Paternalistic Social Assistance: Evidence and Implications from Cash vs. In-Kind Transfers

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Abstract

We estimate and compare impacts of cash and in-kind transfers on the consumption of temptation goods in the same population, and explore normative implications. We use two decades of data from South Carolina on cash benefits from Supplemental Security Income (SSI) and in-kind benefits from the Supplemental Nutrition Assistance Program (SNAP) linked to detailed data on adults' health care use. Our empirical strategy examines outcome changes in the several days following each transfer's scheduled monthly payout. Emergency department visits for drug and alcohol use increase by 20-30 percent following SSI receipt, but do not respond to SNAP receipt. Fills of prescription drugs for new illnesses also increase following SSI receipt but do not respond to SNAP receipt. Motivated by these non-fungibility results, we develop a model of a paternalistic social planner choosing the mix of cash and SNAP for a fixed-budget transfer program when consumers have self-control problems and may engage in mental accounting. We show that the planner's optimal SNAP share is strictly positive and weakly increasing as self-control worsens. Moreover, with heterogeneity in self-control and mental accounting, the planner may choose to use SNAP even when they have access to a uniform Pigouvian tax on the temptation good.

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"Economists appear to feel that paternalism is either too simple or too unattractive a rationale for large scale government programs... But it is hard to escape the conclusion that paternalism remains a fundamental underlying rationale for in-kind transfers."
– Currie and Gahvari (2007)

1 Introduction

One of the primary functions of government is to redistribute resources. In countries across the world, much of this redistribution takes the form of in-kind transfers – such as health care, education, housing and food - rather than cash transfers (Currie and Gahvari 2008). In the U.S. in 2019, over half of transfers were in kind (OECD); indeed, for the non-elderly, cash transfers have all but disappeared in the aftermath of the 1996 welfare reform (Edin and Shaefer 2015; Shmidt et al. 2025).

The widespread use of in-kind transfers is ostensibly in conflict with classic economic theory, which concludes that cash is a superior means of redistribution because it leaves recipients free to optimize the use of the transfer (Atkinson and Stiglitz 1976; Kaplow 2006). Economists have therefore developed an array of theoretical rationales for in-kind transfers, and - more recently - provided empirical evidence consistent with many of them. These include the potential for in-kind transfers to have superior targeting properties (e.g., Nichols and Zeckhauser 1982; Currie and Gahvari 2008; Lieber and Lockwood 2019), create positive pecuniary externalities (e.g., Coate et al. 1994; Cunha et al. 2019; Blanco 2023), provide insurance against commodity price risk (Gadenne et al. 2024), and address the Samaritan's dilemma (Coate 1995).

However, in the minds of much of the populace and policy-makers, the primary rationale for in-kind transfers is a paternalistic one. In surveys, respondents overwhelmingly report that they prefer to provide redistribution through in-kind transfers rather than cash, and their primary explanation is their concern that recipients will spend cash assistance 'inappropriately' (Liscow and Pershing 2022).[1] Likewise, lab-in-the-field experiments indicate a strong preference for providing cash over food stamps (SNAP) as a means of restricting recipient autonomy in order to discourage their consumption of sin goods (Ambuehl et al. 2025). Such paternalistic concerns also motivate policymakers. In 2012, for example, media coverage of individuals reportedly spending cash welfare benefits on temptation goods prompted Congress to require states to adopt policies and practices to prevent these benefits from being used in liquor stores, casinos, or adult-entertainment establishments (USGAO). Similarly, in 2021, then-Senator Joe Manchin reportedly expressed opposition to an expansion of the child tax credit because of concerns that it would be spent on illegal drugs (Shabad et al. 2021). Such paternalistic impulses can be justified by individual optimization failures

[1] Some potential transfer recipients express similar sentiments. Although only one-quarter of below-poverty survey respondents said that they would prefer to receive an in-kind transfer to an equivalent amount of cash, the most common explanation given for this preference is the desire for a self-control mechanism (Liscow and Pershing 2022).

such as time-inconsistent preferences (e.g., Laibson 1997).[2]

Yet as the opening quotation suggests, academic economists have paid relatively less attention to evidence for or implications of paternalistic rationales for in-kind transfers. In this paper, therefore, we begin to fill this gap. We provide empirical evidence that, relative to cash transfers, receipt of in-kind transfers reduces the consumption of temptation goods (specifically drugs and alcohol), and we explore normative implications for the optimal mix of in-kind and cash transfers in the presence of self-control problems.

