators for quarters relative to the start of SNAP enrollment, plus year and month, county, and household type fixed effects.[31] I separately estimate the model for cases that remained enrolled for 6, 12, 18 and 24 months. I transform the estimated coefficients on each lead and lag indicator to the predicted average earnings in each quarter for each spell length.

Figure 6 plots these estimates and distinguishes periods before, during, and after cases' enrollment. On average, patterns are the same for each spell length: earnings are fairly constant in the year before a household enrolls in SNAP, enrollment coincides with a sharp decline in earned income, and households tend to exit the program when their earnings have recovered. For those who exit at six months, earnings rebound to the average predicted pre-enrollment earnings by the first quarter after enrollment. For those who exit at 12 months, earnings recover by the third quarter after enrollment starts and are well above pre-enrollment earnings by the fourth quarter. The same pattern follows for those who exit at 18 or 24 months. Earnings remain depressed in the quarters in which these cases are still enrolled and recover only three or four quarters after enrollment starts. The main takeaway is that enrollment in and exit from SNAP coincides with important changes in households' earned income. SNAP seems to serve the intended purpose of an income support program, cushioning family income during periods of acute financial need, at least among those who enroll. And households whose earnings recover more quickly, on average, tend to exit earlier.[32]

If most cases are income eligible when they exit, as shown in the previous section, but they also exit after their earnings returned to a pre-enrollment average, this implies that many households were eligible for many months before they enrolled. I test this implication by identifying the share of households who appear income eligible in the quarters preceding, during, and after their enrollment. I re-estimate the model described above, but replace the outcome variable with an indicator for whether the case appears eligible.[33] Again, I distinguish between cases enrolled for 6, 12, 18 and 24 months, and I use the estimates to identify the average predicted eligibility level in each quarter relative

[31]Case-level earnings are defined as the sum of individual-level wages in each quarter, summed within the case as it is composed at the start of enrollment. I exclude from this analysis cases that return to SNAP within 12 months after exiting, in order to be clear about earnings among enrollees versus non-enrollees. In the appendix, I present results from a similar analysis in which I do not exclude these cases. The pattern is nearly the same, but average earnings are lower, as expected. All case-level earnings are inflation adjusted to be in 2022 dollars using the R-CPI-U-RS.

[32]I cannot rule out the possibility that the causality runs in the opposite direction – earnings rebound because households must replace income they lost from leaving SNAP, or households increase their earnings when they no longer face the steeper tax rate imposed by the SNAP benefit schedule. However, households who exit at six months experience a recovery in earnings before they exit, which suggests the decision to exit or remain follows from changes in earnings.

[33]I define a case as eligible if their quarterly earned income is below 130% of the FPL for their household size. I use the household composition as of when their enrollment began.

to the start of enrollment. Figure 7 summarizes the results. Enrollment coincides with a sharp uptick in the likelihood of eligibility, mirroring the drop in earnings illustrated in Figure 6.[34] As predicted, the vast majority of households who enroll in SNAP are eligible for many months before they enroll and after they exit.

4.4 Who Leaves in Reporting Months?

Next, I identify which type of participants are more or less likely to exit SNAP in reporting months in order to evaluate the effect of screening processes on targeting. As is typical, I do not observe individuals' latent ability or need for food assistance. Instead, I test whether several individual and household-level characteristics that typically correlate with economic and food insecurity (e.g., current earnings, past earnings, race, language status, household composition) are predictive of exit.

4.4.1 Estimation

I estimate the marginal effects of these characteristics on program exits using a discrete time hazard model (Kalbfleisch and Prentice, 2011; Hoynes, 2000). The model identifies the transition probability $P(d, \mathbf{Z})$, or the likelihood that a subjects exits the program, in period d, conditional on remaining enrolled until period $d-1$ and covariates $\mathbf{Z}$. The hazard rate is modeled as a logit probability.

$$P(d, \mathbf{Z}_{it}) = \frac{\exp(\alpha_d + \mathbf{Z}_{it}\delta)}{1 + \exp(\alpha_d + \mathbf{Z}_{it}\delta)} \tag{1}$$

The vector of indicator variables, α_d, captures each potential period of participation $(d = 1, \ldots, D)$. These dummies non-parametrically account for underlying duration patterns and identify the baseline hazard. Additional covariates, $\mathbf{Z}$, include a series of fixed effects as well as demographic and household characteristics. The fixed effects include calendar year and month, ϕ_t, which vary within each individual's enrollment spell, county of residence, θ_c, which tend not to vary within spells, and household type, η_h, which also tends not to vary within spells.

$$\mathbf{Z}_{it}\delta = \mathbf{X}_i'\beta + \mathbf{X}_i' \times (\text{Report}_{id})\gamma + \phi_t + \theta_c + \eta_h$$

I estimate this model separately for different sets of characteristics, $\mathbf{X}$, including: demographic characteristics (race, preferred language, household type), prior enrollment

[34] This share might not reach 100 percent for at least two reasons. First, I measure eligibility against the 130% FPL gross income test, and many households will still qualify if their earnings are below 200%. Second, the verification process is imperfect, and a small share of households who have incomes above the eligibility threshold for some month during the quarter will be able to remain enrolled.

in TANF, an indicator for eligibility, and binned levels of earnings or benefit amounts. Demographic characteristics are constant throughout all individuals' spells, while eligibility status, earnings levels, and benefit levels can change each month. I also identify whether the effect of those characteristics varies between reporting and non-reporting months by interacting the relevant characteristic with an indicator for whether the period d is a month in which the case would have to complete a semi-annual report or a recertification. The key parameters in the logit model are β and γ. These capture the relationship between characteristic and likelihood of exit separately in reporting and non-reporting months.

I restrict this analysis to spells that started between January 2014 and January 2022 so as to not confuse effects between two reporting regimes and ensure I have earnings data for all months enrolled and up to 12 months after initial enrollment. Since this analysis is highly computationally intensive, I rely on a five percent random sample of all individual spells. I cluster standard errors at the individual-spell level. After estimating Equation 1, I transform the estimated coefficients from log-odds to the predicted marginal effect of each characteristic on the likelihood of exit in reporting and non-reporting months.[35]

4.4.2 Results

Table 3 reports the relationship between eligibility and likelihood of exit in reporting and non-reporting months. Both eligible and ineligible households are roughly six times more likely to exit in reporting months – 11.6 percent compared to 2.1 percent and 32.5 compared to 5.3 percent, respectively. Ineligible households are nearly three times more likely to exit in a reporting month than eligible households. Ineligible households are also more likely to exit in non-reporting months, but the hazard rate compared to eligible households is slightly higher in reporting months.[36]

Figure 8 summarizes the relationship between earned income and benefit amounts received at time d on likelihood of exit. There is a limited relationship between benefit levels and exit likelihood in non-reporting months, but a much clearer effect in months when households must verify eligibility. Every $50 in additional benefits is associated with a three to five percentage point decrease in the likelihood of exit in reporting months, up to about $400 in benefit levels at which point the effect plateaus. There is also a clear relationship between earnings and likelihood of exit, especially in reporting months. Every $500 is associated with a three to five percentage point increase in the likelihood of exit.[37]

[35] Appendix Tables 4 to 10 summarize estimates from each logit regression and the transformation to average and marginal effects.

[36] That just one-in-three ineligible households exit SNAP in a reporting month might reflect both Type 2 errors and an imperfect measure of eligibility.

[37] The exit rates for the baseline in each analysis is summarized in the footnotes in the corresponding figures and the corresponding tables in the appendix. The baseline exit rate in reporting months for cases with no earned income is 11 percent and for cases with the lowest benefit levels is roughly 38 percent.

Relative to households with zero earned income, households with more than $5,000 in estimated monthly earnings are 42 percentage points more likely to exit. There is also a relationship, but a more limited one, between earnings and exit in non-reporting months, which reflects the fact that households can leave the program within a reporting period if their income increases enough that they become ineligible.

The associations summarized in Figure 8 are not necessarily evidence of improved targeting. The association between current earnings and likelihood of exit might capture the mechanical effect of eligibility verifications. I account for this concern by using households' earnings 12 months before they enrolled, a arguably better proxy for ongoing need for SNAP. Figure 9 summarizes the relationship between likelihood of exit and this earnings variable. Again, I document a relationship between earnings and likelihood of exit in a reporting month, but this effect is more muted. For each additional $500 in prior average monthly earnings, the likelihood of exit increases by just one percentage point. Households with monthly earnings of more than $5,000 one year before enrolling are 10 percentage points more likely to exit in a reporting month than households with average monthly prior earnings of $0.

The relationship between exit and other case and demographic characteristics is less clear. There are no meaningful differences in exit rates in non-reporting months across these demographic characteristics (Figure 10, Panel A). In reporting months, I observe limited variation (Panel B). Relative to White enrollees, Black and American Indian/Alaskan Native recipients are slightly less likely to exit, while Hispanic and East Asian/Pacific Islander recipients are more likely to exit. After controlinng for earnings, only the difference between Black and White recipients remains. Individuals who were enrolled in TANF before their current enrollment in SNAP started are also slightly more likely to remain enrolled. Non-English speakers appear just as likely to exit as English speakers. Household compositions appears much more predictive of exit in reporting months. Seniors and households with children are clearly less likely to exit than single adults without children. That adults with children have have lower exit rates that childless adults is robust to controlling for concurrent earnings.

It is not obvious how these household and demographic characteristics correspond with actual need for food assistance. Indeed, there might be important interactive effects between one's race, household composition, language status and earnings in predicting economic insecurity. Next, I identify how combinations of demographic and household characteristics are associated with food insecurity and relate this imputed measure of need for food assistance to likelihood of exit. I use the Current Population Survey's Food Security Supplement (FSS), which asks respondents about their ability to access and afford food. I identify how respondent demographics and household characteristics relate to a measure of food insecurity.[38] I assign each SNAP recipient the predicted level of food insecurity estimated for their counterpart in the FSS, and run a version of Equation 1 in which the vector of characteristics is the binned values of predicted likelihood of food insecurity. As above, I use the coefficients estimated in this regression to identify the marginal percentage point effect of the imputed levels of food insecurity on likelihood of exit.

Figure 11 summarizes the results from this analysis, focusing only on effects in reporting months. When using only on demographic characteristics to predict food insecurity, I find a clear but limited relationship between food insecurity and likelihood of recertifying. Households with the highest levels of predicted food insecurity are more than twice as likely (10 percentage points more likely) to recertify than households with the lowest food insecurity level – an average exit rate of ten percent compared to 20 percent, respectively. When I use both demographic characteristics and earnings to predict food insecurity, I recover a much stronger relationship. Households with the highest level of food insecurity are about 39 percentage points more likely to recertify than households with the lowest level; the latter households have nearly a 1-in-2 chance of exiting in a reporting month, while the former exit only five percent of the time. In both versions, there is almost no relationship between imputed food insecurity and likelihood of exit in non-reporting months.

4.4.3 Evaluation of 2013 Reform

Finally, I evaluate whether the 2013 reform increased retention differently between households with higher or lower levels of imputed food insecurity. I identify the reform's impact by comparing retention between cases that enrolled in August or September 2013 to those that enrolled in June or July 2013. The latter cases would have had to submit a quarterly report before October 2013, while the former would only have to submit the new semi-annual report. Panel A of Figure 12 plots the different survival rates for these two sets of cases. The reform increased the six-month survival rate for treated cases by 11 percent (87 percent compared to 78.3 percent). Treated cases were also more likely to remain continuously enrolled up to 18 months after enrollment.

Panel B illustrates how this effect differs between cases predicted to have high versus

[38]Specifically, I estimate a logit model of respondents' reported food insecurity on binned values of their age, race, number of children, presence of other adults, state, survey year, and earnings. I then use the estimated coefficients to predict each respondent's likelihood of being food insecure, resulting in a measure of predicted food insecurity for every observation that ranges from zero to one. For all possible combinations of these characteristics, I then identify the average predicted level of food insecurity for all combinations of characteristics included in the prediction exercise. Refer to Appendix C for more information about this procedure.

low food security.[39] The markers represent the difference in the survival rates between treated and control cases by predicted food security level. Both types of treated cases exhibit increased retention, but the effect was largest for households with the highest level of food security. The increase in the six-month survival rate was 10 percentage points for high food security cases, compared to 7 percentage points for low food security cases. The gap persists but shrinks after six months.

4.5 Welfare Effects

The welfare effects of a given policy reform depend on how beneficiaries value their benefits, the fiscal externalities associated with receipt of those benefits, and the cost of actually administering the policy. To assess the net effect of those benefits and costs in this context, I conclude with a stylized calculation of the the marginal value of public funds (MVPF) associated with eliminating the quarterly reporting requirement in 2013. The MVPF is the ratio of recipients' willingness to pay for a program's expansion and the public cost of that expansion (Hendren and Sprung-Keyser, 2020): $\text{MVPF} = \frac{\text{WTP}}{\text{Net Cost}}$.

In this setting, the numerator represents participants' willingness to pay to eliminate the reporting requirement, and the denominator represents the total fiscal impact on the government from its elimination, accounting for the additional benefits disbursed, other fiscal externalities, and administrative costs saved. I express the ratio of private benefits and public costs as follows:

$$\text{MVPF}_{\text{reform}} = \underbrace{\left[B\frac{dE}{dR} + \left[E + \frac{dE}{dR}\right]\frac{dC_p}{dR}\right]}_{\text{Change in Private Welfare}} \underbrace{\left[(B+\kappa)\frac{dE}{dR} - \left[E + \frac{dE}{dR}\right]\frac{dC_g}{dR}\right]^{-1}}_{\text{Change in Public Expenditures and Fiscal Effects}}$$

The numerator is the sum of two components: the additional benefits disbursed due to the reform and the private costs of completing and submitting a report.[40] The latter

[39]"High" food security recipients are those whose predicted food insecurity value is less than .25. "Low" food security recipients are those whose value is greater than .25. The sample is nearly evenly split between these two groups. This sample is restricted to the roughly 80 percent of cases with a working-age adult, since senior-only cases face a different reporting schedule and I do not observe earnings for children-only cases, a key input for predicting food insecurity.

[40]I assume that recipients value their benefits at their full cost. This is a typical starting point in the MVPF literature, motivated by the assumption that a recipient's behavioral response to a "small" policy expansion or contraction will have zero impact on their utility. Hoynes and Schanzenbach (2009) conclude that recipients spend SNAP benefits as if they are equivalent to cash, but Hastings and Shapiro (2018) and Whitmore (2002) find that recipients value a dollar from SNAP at only $0.50 and $0.80, respectively. Hendren and Sprung-Keyser (2020) estimate that adults' WTP for $1 of SNAP benefits is $.59. However, incorporating the improvements to children's lifetime earnings and decreases in mortality pushes that estimate to $1.09. In a similar exercise, Gray et al. (2023) use a WTP equal to 1. To be most consistent with the literature and simplify the calculation, I do the same.

savings are realized by both inframarginal and marginal enrollees. The denominator is comprised of three components: the change in expenditures on benefits, the fiscal externalities associated with additional enrollment, and the public cost of processing a quarterly report.[41]

I extend the standard calculation by accounting for the reform's effects on targeting, borrowing a framework introduced by Finkelstein and Notowidigdo (2019). Suppose there are two types of participants $j \in \{L, H\}$ with latent wage θ_j where $\theta_H > \theta_L$. The reform impacts each type's enrollment differently, and each type's enrollment implies different fiscal impacts on the government. I expand the expression above as follows:

$$\text{MVPF}_{\text{reform}} = \frac{\bar{B}_L \frac{dE_L}{dR} + \bar{B}_H \frac{dE_H}{dR} + \left[E_H + E_L + \frac{dE_L}{dR} + \frac{dE_H}{dR}\right] \frac{dC_p}{dR}}{(\bar{B}_L + \kappa_L)\frac{dE_L}{dR} + (\bar{B}_H + \kappa_H)\frac{dE_H}{dR} - \left[E_H + E_L + \frac{dE_L}{dR} + \frac{dE_H}{dR}\right] \frac{dC_g}{dR}}$$

$\bar{B}_j$ indexes the average monthly benefit received by type j. $\frac{dE_j}{dR}$ is the change in enrollment for type j induced by the reform. κ_j indexes the net fiscal externalities associated with SNAP receipt for type j. C_p and C_g index the private cost of completing and the public cost of processing an eligibility report, respectively. Critically, C_p and C_g are not scaled by the change in enrollment, since the recertification is eliminated for all enrollees. Instead, they are scaled by the change in marginal enrollees plus the inframarginal enrollees, E_j.[42] I assume that neither of these costs vary by type.[43]

Since the reporting reform changed the likelihood that recipients remain enrolled beyond the month that the report was due, I modify the framework above to sum the benefits and costs associated with the additional months of enrollment that the reform

[41]Relative to other applications of the MVPF framework, the addition of the cost savings term in the denominator is novel. Most, if not all, of the policies considered by Hendren and Sprung-Keyser (2020) represent forms of additional public spending, whether in the form of new payments to individuals, tax cuts, or other expansions of government-administered programs, whereas this setting involves the removal of a costly ordeal that results in higher spending. A consequence of placing this term in the denominator is that, if the administrative cost savings exceeds the costs of the newly disbursed benefits, the ratio can become negative – an atypical result in the MVPF literature. The correct interpretation of such a findings is that the benefits of the reform greatly exceed its costs, and the MVPF is infinite. Instead of a ratio, the welfare change could also be expressed as the difference between the private benefits and the public costs. Negative results using that expression are more common. I use the MVPF to permit comparisons with other policy alternatives.

[42]This assumption represents a correction from earlier versions of this paper, in which I scale this cost by the change in enrollment. This correction has a significant effect on my resulting estimate.

[43]This assumption may be wrong, but the direction of the error is unclear. I don't take a stand on whether the private costs of navigating an administrative ordeal are higher for one type or another. However, as long as we assume the costs are roughly the same order of magnitude, this assumption has little effect on my final estimate. In the case of C_g, the assumption is more likely to hold.

induces, allowing retention effects to vary each month over recipient type. For simplicity, I consider the reform's effects on each type's retention between four and six months after enrollment, but one could easily extend this calculation beyond six months.[44] The numerator captures the sum of benefits paid out in months four through six, scaled by the increased enrollment of type j in each of those months, $\frac{dE_{jm}}{dR}$. In the denominator, there is the same summation of $\bar{B}_j$, as well as the net fiscal externalities associated with benefit receipt in each of those months. The personal and public savings from not having to administer the quarterly report are outside the monthly summations, since they are realized only once.

$$\text{MVPF}_{\text{reform}} = \frac{\sum_j \left(\sum_m \bar{B}_j \frac{dE_{jm}}{dR} \right) + \left[\sum_j (E_j + \frac{dE_{j1}}{dR}) \right] \frac{dC_p}{dR}}{\sum_j \left(\sum_m (\bar{B}_j + \kappa_j) \frac{dE_{jm}}{dR} \right) - \left[\sum_j (E_j + \frac{dE_{j1}}{dR}) \right] \frac{dC_g}{dR}}$$

Next, I parameterize each term in the model. I use imputed food insecurity levels to identify the two types of recipients.[45] Recipients with seemingly less need for SNAP are represented by type H, and recipients with greater need are type L. Among cases that initially enrolled in 2013, before the reform's enactment, $\bar{B}_L$ was \$356 and $\bar{B}_H$ was \$301. I multiply these benefits by the increased enrollment in each month for each type. The change in retention for each type j in each month is summarized in Panel B of Figure 12.[46]

I define C_j as the time cost to the recipient of completing the quarterly report. Assuming that the report takes two hours to complete, and that the opportunity cost of that time for recipients is twice the minimum wage in California in 2013, the average private cost of completing a quarterly report is roughly \$20.[47] I assume the public cost of administering a

[44] By lowering the cost of participation, the reform could also induce non-recipients to apply and enroll in SNAP. Such a response would affect the MVPF calculation associated with this type of reform, both in terms of additional application costs and additional benefits disbursed. The net cost would depend on the change in the composition of the aggregate caseload. I do not account for these effects in this exercise. It's notable that there is no abrupt change in aggregate enrollment after October 2013, suggesting that this response, if present, was not dramatic.

[45] Refer to Section 4.4.3 and Appendix C for descriptions about how these definitions are constructed and assigned.

[46] Note that the MVPF is inversely related to the size of the average benefit. As benefits decrease, the cost of the verification process looms larger and pushes the MVPF higher. Intuitively, the stakes of the eligibility decision matter. Costly processes are less efficient if the benefit dollars in question are small. Type H's lower average benefit also tends to limit the cost of worse targeting from a welfare perspective.

[47] Summarizing other survey findings, Isaacs (2008) finds that it takes recipients about five hours to complete an initial application and 2.5 hours to complete a recertification. I follow Finkelstein and Notowidigdo (2019) in assuming the value of enrollees' time corresponds with their relevant minimum wage. This estimate is likely understated for several reasons. First, it only accounts for the time it takes to fill out a report, and ignores any psychological stresses associated with completing and submitting one, and worrying about whether it will be approved. Second, it ignores the psychological and health consequences of potentially going without benefits for some period of time (Edin et al., 2013; Shapiro, 2005; Seligman et al.,

quarterly report is roughly $50, and the cost of reviewing a submission is the same for each type.[48] Again, because these costs are saved for all recipients, neither term is multiplied by the estimated changes in enrollment. Since all the marginal changes in enrollment are represented as percent changes within each type, E_H and E_L are both set equal to 1.[49]

Identifying the fiscal externalities associated with SNAP enrollment is more complicated. I do not identify a labor supply response to SNAP receipt in this paper.[50] Instead, I follow Hendren and Sprung-Keyser (2020)'s calculation of the net fiscal cost associated with the introduction of SNAP, in which they distinguish this effect between adults and children.[51] For adults, Hendren and Sprung-Keyser (2020) report a fiscal externality $\kappa_a \sim \$0.16$ for every $1 in their SNAP benefits, identified from the labor supply response estimated in Hoynes and Schanzenbach (2012). For young children, they report a fiscal externality $\kappa_c \sim -\$0.11$ for every $1 in their SNAP benefits, identified from the long-term earnings effects shown by Bailey et al. (2020). Following Finkelstein and Notowidigdo (2019), I assume that SNAP receipt among seniors imposes no indirect revenue consequences. In order to scale the fiscal costs associated with the additional benefits paid out due to the reform, I multiply the average benefits, $\bar{B}_j$, by the share of

2014) due to an inadvertent rejection. Recipients might be willing to pay some positive amount to eliminate that possibility.