Our empirical setting is the trade-off for low-income American adults between cash transfers in the form of Supplemental Security Income (SSI) and in-kind food provision in the form of the Supplemental Nutrition Assistance Program (SNAP). Both SSI and SNAP are large-scale, federally-funded, mean-tested transfer programs. SSI provides cash assistance and, in most cases, access to Medicaid to low-income individuals who are elderly or disabled. In 2023, SSI expenditures were \$61.4 billion per year, and SSI covered about 7.4 million Americans (SSA 2024). SNAP provides food vouchers to low-income individuals which provide a 100% food subsidy up to the value of the voucher, with no subsidy on the margin for additional food purchases. SNAP is the second-largest means-tested program in the United States (Carrington et al. 2013) and one of the only that is virtually universally available to low income individuals. In 2023, expenditures on SNAP were \$112.8 billion, and SNAP covered about 42.1 million Americans (Jones and Toossi 2024).

We analyze a customized data set that contains two decades of data (1998-2019) on cash and SNAP benefit receipt for individuals in South Carolina, linked to detailed information on their use of health care. Our empirical strategy exploits variation in the date of benefit receipt within the month. For SNAP, we follow Cotti et al. (2018) and Cotti et al. (2020) and take advantage of the fact that in South Carolina, SNAP benefits are paid monthly on a date that varies based on the last digit of the recipient's case number; this generates plausibly-exogenous, individual-level variation in the day of the month that SNAP is received. For SSI, we follow Dobkin and Puller (2007) who analyze changes in outcomes around the receipt of SSI benefits on the first of the month;[3] we augment this strategy by comparing changes in outcomes for SSI recipients with those for other low-income adults who are likely not on SSI.

Our primary empirical analysis examines the impact of monthly receipt of each benefit on temptation goods, specifically drugs and alcohol which we proxy for by emergency department (ED) visits for drug and alcohol use. We also look at impacts on prescription drugs fills, our proxy for consumption of non-temptation, non-labeled goods; we focus on first-time fills of prescriptions for new conditions (a.ka. "first fills") in order to better capture consumption rather than merely the timing of purchases. Our evidence is consistent with a higher marginal propensity to consume

[2]Other paternalistic rationales include social preferences for ensuring a minimum consumption of specific commodities (e.g., Musgrave 1959; Tobin 1970; Olsen 1980; Harberger 1984).

[3]Other highly related work includes Shaner et al. (1995); Phillips et al. (1999); Stephens Jr (2003); Evans and Moore (2011, 2012)

temptation goods out of cash transfers than out of food vouchers. Specifically, looking at impacts in the week after benefit receipt, we find that receipt of SSI benefits is associated with a 20 to 30 percent increase in ED visits for drug or alcohol use, while such visits do not change following the receipt of SNAP benefits. We also find that first fills increase by about 20 to 40 percent in the week following receipt of SSI, but do not increase in response to SNAP receipt; this is consistent with a higher marginal propensity to consume non-labeled non-temptation goods out of cash than out of SNAP. Even after we adjust for the fact that in our population SSI benefits are likely about 4 times higher than SNAP benefits, we can reject the null hypothesis that, *in the same population* the impacts of the two types of benefits on the consumption of temptation goods or on the consumption of non-labeled, non-temptation goods are the same.

These non-fungibility results between cash and SNAP are striking in light of the substantial existing empirical evidence that SNAP benefits tend to be infra-marginal for food consumption: the vast majority of SNAP recipients spend more on food than they receive in SNAP benefits (Trippe and Ewell 2007; Econometrica 2012; Hoynes et al. 2015; Hastings and Shapiro 2018).[4] Hastings and Shapiro (2018) show that if households engage in mental accounting, this can generate higher marginal propensities to consume food out of SNAP than out of cash, even if SNAP is inframarginal. We augment their model to allow for the presence of temptation goods like drugs and alcohol that provide positive utility when consumed but have negative utility consequences in subsequent periods. We also show that in this set-up, our empirical evidence of non-fungibility in response to anticipated, intertemporal fluctuations in the timing of benefit receipt implies non-fungibility in response to permanent benefit receipt.