[48]Isaacs (2008) estimates that the national average of annual administrative cost associated with SNAP enrollment, including all reporting costs, is about $178 per recipient in 2006 dollars. Mills et al. (2014) reports that the average administrative cost of program churn – which largely captures the public costs of processing new applications instead of recertifications – across six states is approximately $80 in 2011, or $85 in 2013. The estimates in higher cost-of-living states, Maryland and Virginia, which are better comparisons for California, were $103 and $141 in 2013 dollars, respectively. Gray et al. (2023) use a per-recertification cost of $154 in 2018 dollars, or $141 in 2013 dollars. Homonoff and Somerville (2021) report that average certification costs for each case in California is $600. Geller et al. (2019) estimate the annual per-case administrative cost in California in 2016 dollars to be $800. Assuming re-verifications are roughly one-quarter the cost of an application, but occur at least twice as frequently, that corresponds to between roughly $100 and $200 per report. I use an estimate of $50, which is at the far lower end of these other estimates. This choice is meant to be conservative and reflects the possibility that quarterly reports were less costly to process than annual recertifications.

[49]I could set each to .5, representing their respective shares of the caseload. I would then need to halve each dE/dR term, so that the enrollment changes were relative to the whole caseload, and not the change in enrollment with respect to each type. Either approach would produce the same estimate.

[50]I anticipate the labor supply responses to this reporting interval reform would be low. Pei (2017) finds little evidence of dynamic labor supply responses to lengthening Medicaid reporting intervals.

[51]Since I assume labor supply effects are constant across type and benefits decline with net income, the fiscal externalities associated with increased enrollment could be higher for type L, which implies a decrease in targeting increases social welfare. As Finkelstein and Notowidigdo (2019) point out, this violates the standard intuition that delivering more assistance to individuals with greater need and higher marginal utility of consumption should increase social welfare. Estimates of labor supply response to SNAP benefits that vary with income or characteristics of ability would improve the accuracy of MVPF estimates and might yield results more in line with the standard intuition. Incorporating welfare weights into calculations of MVPF would also change the welfare consequences of targeting. For my part, I allow the direction and magnitude of fiscal externalities to vary over adults and children. Since food security tends to be lower for households with more children, my estimates should be more in line with the standard intuition.

enrollees of each type j that are adults, children, and seniors and their respective fiscal externalities.

$$\begin{aligned}\kappa_L &= \bar{B}_L(\pi_{La}\kappa_a + \pi_{Lc}\kappa_c + \pi_{Ls}\kappa_s) \\ &= \$356(.566(.16) + .428(-.11) + .005(0)) \\ &= 15.48\end{aligned} \qquad \begin{aligned}\kappa_H &= \bar{B}_H(\pi_{Ha}\kappa_a + \pi_{Hc}\kappa_c + \pi_{Hs}\kappa_s) \\ &= \$301(.731(.16) + .256(-.11) + .012(0)) \\ &= 26.73\end{aligned}$$

With estimates for each parameter, I calculate the MVPF as follows:

$$\text{MVPF}_{\text{reform}} = \frac{\$301(.24) + \$356(.19) + \$20(2.14)}{(\$301 + \$26.73).24 + (\$356 + \$15.48).19 - \$50(2.14)} = 4.25$$

The MVPF associated with the reform is 4.25, meaning the benefits of the reform far exceed the costs. Figure 13 illustrates the contribution of each component of the ratio to the final estimate.[52] More liberal choices regarding the private and public costs of completing and administering these verifications or a more conservative estimate of adults' labor supply response would push this estimate even higher. SNAP receipt has also been shown to improve short- and long-term health outcomes, increase life expectancy, reduce criminal recidivism, and decrease use of other public programs. Accounting for these externalities in the denominator would also raise the estimate. More conservative choices would lower it, but to conclude the MVPF was less than 1 would require arguably unreasonable parameter selections. For example, even if recipients valued SNAP benefits at half their cost, this reform would still have increased welfare.

Hendren and Sprung-Keyser (2020) (Table II) report estimates of MVPF for SNAP from three interventions aimed at expanding SNAP. Aggregating estimates of direct and indirect effects from multiples studies of SNAP, the authors conclude that the MVPF for increasing take-up of SNAP among seniors is between .89 and .92 Finkelstein and Notowidigdo (2019), and the MVPF for the program's initial introduction was 1.04 (Bailey et al., 2020).[53] Gray et al. (2023) estimate an MVPF between 0.9 and 1.40 from eliminating ABAWD work requirements.

The MVPF for this reform is much larger than these other estimates, which suggests that widening the reporting interval would be a highly efficient way to expand SNAP and increase take-up, despite worse targeting. This type of program expansion is especially attractive from a MVPF perspective, in large part, because it involves eliminating costly requirements for both recipients and government. This is in contrast to outreach efforts

[52]Note that I use unrounded values for each input, so readers' calculations using the estimates represented in the text may differ from what's reported.

[53]Bailey et al. (2020) report their own estimate of the MVPF associated with SNAP's introduction, which is 56. The massive difference is due to how the authors value the expected difference in life expectancy due to SNAP receipt.

that can be expensive to administer. Unless particular outreach efforts are shown to be highly cost-efficient and effective at eliciting applications among the most disadvantaged non-participants or families with children, lowering administrative burdens and increasing retention is likely to be a more attractive way to efficiently improve take-up.

5 Conclusion

This paper provides new evidence that administrative burdens lower participation in SNAP. Using enrollment data for 16 million unique individuals spanning nearly two decades from the country's largest SNAP program, I show that program exits are concentrated in reporting months and lengthening the period in between when households must verify their eligibility increases retention. I also show that Type 1 errors are widespread. Most households who exit in these months appear eligible before and after they leave, a finding that is robust to multiple definitions of eligibility. For every one ineligible household induced to leave in a reporting month, two eligible households also leave.

At the same time, reporting requirements serve a targeting purpose. They appear to lower Type 2 errors and lessen participation at higher rates among no-longer eligible participants and households with higher earnings. Other measures of disadvantage, including lower prior earnings and characteristics predictive of food insecurity, are also positively associated with likelihood of remaining enrolled through a reporting month. A principal contribution of the paper is to quantify this trade-off between take-up and targeting using detailed and extensive program data and to provide evidence about the scale of each type of screening error.

Whether positive screening effects justify lower take-up depends on how much it costs to administer these procedures and the net cost of redistribution. Leveraging enrollment effects from a reform that widened the reporting interval in California, and relying on others' estimates of those costs and benefits, I present evidence that administering fewer and less frequent recertifications can efficiently improve take-up.

This paper does not address whether alternative procedures can more efficiently screen for eligibility. Recent work finds that business processes and simpler procedures can affect retention (Gray, 2019; Homonoff and Somerville, 2021; Wu and Meyer, 2021). Policymakers might consider limiting the information and documentation required in these reports, and how state administrative data could be used to screen out no longer eligible households, instead of soliciting this information from recipients themselves. Measuring the impact of these procedures and comparing their effects to even longer reporting intervals is an important avenue for future work.

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Tables and Figures

Table 1: Demographic characteristics for primary taxpayer in SNAP sample

	2006	2009	2012	2014	2019	2021
Age						
0-18	.599	.566	.524	.490	.469	.379
19-65	.378	.408	.438	.454	.453	.450
65+	.023	.026	.038	.056	.078	.171
Household type						
Children only	.188	.182	.162	.144	.129	.080
Working-age adults only	.126	.156	.189	.214	.228	.251
Single working-age adult w/ children	.445	.388	.366	.355	.355	.311
2+ working-age adults w/ children	.216	.246	.242	.228	.206	.180
Seniors only	.019	.021	.032	.047	.069	.158
Seniors with children	.004	.004	.004	.005	.006	.007
Race						
White	.220	.220	.220	.214	.210	.203
Hispanic	.461	.498	.504	.503	.494	.434
Black	.167	.140	.124	.118	.121	.118
Asian/NH/PI	.033	.032	.031	.034	.029	.040
SE Asian	.049	.039	.037	.037	.036	.046
AI/AN	.008	.007	.006	.006	.006	.005
Other	.062	.064	.077	.088	.105	.155
Language						
English	.731	.712	.718	.724	.735	.734
Spanish	.210	.241	.240	.234	.221	.191
Other	.060	.047	.043	.042	.044	.075
Earnings						
On case with earnings	–	–	.397	.554	.560	.308
Average earnings ($)	–	–	6,141	11,916	12,720	8,826
Observations	2,877,915	4,108,240	5,557,976	6,039,948	5,447,710	6,103,451

Notes. Table 1 summarizes the composition of the SNAP caseload in California for select years in my sample. I define the caseload to be all unique individuals enrolled for at least one month in the calendar year. Among these individuals, I identify the share in each of three age bins; the share in six different household types; the share in each of seven race codes; the share who speak English, Spanish or neither; and the share in cases with non-zero versus zero earned income.

Table 2: Comparing reentry rates in MEDS to CDSS's reported churn rates

Months	CDSS churn rate	MEDS reentry rate
1	11.8	10.9
3	14.3	18.2
6	–	30.2
12	–	42.2
18	–	48.3
24	–	52.6

Notes. Table 2 summarizes the share of individuals who, after exiting, reenter SNAP within six different timelines, limited to individuals who exited after 2014. I calculate the share of individuals who exit the program and then re-enroll within t months, restricting attention to uncensored observations.

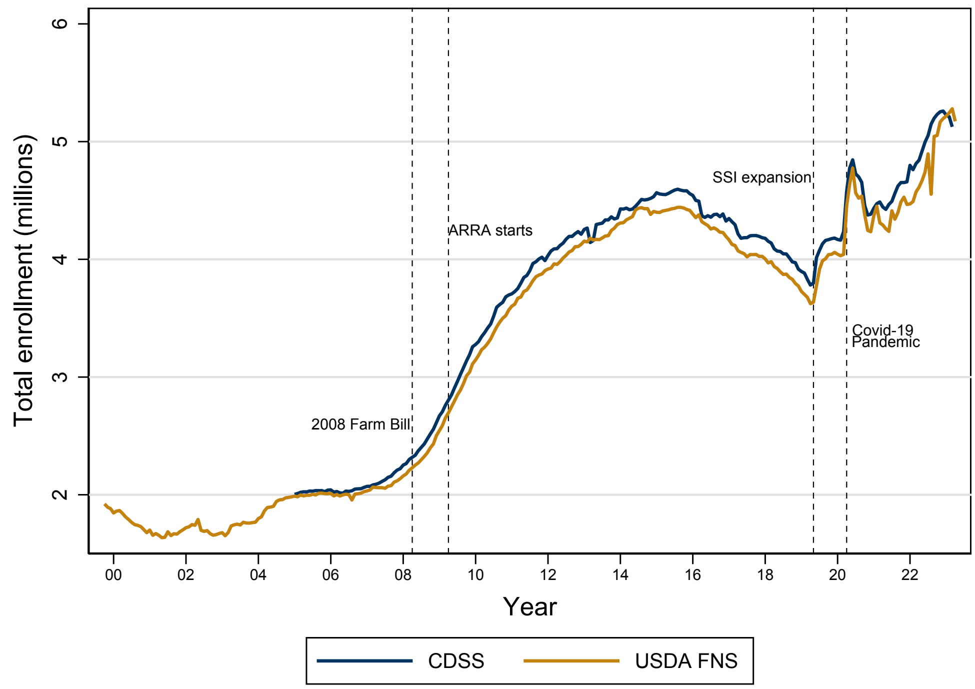
Table 3: Estimated average and marginal effect of imputed eligibility status on likelihood of SNAP exit in reporting and non-reporting months

	Marginal effect		Average effect	
	Non-reporting month	Reporting month	Non-reporting month	Reporting month
Ineligible	0.000	0.000	0.053	0.325
	(.)	(.)	(0.000)	(0.001)
Eligible	-0.032	-0.209	0.021	0.116
	(0.000)	(0.001)	(0.000)	(0.000)
N	12,154,197	12,154,197	12,154,197	12,154,197
Persons	699,211	699,211	699,211	699,211
County	X	X	X	X
Year/Month	X	X	X	X
Demographics	X	X	X	X

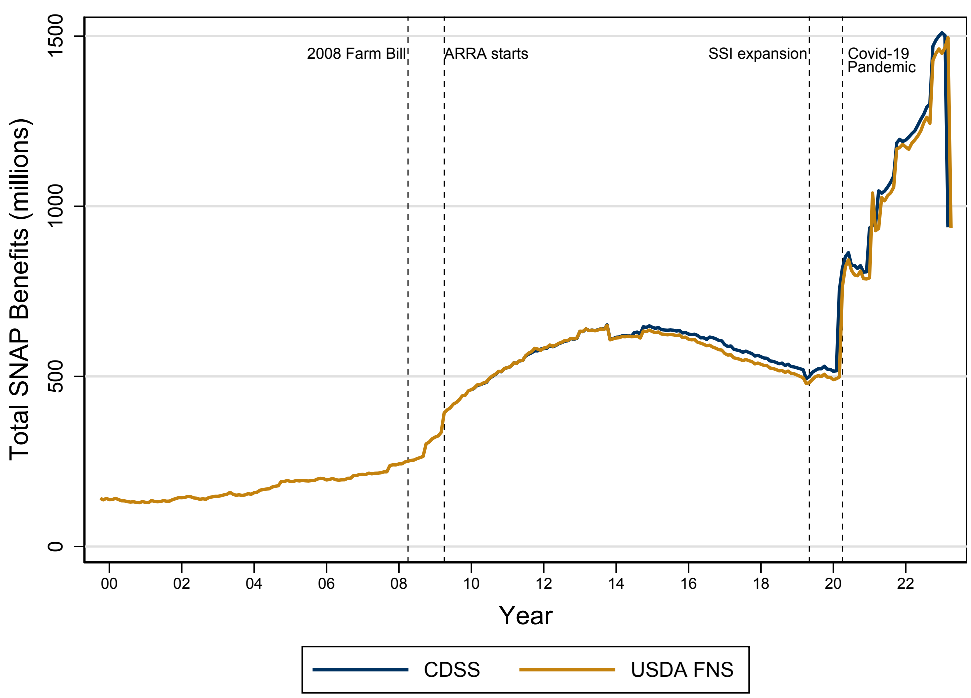
Notes. Table 3 reports estimates from Eq. 1, then transformed into percentage point effects relative to the baseline and an average effect for each value, in which main predictor is eligibility status.

Figure 1: Total monthly SNAP enrollment and disbursements in California, 2000-2023

(a) Recipient-level enrollment



(b) Total Benefits



Notes. Figure 1 plots total SNAP enrollment and benefits in California from two data sources. The USDA counts are the official figures reported by the counties to the state, which are then reported to FNS at USDA. The CDSS enrollment count is the sum of individuals recorded as being enrolled in SNAP each month in the Medicaid Monthly Eligibility Files. The total benefits according to CDSS represent the sum of case-level benefits observed in the state's issuance file.

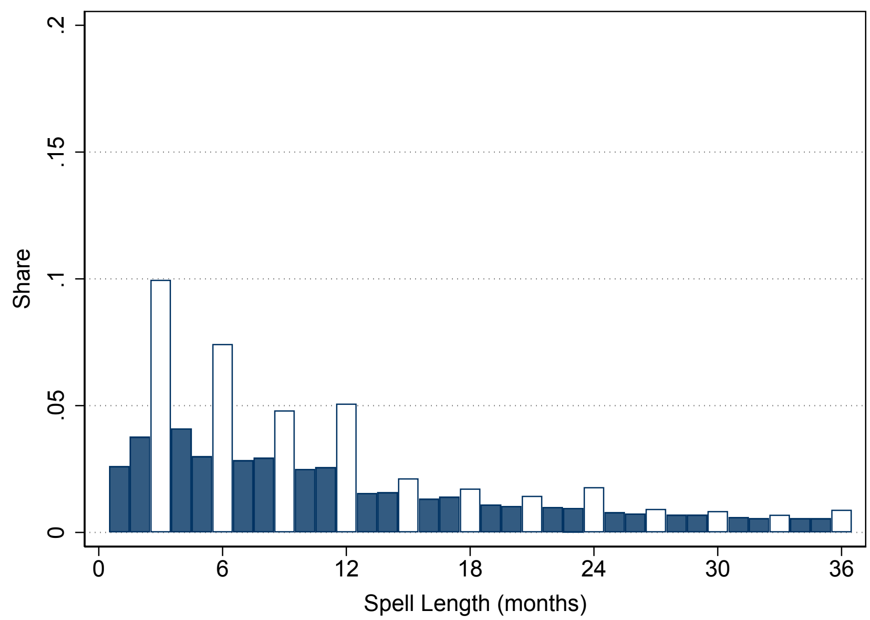
Figure 2: SNAP reporting schedule in California

	Months since enrollment						
	0	6	12	18	24	30	36
Working-age households	Enroll	SAR-7	RRR	SAR-7	RRR	SAR-7	RRR
Seniors or disabled persons w/ earnings	Enroll		SAR-7		RRR		SAR-7
Seniors or disabled persons w/o earnings	Enroll		SAR-7		SAR-7		RRR

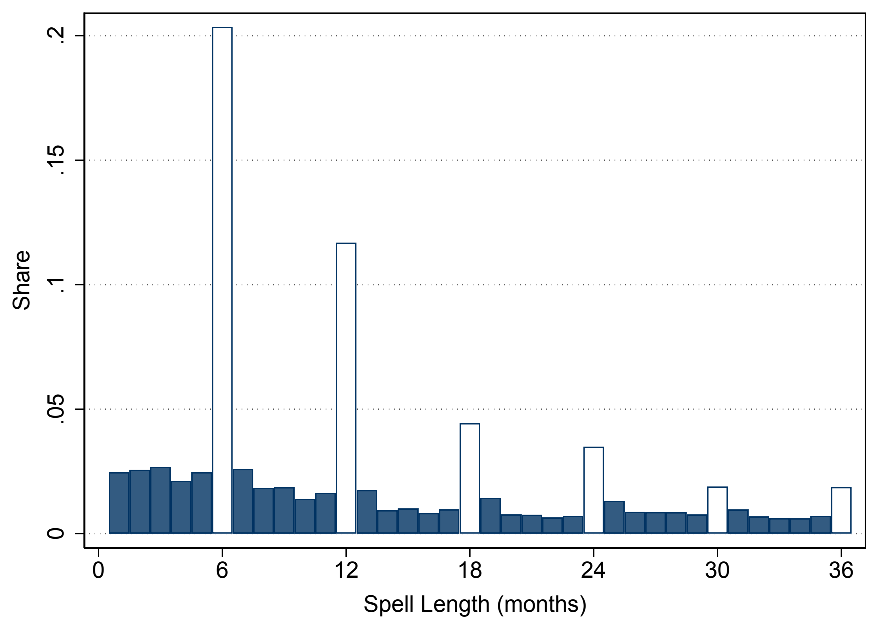
Notes. Figure 2 illustrates the reporting schedule for three types of households. Most households must complete a periodic report (known as a Semi-Annual Report, or a SAR-7) six months after enrolling, and every twelve months thereafter. The household must complete a short form, identifying whether household members, sources of income, and deductible expenses have changed, and if so, how. Six months later, and twelve months after enrolling, the household must complete a full recertification (known as the RRR). This entails completing a longer form (known as a CF-37), including much of the same information, providing proof of earnings, and completing an interview with county staff. Households with seniors or individuals with a disability and without working-age adults, but who have some earned income, are allowed to extend the recertification schedule, such that they complete the SAR-7 twelve months after enrolling, and the RRR twenty four months after enrollment. Finally, households with seniors or disabled persons but no earned income only need to complete the RRR every 36 months and the SAR-7 every 12 months.