We use this framework for normative analysis of a paternalistic social planner's optimal choice of how to split an exogenous transfer budget between SNAP and cash when individuals over-consume temptation goods due to self-control problems, or more generally, when the social planner prefers that the consumer choose a level of food consumption that exceeds what she would choose. Relative to SNAP, cash has the disadvantage that it increases consumption of temptation goods, but the advantage of allowing for consumption of other goods not covered by SNAP.[5] In the presence of self-control problems, the planner's optimal choice will always include strictly positive amounts of SNAP. The planner's optimal SNAP share is increasing as time-inconsistency increases, or more generally in the wedge between the food consumption the individual chooses and what a paternalistic social planner prefers. It is also weakly decreasing in the extent of mental accounting

[4] Data from the Current Population Survey Food Security Supplement indicate that about three-quarters to eighty percent of households spent more on food than their food stamp benefits in 2005 and 2010 (Trippe and Ewell 2007; Econometrica 2012). Data from the Consumer Expenditure Surveys, from 1990 - 2013 indicate that about 84 percent of SNAP recipient households spend more on food at home than the SNAP benefit level (Hoynes et al. 2015). Transaction data from a large U.S. grocery retailer from 2004 through 2016 indicate that for 94 percent of households who ever use SNAP, average SNAP-eligible spending in non-SNAP months is higher than average SNAP benefits in SNAP months (Hastings and Shapiro 2018).

[5] In this sense, the planner's tradeoff between cash and SNAP is similar to the tradeoff between commitment and flexibility studied by Amador et al. (2006).

so that, if mental accounting is strong enough, the planner will choose a SNAP share that preserves the infra-marginality of SNAP benefits.[6] Moreover, when we allow for heterogeneity across agents in both the extent of self-control problems and the extent of mental accounting, the social planner may choose to use SNAP even when they have access to a Pigouvian tax on the temptation good.

Our paper relates to several distinct literatures. Most broadly, as noted at the outset, it contributes to an active literature on economic rationales for in-kind transfers (e.g., Nichols and Zeckhauser 1982; Currie and Gahvari 2008; Lieber and Lockwood 2019; Coate et al. 1994; Cunha et al. 2019; Blanco 2023; Gadenne et al. 2024; Coate 1995). We expand this literature by focusing on paternalism, a relatively-understudied but potentially practically important rationale for the wide-spread use of in-kind transfers.[7] Our normative, theoretical framework draws directly on the literature on time-inconsistent preferences (e.g., Thaler and Shefrin 1981; Laibson 1997; O'Donoghue and Rabin 1999; Banerjee and Mullainathan 2010) and mental accounting (e.g., Thaler 1985, 1999), while our analysis of the optimal role for in-kind transfers in the presence of "temptation goods" contributes to a related literature in behavioral public finance on internalities and optimal sin taxes (e.g., O'Donoghue and Rabin 2006; Gruber and Köszegi 2001; Allcott et al. 2019a; Farhi and Gabaix 2020), as well as optimal income taxation in the presence of present bias (Lockwood 2020).

Our empirical work provides a health care-based test of the fungibility of in-kind transfers that complements existing, consumption-based tests of fungibility. These consumption-based tests have yielded mixed results across and within contexts.[8] Most closely related to our setting are papers examining whether the marginal propensity to consume food (MPCf) out of SNAP is higher than out of cash. Consistent with our non-fungibility results, Hastings and Shapiro (2018) and Song (2022) find a much higher MPCf out of SNAP than out of cash when examining detailed data on purchases; however, consistent with fungibility, work studying the initial roll out of the Food Stamp program in the 1960s was unable to reject the hypothesis that the MPCf out of food stamps and cash were the same (Hoynes and Schanzenbach 2009).[9]

[6]The early literature on mental accounting motivated it as a way to overcome self-control problems (see, e.g., Thaler (1985); for more recent theoretical work in this vein see e.g. Galperti (2019)). In a similar spirit, our paternalistic social planner may use individuals' mental accounting behavior to optimally design the safety net in a way that mitigates against the consequences of their self-control problems.

[7]Another widely-conjectured but relatively-understudied rationale for in-kind transfers is based on political economy (Currie and Gahvari 2008). One type of political economy rationale is based on the appeal to voters, which in turn may be due to their paternalistic concerns. Other political economy rationales are based on the creation of constituencies who receive benefits from the in-kind nature of the transfers, such as the farming interests that supported the creation of the food stamp program in the U.S. (Hoynes and Schanzenbach 2009; Currie 2006).

[8]Evidence against fungibility includes a randomized evaluation in Indonesia of moving from an infra-marginal in-kind transfer of rice to a voucher that can be used for eggs and rice which finds that the voucher increases consumption of eggs (Banerjee et al. 2023b); there is also evidence that labeled cash transfers (without any requirement for spending the transfer on the labeled good) increase consumption of the labeled good (e.g., Benhassine et al. 2015; Beatty et al. 2014; Kooreman 2000). On the other hand, consistent with fungibility, a randomized evaluation of an infra-marginal food assistance program in Mexico finds no evidence that it increased food consumption relative to an equivalent cash transfer (Cunha 2014).