Figure 3: Frequency distribution of continuous SNAP enrollment durations

(a) Spells beginning 2005 - 2011

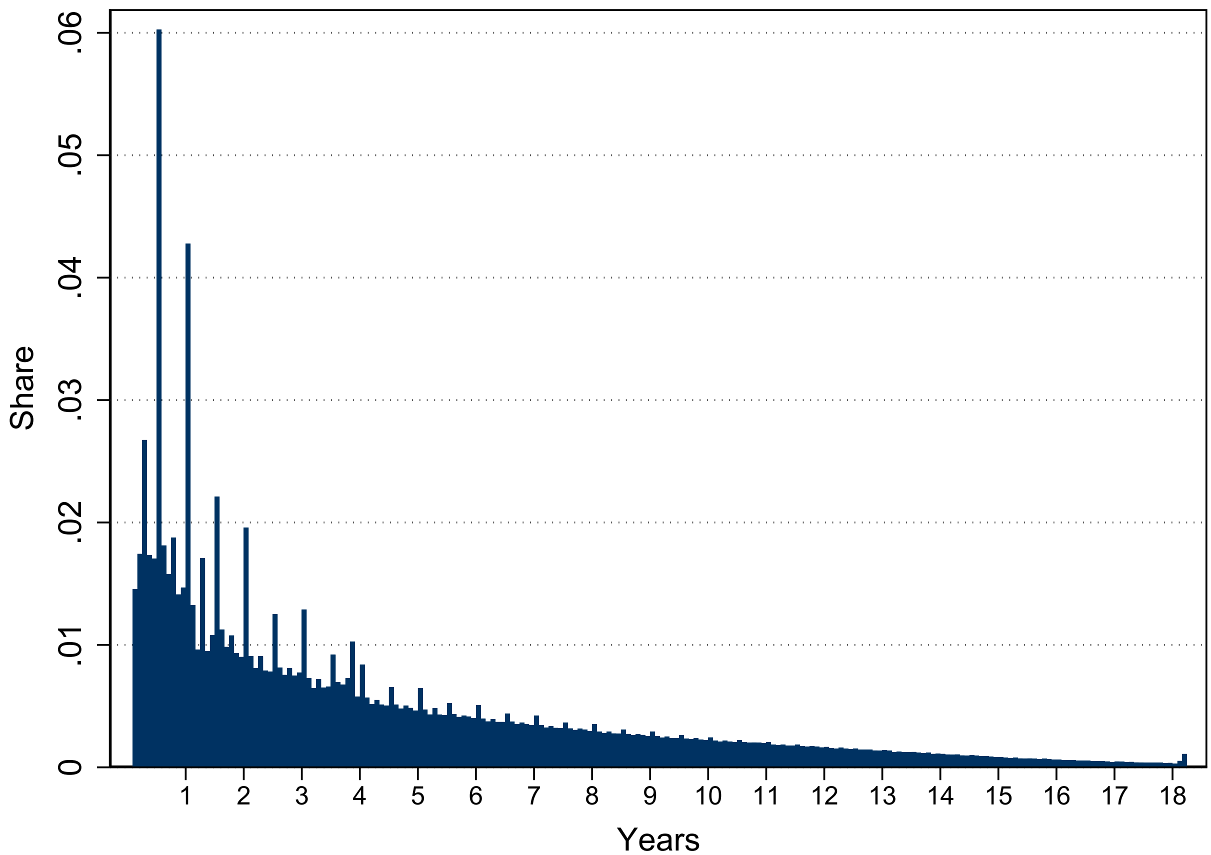


(b) Spells beginning 2014 - 2021



Notes. Figure 3 summarizes the frequency of continuous enrollment spell lengths – periods of consecutive months in which an individual receives SNAP. I plot two versions of this distribution. Before October 2013, households had to recertify every three months. Since then, most households must reverify eligibility every six months. Panel A includes spells that started at least two years before October 2013, and Panel B includes spells that began after October 2013. The white bars represent spell lengths that align with reporting periods. Before 2013, the most common enrollment spell was three months, which is when households had to submit their first quarterly report. Since then, less than three percent of cases end at three months, and the most common spell length is six months, corresponding to the typical initial reporting month.

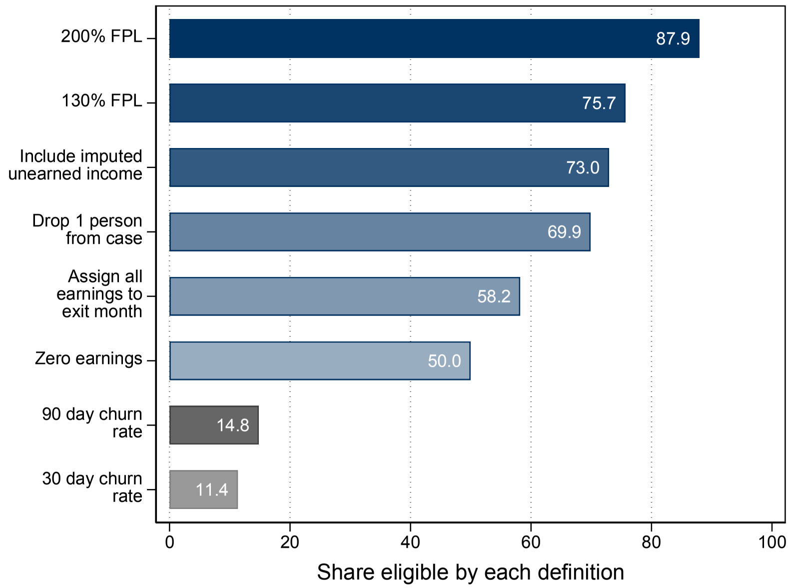
Figure 4: Frequency distribution of total months enrolled in SNAP



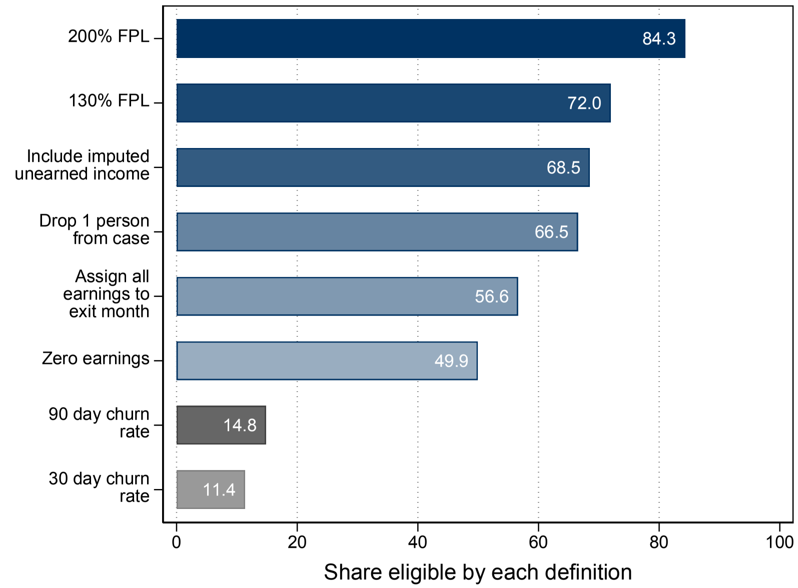
Notes. Figure 3 summarizes the frequency of total months each recipient was enrolled in SNAP in California between January 2005 and March 2023.

Figure 5: Share of cases exiting SNAP that appear income eligible

(a) Earnings from the quarter in which the case leaves SNAP

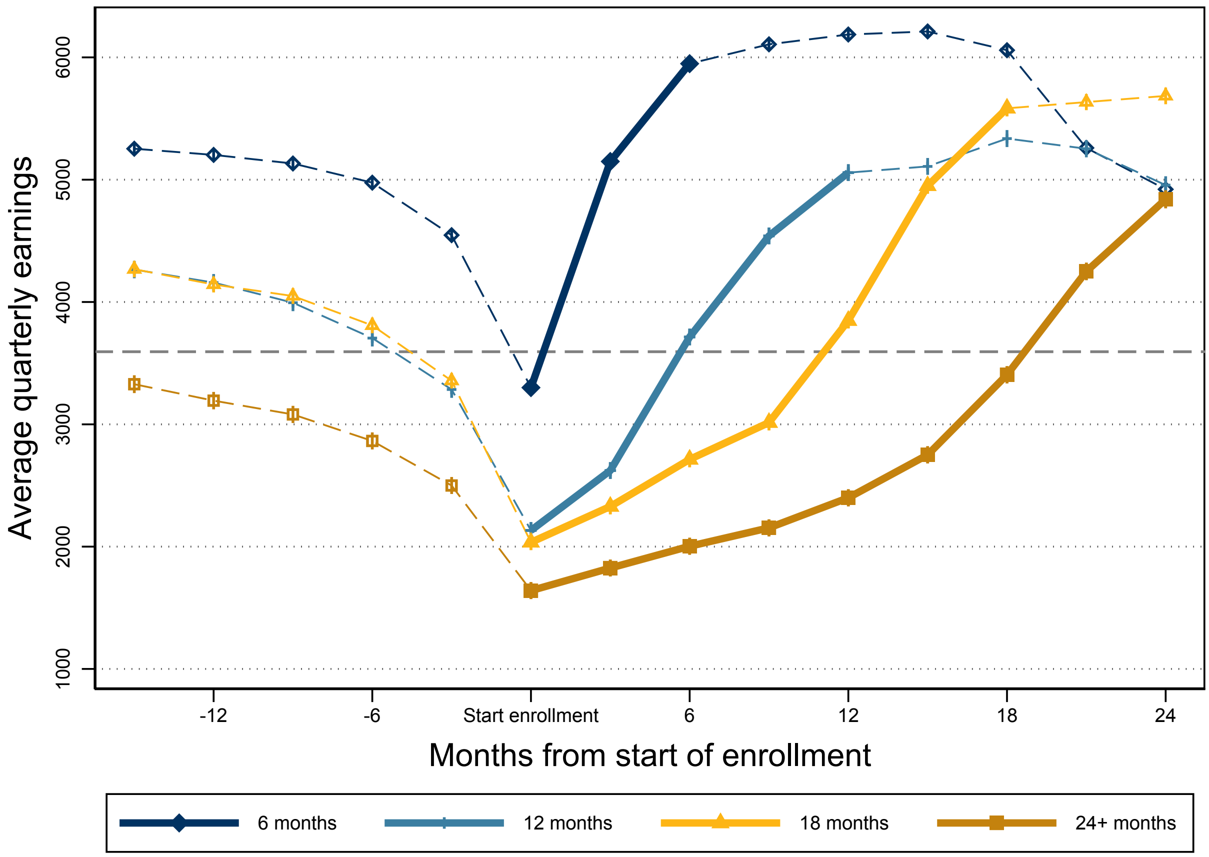


(b) Earnings from the quarter after the case leaves SNAP



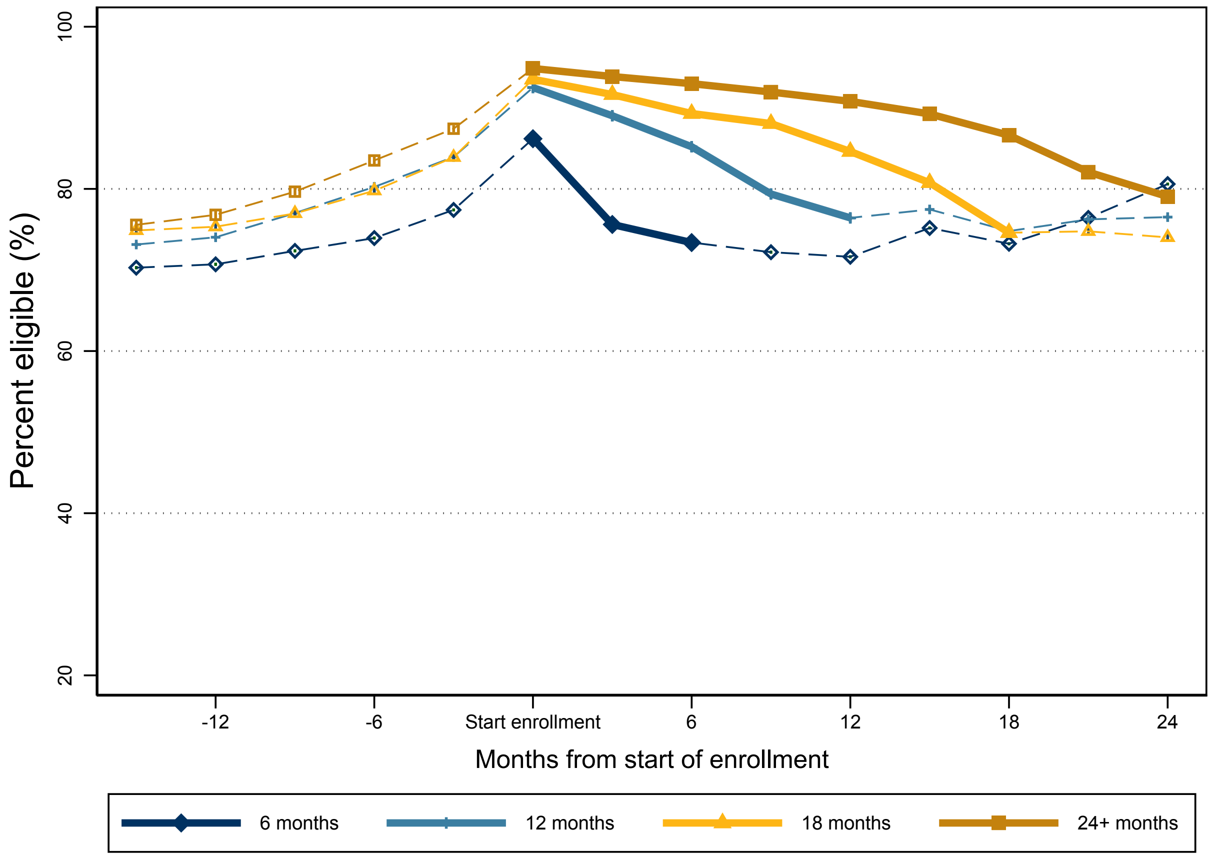
Notes. Figure 5 reports the share of cases that exit SNAP but appear income eligible according to various eligibility definitions. I restrict to cases that leave SNAP at the end of a calendar quarter between December 2013 to December 2021. Panel A uses earned income from the quarter in which the case leaves SNAP, and Panel B uses earned income from the quarter immediately after the case leaves SNAP. In the first definition, I compare one-third of a household's total earned income to 200 percent of its monthly FPL. In the second, I use 130 percent of the households' FPL. Third, I identify whether one-third of a household's total quarterly income, plus the average unearned income for its households type assigned using the procedure described in the appendix, exceeds 130 percent of the household's FPL. Fourth, I identify whether one-third of a household's total quarterly income exceeds 130 percent of the household's FPL, assuming their household size was reduced by one person. Fifth, I identify whether a households' total quarterly income exceeds 130 percent of the household's FPL. This test is equivalent to assuming that the household receives all of their quarterly income in the month of, or immediately following, their exit.

Figure 6: Average quarterly earnings before, during, and after SNAP enrollment by spell length



Notes. Figure 6 plots average inflation-adjusted, case-level earnings for each quarter relative to the quarter before enrollment starts. I separately estimate effects for cases that exited SNAP at 6, 12, 18 and 24 months after initial enrollment. I identify these averages by regressing quarterly earnings on a vector of dummies for each quarter relative to the quarter before enrollment in SNAP starts, as well as fixed effects for calendar quarter, demographic characteristics and household type. I limit to spells that began after December 2013 and ended before December 2021, and for which I have complete earnings information and the standard reporting window was six months. I also restrict to cases that enroll at the start and exit at the end of calendar quarters (e.g., enroll in January and exit in June), so that I am able to distinguish between income earned while enrolled and not enrolled. Finally, I restrict to spells in which the recipient does not return to SNAP within 12 months after exiting. Post regression, I predict average earnings for each relative quarter separately for each spell length, and at the means of the other covariates. The solid lines and markers indicate quarters in which the case is still enrolled in SNAP, while hollow markers and dashed lines represent quarters in which the case is not enrolled. The dotted horizontal line identifies the average quarterly earnings ($3,593) in quarters within one year on either side of when enrollment starts. Earnings values are inflation adjusted to 2022 dollars using the Consumer Price Index retroactive series using current methods (R-CPI-U-RS).

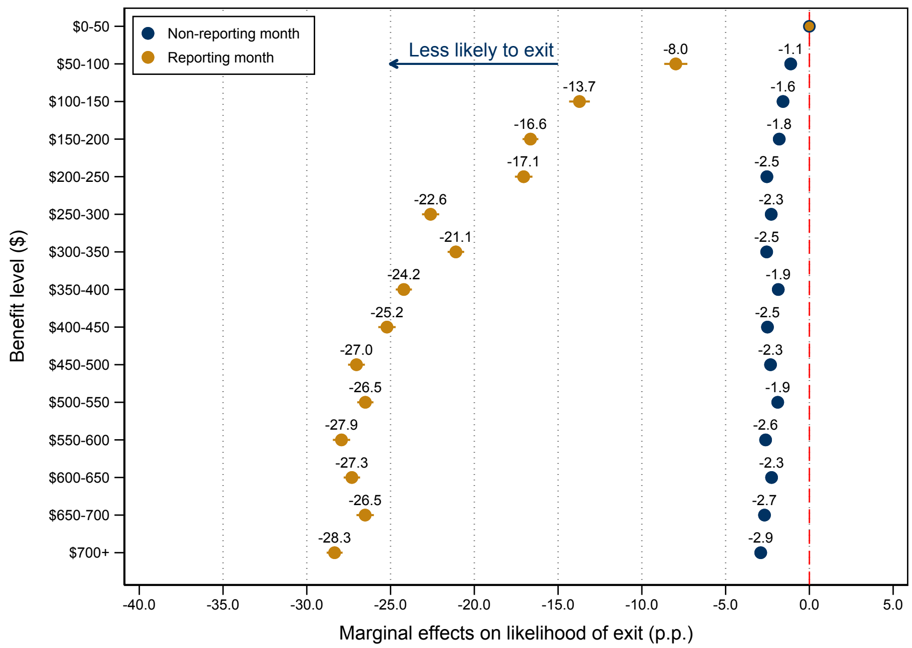
Figure 7: Share of cases that appear income eligible each quarter relative to case's initial enrollment in SNAP



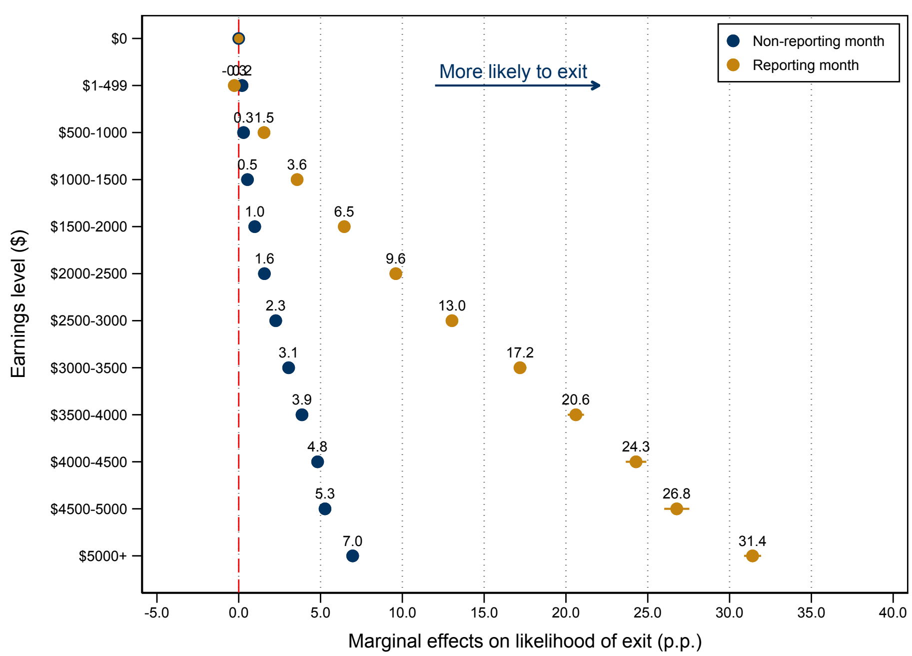
Notes. Figure 7 plots the share of cases that appear income eligible each quarter relative to when they first enroll separated by spell length. Analysis is restricted to spells between 2014 and 2019, for which I have complete earnings information and the standard reporting window was six months. I also restrict to cases that begin at the start and end at the close of quarters, so that I am able to distinguish between income earned while enrolled and not enrolled. These shares might not reach 100 percent, as one might expect, for several reasons. Some households will still qualify even if their income exceeds 130 percent FPL, because they are able to deduct the cost of numerous expenses. It is also the case that the verification process is imperfect, and a small share of households who have incomes above the eligibility threshold for some month during the quarter will be able to remain enrolled.