[9]Additional, albeit much more indirect, evidence against fungibility comes from the growing body of evidence

Finally, and most narrowly, we contribute to the existing empirical literature in the U.S. on the causal impacts of cash or SNAP (separately) on temptation goods and on health; we review this literature - which has produced mixed results - in more detail in Appendix A, and discuss the relevant findings in the context of our results below. Our study provides what is to our knowledge the first direct, head-to-head comparison of the impact of cash and SNAP *for the same individuals*.[10]

The rest of the paper proceeds as follows. Section 2 presents our empirical setting and estimating equations. Section 3 presents our data, key variable definitions and main analytic samples. Section 4 presents the empirical results and Section 5 presents a normative model that is motivated by these results and explores their implications for optimal transfer policy. There is a brief conclusion.

2 Empirical Framework

2.1 Benefits Schedule

Our empirical strategy exploits variation in South Carolina in the timing of benefit payments within and across people. SSI benefits are paid on the first of the month in every state, unless the first falls on a weekend or on a federal holiday (which potentially applies only to New Year's Day or Labor Day); in that case, payout occurs on the first preceding weekday (SSA 2023). Thus in practice, SSI benefits are paid on the first of the month in about 5/7th of the months, and on dates between the 27th and the 31st in the remaining 2/7ths of the months.

The monthly timing of SNAP benefit payments varies across states and time (Cotti et al. 2016). In South Carolina during our 1998-2019 analysis period, SNAP benefits were paid on one of 15 possible days between the 1st and the 19th of the month, with the payment day determined by the last digit of the recipient's case number and when they enrolled in SNAP. Specifically, if the person's latest enrollment was before September 1st, 2012, benefits were paid on the first of the month for case numbers whose last digit is a 1, on the second of the month for case numbers whose last digit is 2, and so forth through the last digit of 0 for which benefits were paid on the 10th of the month. If the person's latest enrollment - either as a new or re-enrollee - started on or after September 1st 2012, 10 days were added from the mapping of the case numbers to day of the month for odd-numbered last digits of case numbers, while the receipt dates for even-numbered last digits of cases remained the same (see Appendix Table OA.1). Thus during our sample period there are 15 possible payout days for SNAP benefits, depenidng on the last digit of one's case number and whether one's case began before or after September 2012. This payment schedule is not adjusted if the payment date happens to fall on a weekend (USDA 2023).

that labor earnings drop substantially following shocks to unearned income via lottery winnings (e.g. Golosov et al. (2024)) but that SNAP receipt does not affect labor market participation (e.g. Gray et al. (2023); Cook and East (2023, 2024).

[10] The only other direct comparison of this type that we know of is Bitler et al. (2022), who caution that their evidence is only 'suggestive' due to potential compositional biases in their design.

Our empirical strategy will examine how various outcomes change relative to the day of benefit *receipt*. Importantly, the date of benefit receipt and benefit payment were the same during our analysis period. SNAP benefits were distributed via electronic benefit transfer over the entire analysis period (Tiehen et al. 2024); SSI benefits were delivered primarily electronically through 2012 - with the share of SSI recipients who received checks by mail declining from roughly three-fifths in 1998 to 15% in 2012 (SSA 2024) - and electronically to essentially everyone starting in 2013 (SSA 2014). SSI checks that were mailed were timed to arrive on the 1st of the month or the first weekday prior to that if the 1st was a weekend or federal holiday (SSA 2013).

2.2 Estimating equations

SSI. To identify the impact of monthly SSI benefit receipt we estimate the following linear regression:

$$y_{dg} = \sum_{\substack{r=-13 \\ r\neq -r}}^{13} (\alpha_r 1[r(d) = r] + \beta_r SSI_g \cdot 1[r(d) = r]) + \gamma SSI_g + \Omega_d + \epsilon_{dg} \tag{1}$$

The analysis takes place at the level of the calendar day d by group g, where d denotes a specific calendar date in terms of day-month-year (such as March 7th, 2006) and group g denotes whether or not that person-days are on SSI. We let r index days relative to the day that SSI is paid out, which we denote by $r = 0$; $\mathbb{1}[r(d) = l]$ are a series of indicator variables for day d corresponding to relative day r. We omit the day prior to SSI payout ($r = -1$) and restrict our analysis sample to the payout day and 13 days on either side of it.[11] We let SSI_g denote an indicator variable for the 'on-SSI' group, and we allow the coefficients on the relative day indicators to vary based on this; we also control for fixed outcome differences between groups (SSI_g).