Figure 8: Likelihood of exiting SNAP by household benefit amount and earned income

(a) Benefit amount

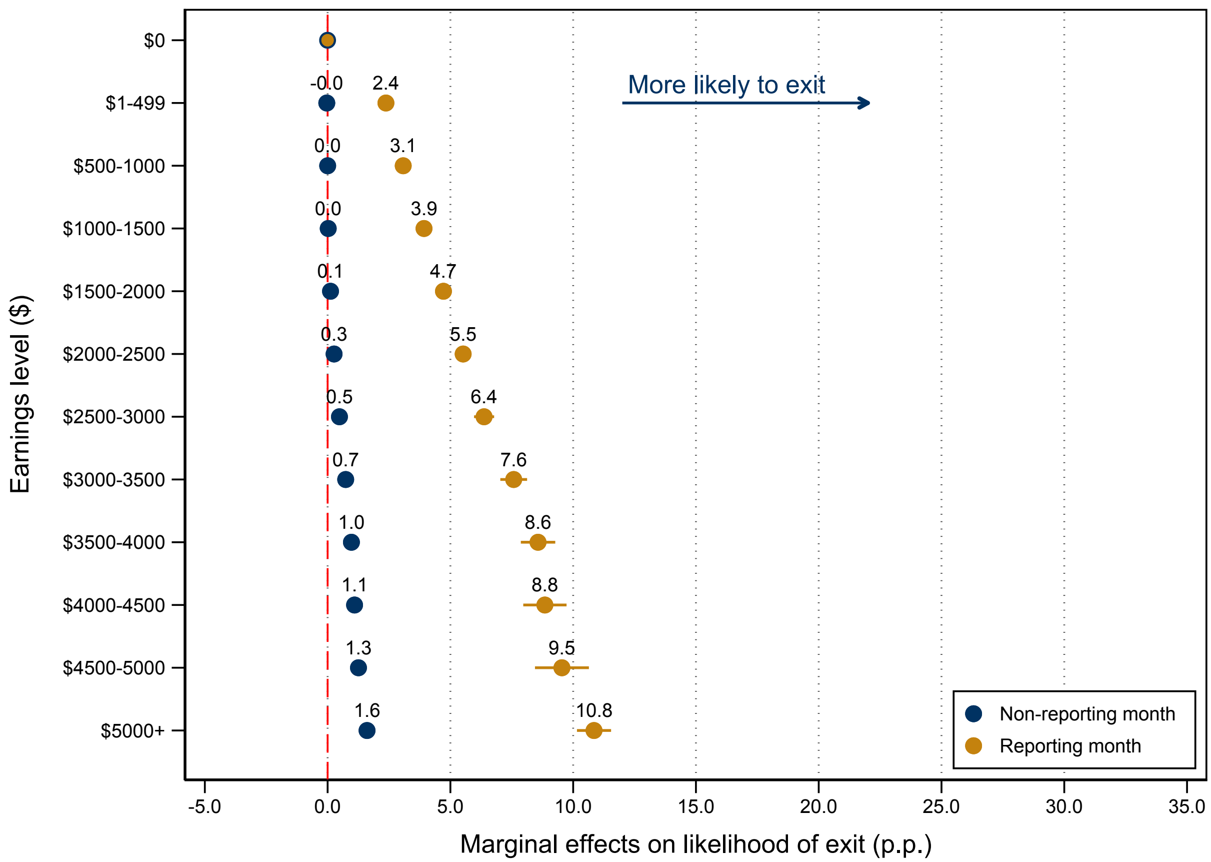


(b) Earned income



Notes. Figure 8 reports the marginal effect on likelihood of exit in reporting and non-reporting months by monthly earnings levels and benefit amounts in reporting and non-reporting months. I calculate these effects by first estimating Equation 1 and then identifying the difference between the predicted probabilities of exit for each benefit and earnings level, relative the baseline, at the mean effect of all other covariates in that model. The baseline likelihood of exit for households with $0-50 in SNAP benefits is 4.6 percent in non-reporting months and 37.7 percent in reporting months. The baseline likelihood of exit for households with no earnings is 1.8 percent in non-reporting months and 10.6 percent in reporting months.

Figure 9: Likelihood of exiting SNAP in a reporting month by household earnings 12 months before initial enrollment

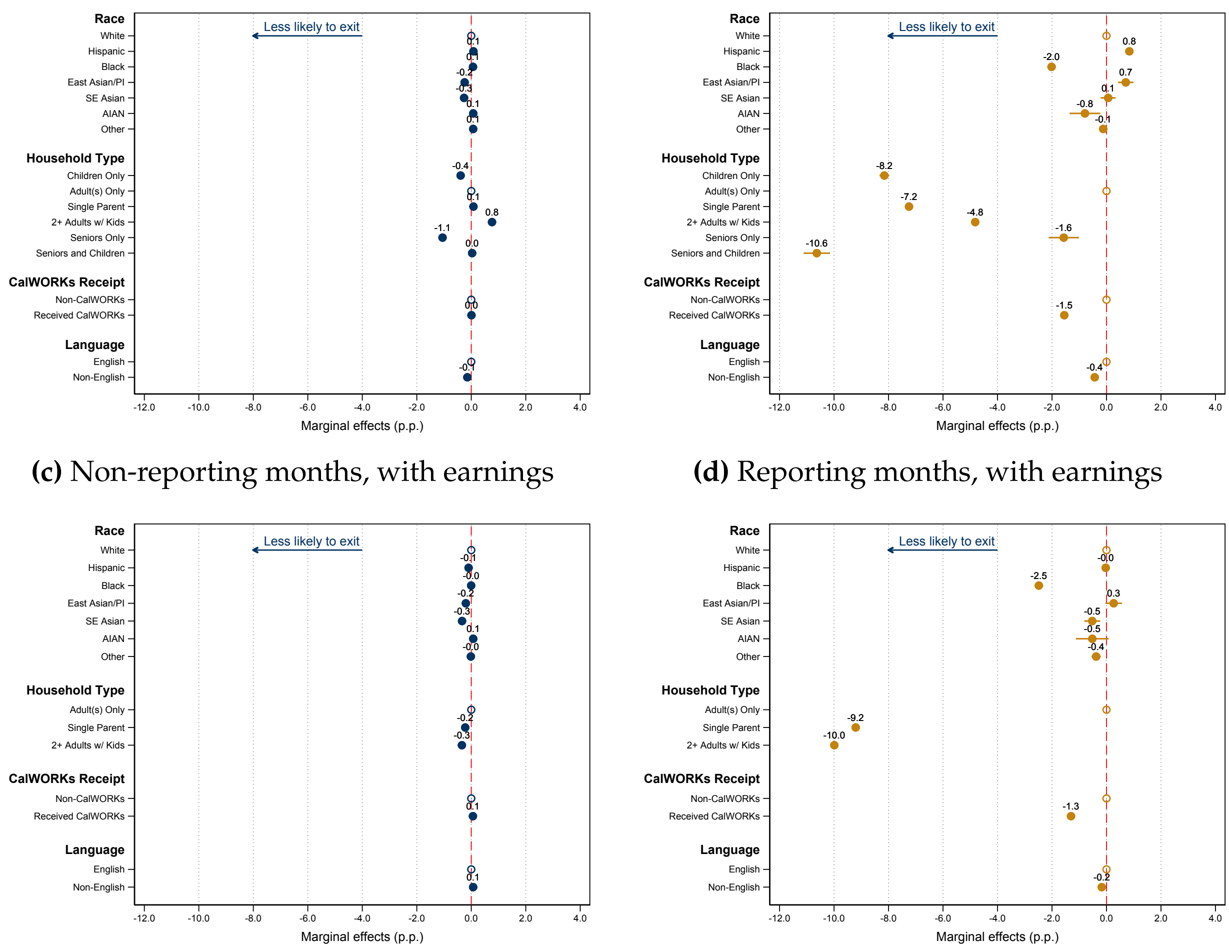


Notes. Figure 9 reports the marginal effect on likelihood of exit in reporting and non-reporting months by earnings levels 12 months before enrollment starts. I calculate these effects by first estimating Equation 1 and then identifying the difference between the predicted probabilities of exit for each benefit and earnings level, relative to the baseline, at the mean effect of all other covariates in that model. The baseline likelihood of exit for households with $0 in earnings one year before enrollment starts is two percent in non-reporting months and 14 percent in reporting months.

Figure 10: Likelihood of exiting SNAP by demographic characteristics

(a) Non-reporting months **(b)** Reporting months

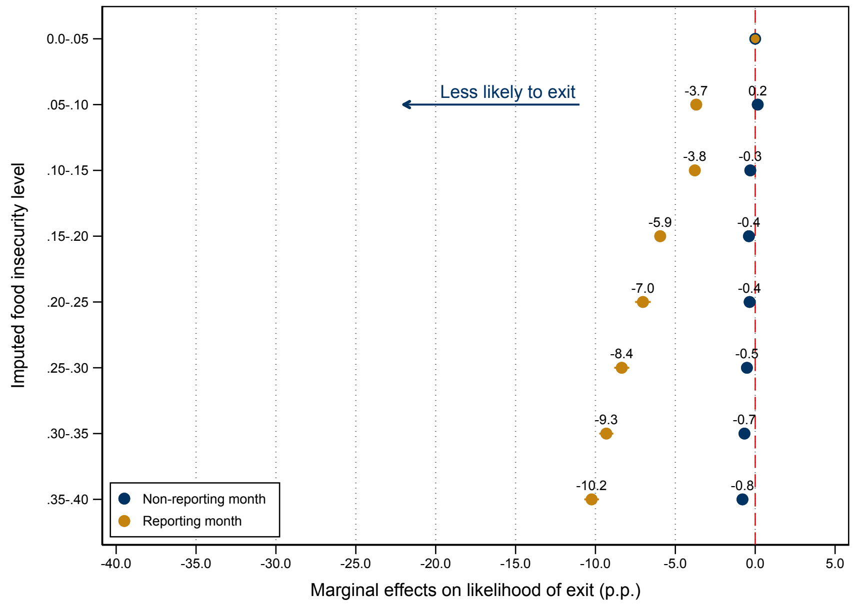
(c) Non-reporting months, with earnings **(d)** Reporting months, with earnings



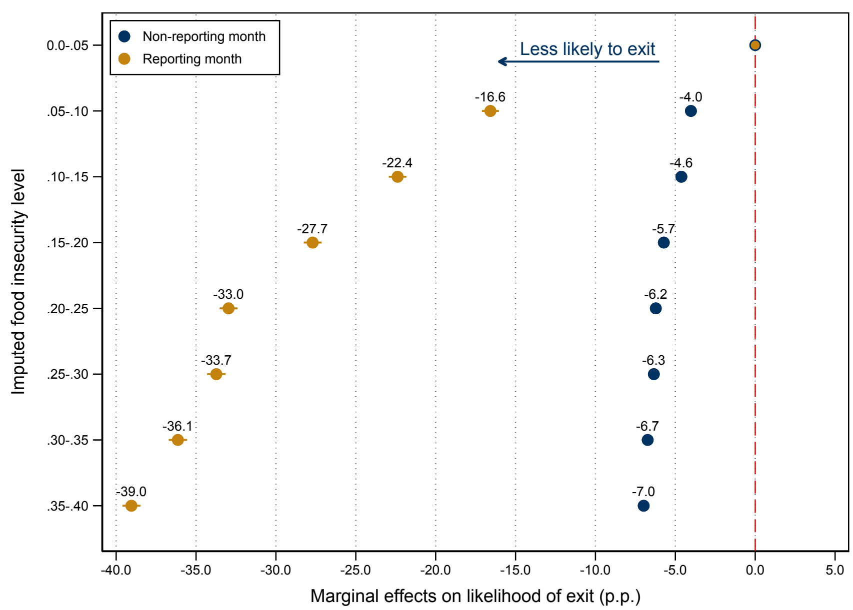
Notes. Figure 10 reports the marginal effect on likelihood of exit in reporting and non-reporting months by listed demographic characteristics. Panels a and b report estimates for non-reporting months; Panels b and d report estimates for reporting months. In Panels c and d, I control for enrollees' current earnings. I calculate these effects by estimating Equation 1 and then identifying the difference between the predicted probabilities of exit for each demographic characteristic, relative to the baseline, at the mean effect of all other covariates in that model. When not accounting for earnings, the baseline exit rate in non-reporting months is .022 percent for White enrollees, .023 percent for adult(s) only cases, .023 percent for enrollees whose primary language is English, and .022 percent for enrollees who had not enrolled in TANF. The baseline exit rate in reporting months is 14.0 percent for White enrollees, 19.3 percent for adult(s) only cases, 14.3 percent for enrollees whose primary language is English, and 14.9 percent for enrollees who had not enrolled in TANF. When accounting for earnings, the baseline exit rate in non-reporting months is .024 percent for White enrollees, .023 percent for adult(s) only cases, .023 percent for enrollees whose primary language is English, and .022 percent for enrollees who had not enrolled in TANF. The baseline exit rate in reporting months is 14.6 percent for White enrollees, 11.9 percent for adult(s) only cases, 14.3 percent for enrollees whose primary language is English, and 14.9 percent for enrollees who had not enrolled in TANF.

Figure 11: Relative likelihood of exiting SNAP by imputed food insecurity level

(a) Without earnings



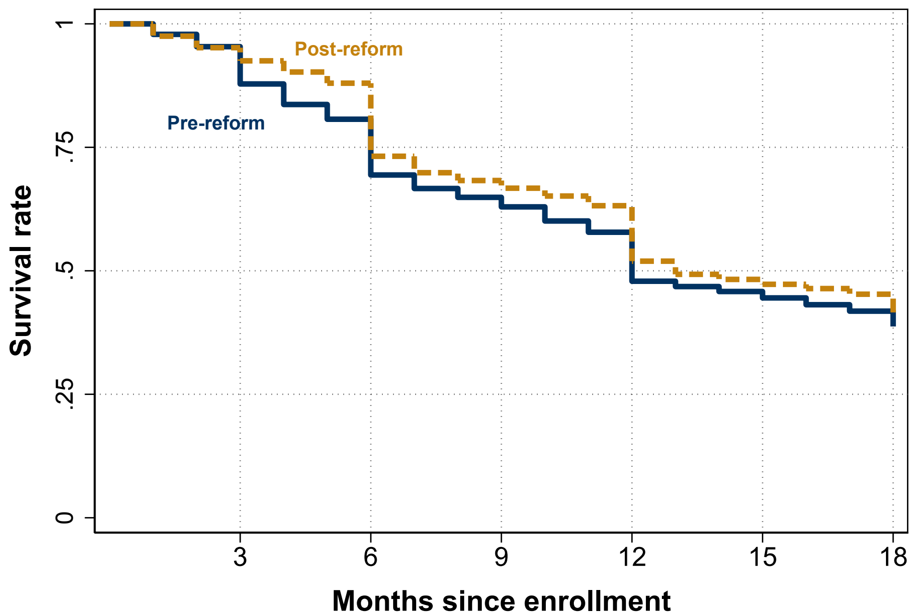
(b) With earnings



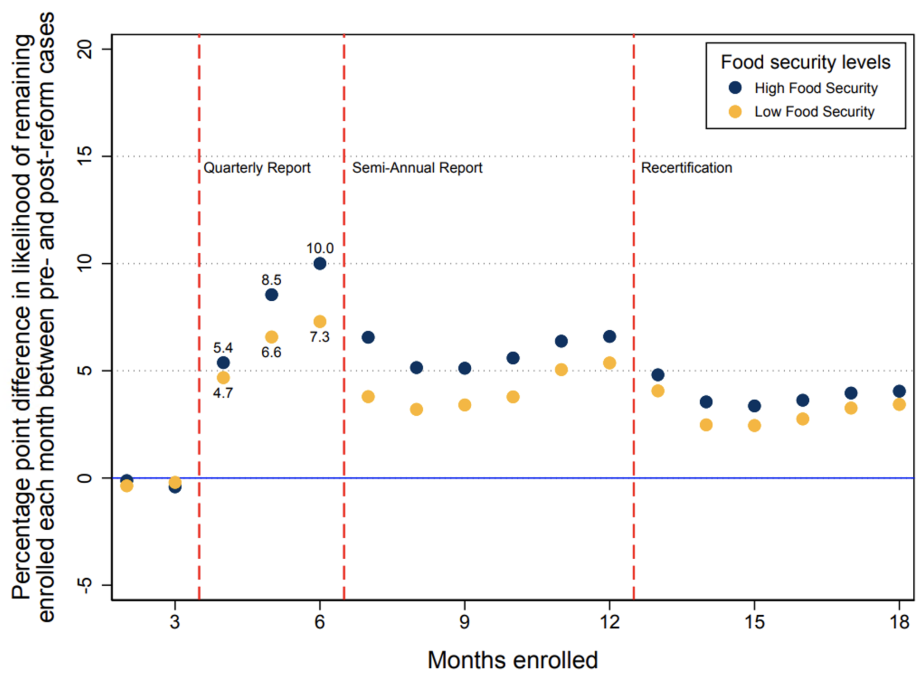
Notes. Figure 11 reports the marginal effect on likelihood of exit in reporting and non-reporting months by levels of imputed food insecurity. Estimares are derived via the procedure summarized in subsection 4.4. In order to demonstrate the important of earnings to food insecurity, and to isolate the relevance of demographic characteristics like race and household composition by themselves, I separately estimate these effects using and not using earnings in the food insecurity assignment. For Panel A, I assign households a predicted level of food insecurity without using their earned income. For Panel B, I incorporate households' earnings. See Appendix C for more information about this imputation. The baseline likelihood of exit for households with lowest level of imputed food insecurity (not including earnings) is three percent in non-reporting months and 20 percent in reporting months. The baseline likelihood of exit for households with lowest level of imputed food insecurity (including earnings) is eight percent in non-reporting months and 45 percent in reporting months.

Figure 12: Survival rate for SNAP recipients before and after reporting reform

(a) Average survival rate for pre-reform and post-reform cases among lowest food security recipients



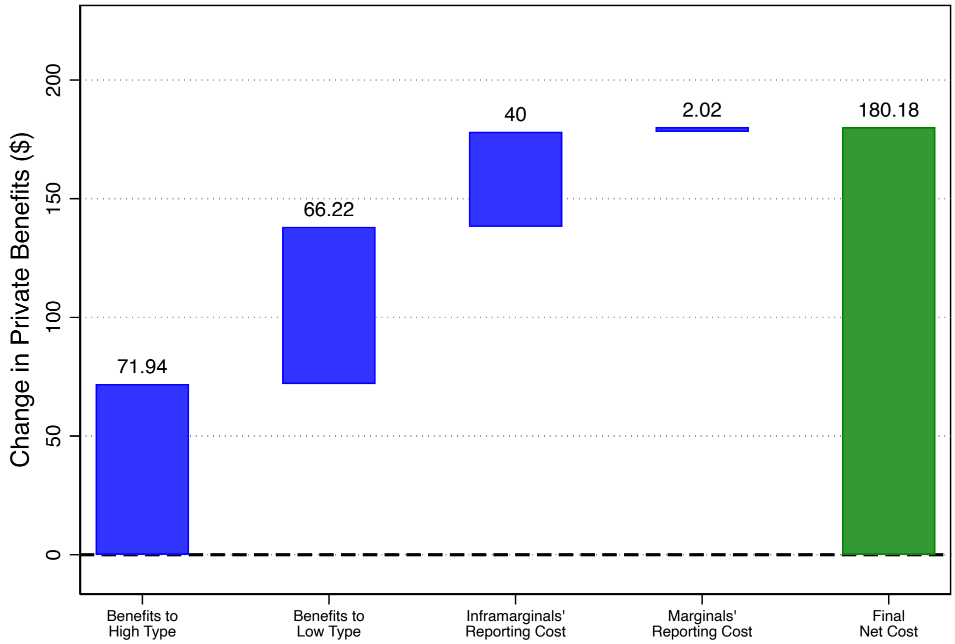
(b) Differences in survival rates between pre-reform and post-reform recipients by levels of predicted food insecurity



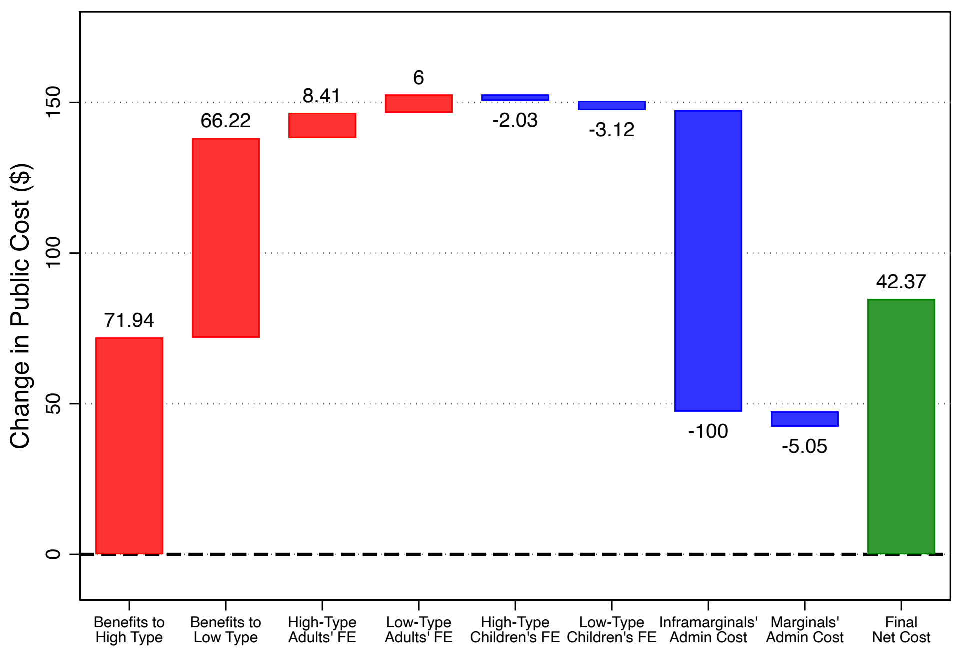
Notes. Figure 12 illustrates the effect that the 2013 reporting reform had on enrollment. Panel A plots survival rates for recipients that enrolled between January and June 2013 (pre-reform) versus those that enrolled between July 2013 and December 2013 (post-reform). The reform decreased the exit rate at three months, but the average survival rates converge after six months. Panel B distinguishes this effect between recipients identified as high and low food security.

Figure 13: Decomposition of private benefits and public costs associated with the 2013 reporting reform

(a) Net Private Benefit Decomposition



(b) Net Public Cost Decomposition



Notes. Figure 13 illustrates the contribution of the benefits and costs associated with the elimination of the quarterly reporting requirement in 2013. Each bar corresponds to a component in the marginal value of public funds calculation described in subsection 4.5. Panel A decomposes the benefits to recipients. Panel B decomposes the costs borne, or saved, by the government. Blue bars represent positive contributions (benefits or cost savings), while red bars represent negative terms (costs). The green bars reflect the total net cost to the government and beneficiaries. The ratio of those bars corresponds to the MVPF reported in Section 4.5.