The regression also includes a number of fixed effects as controls, Ω_d. Specifically, following the approach of Evans and Moore (2012) we include fixed effects for calendar month, calendar year, day of the week, and 21 "special days".[12] We assume that these various calendar time measures have the same effect regardless of the individual's group. We report standard errors clustered at the calendar day d (i.e. day-month-year) level.

In what follows, we will report two sets of estimates for how outcomes change around the timing of SSI payout, one of which is based solely on the within-month pattern of outcomes relative to the date of benefit receipt for SSI recipients and the other additionally uses the within-month pattern

[11] Specifically, we include separate indicators for relative days -13 to -2 and 0 to 13. We omit from the analysis the few days in each month that are neither. This way, every calendar day has a unique relative day.

[12] The special days are: January 1st and 2nd, the Friday through Monday associated with all federal holidays that occur on Mondays (Presidents' Day, Martin Luther King Jr. Day, Memorial Day, Labor Day, Indigenous People's Day), Super Bowl Sunday and the following Monday, Holy Thursday through Easter Sunday, July 4, Veterans Day, the Monday to Sunday of the week of Thanksgiving, a dummy for the days from the day after Thanksgiving to New Year's Eve, plus single-day dummies for December 24 through December 31.

of outcomes for low-income individuals who are likely not SSI recipients as a contrast. Specifically, the $(\alpha_r + \beta_r)$ coefficients reveal the within-month pattern of outcomes for SSI recipients, while the β_r coefficients reveal the within-month pattern of outcomes for SSI recipients *relative to* other low-income adults who are not SSI recipients. A priori, we expect that using only the within-month pattern for SSI recipients (the $(\alpha_r + \beta_r)$ coefficients) may overstate the effect of SSI payment since the 'around the first of the month' timing of SSI receipt may be correlated with the receipt of other (unobserved) benefits. We expect that the difference-in-difference analysis of within-month patterns for SSI recipients relative to likely non-recipients (the β_r coefficients) likely under-states the effect of receiving the SSI payment for two reasons. First, unlike SSI recipients who are restricted from substantial earnings, those actually not on SSI may be employed and receiving pay checks timed around SSI benefit receipt dates; if paycheck receipt is driving some of the changes in outcome for the likely not on SSI group but not for the SSI group, the contrast in patterns between the two groups may under-estimate the impact of SSI. Second, as we discuss in the next section, some of our 'likely not on SSI' group may in fact be on SSI. Together, therefore, we think the two approaches likely provide bounds on the impact of SSI benefit receipt.

SNAP. To identify the impact of the monthly SNAP benefit receipt we estimate the following linear regression:

$$y_{dcs} = \sum_{\substack{r'=-13 \\ r' \neq -1}}^{13} \beta_{r'} 1[r'(dcs) = r'] + \delta_{c,s} + \Omega_{d,s} + \kappa_{k,s} + \epsilon_{dcs} \tag{2}$$

Here, d once again denotes a specific calendar date, but now the binary group g (for on SSI vs not) is replaced by 20 groups (c, s) that map to 15 different possible payout dates for SNAP benefits. These groups are based on the 10 possible last digits of one's SNAP case number (c) and whether one's SNAP case was assigned before or during/after September 2012 (s), when the mapping rule from SNAP case number to payout day changed (Appendix Table OA.1). We expect that case numbers are randomly assigned and therefore, within an assignment regime s, SNAP payout days will be uncorrelated with beneficiary characteristics; this is confirmed by balance tests (Appendix Tables OA.2 and OA.3). We therefore control for a series of fixed effects for the last digit c of an individual's case number interacted with whether the case was assigned before or after September 2012 $(\delta_{c,s})$.

We let r' index days relative to the day that SNAP is paid on, which we denote by $r' = 0$, and $\mathbb{1}[r'(dcs) = r']$ are a series of indicator variables for relative day r'. Once again, we omit the day prior to SNAP payout $(r' = -1)$, and restrict our analysis sample to the payout day and 13 days on either side of it. The key variable of interest $(\beta_{r'})$ show the within month pattern for SNAP recipients relative to the day of SNAP receipt.

We once again include fixed effects for calendar month, calendar year, day of the week and special days as in equation (1), but now we include these fixed effects separately by case assignment regime s ($\Omega_{d,s}$), since SNAP payout day is randomly assigned within the assignment regime s. More importantly, we now include fixed effects for the day of the month (again by assignment regime (s); the $\kappa_{k,s}$ are a series of indicators for which day of the month it is (from the 1st potentially through the 31st). Unlike for the analysis of the impact of SSI benefits in equation (1), there is variation across SNAP recipients in the payout day. We therefore do not need a control group of individuals not on SNAP, and instead we control directly for day-of-the-month fixed effects.[13] We report standard errors clustered at the calendar day d level.

3 Data

Our data include all individuals in South Carolina born in 1970 or earlier who were on Medicaid at some point between 1998 and 2019, about a half million unique individuals. We obtained linked, longitudinal, individual-level administrative data for these individuals covering the period 1998-2019. The data contain information on the dates and amounts of SNAP (and TANF) benefit receipt, basic demographics, year of death (if any) and detailed information on the timing and nature of health care utilization, including all-payer hospital and ED records and all types of Medicaid utilization.

The data come from four different sources in South Carolina: Department of Social Services (DSS) records on SNAP and TANF recipients, Medicaid enrollment and utilization records; emergency and hospital discharge data for all payers; and vital statistics death certificate data.[14] The DSS records contain the months that each individual receives SNAP and the months that they receive TANF. For each person-month receiving SNAP, we also observe the benefit amount, the benefit type (i.e. regular, supplemental, expedited, corrected), and the last digit of the case number. The Medicaid data contain information on the months that each individual was enrolled in Medicaid and her Medicaid eligibility category (one of which is via SSI receipt) at the beginning of each eligibility spell, as well as basic demographic information including year of birth, gender, race, and a household ID that allows us to identify members of the same household within our sample. We also use the Medicaid health care utilization data to measure Medicaid-covered prescription drug fills, both overall and by type of drug. The all-payer hospital and ED records provide our information on ED visits; specifically they contain encounter-level information with exact admission dates, primary and additional diagnoses (ICD9/10 codes), procedures, and other encounter-specific details from the universe of hospitalizations and ED visits in SC. Finally, the Vital Statistics death certificate data contain year of death (if any).

[13] In practice, we show in the robustness analysis below that results look very similar if we do not allow the fixed effects to vary across assignment regime. We also show that estimates of either equation (1) or (2) are not sensitive to excluding the covariates in .

[14] The South Carolina Office of Revenue and Fiscal Affairs linked the individuals across the data sets using a multi-level algorithm that includes social security number and basic demographic information of the individual.

3.1 Variable Definitions

Identifying benefit receipt. We identify benefit receipt at the person-month level. We code a person-month as receiving SNAP based on whether they received a positive SNAP benefit amount that month. We do not directly observe receipt of SSI benefits; instead, as in Dobkin and Puller (2007), we code a person-month as receiving SSI if they are enrolled in Medicaid and if, at the start of the current Medicaid eligibility spell, their Medicaid eligibility was through an SSI-related eligibility category.[15]

This approach to identifying person-months on SSI is unlikely to generate false positives, but may well create false negatives, since individuals can be enrolled in SSI but receiving Medicaid through a different eligibility category. For this reason, when we estimate the impact of SSI using a difference-in-differences design in which we contrast the within-month pattern of outcomes for person-months we have identified as on SSI to the within-month pattern for person-months who are likely not SSI recipients, we may be mistakenly including some SSI recipients in the 'likely not on SSI' category, and thus under-estimating the impact of SSI.[16]

Outcomes. We use the health care data to proxy for consumption of two types of goods: temptation goods, and non-labeled, non-temptation goods.[17] Following Dobkin and Puller (2007), we proxy for consumption of temptation goods based on drug and alcohol related ED visits. For some supplemental analyses we analyze other types of ED visits as well.[18]

We use Medicaid-covered prescription drug fills to proxy for consumption that is neither a temptation good nor the labeled good. Prescription drug co-pays in South Carolina's Medicaid program were \$2 per either brand or generic drug for individuals older than 19 years old at the start of our study period. They increased to \$3 in 2001 and further to \$3.40 in 2011 (KFF 2025).[19]

Prescription drug purchases may reflect planned, regular re-fills of chronic medications, where the timing of purchase may not reflect the timing of consumption, as well as drugs for newly

[15] In South Carolina, SSI recipients are automatically enrolled in Medicaid upon the start of their SSI spell (Rupp and Riley 2016; SCDHHS 2022).

[16] We found it challenging to gauge the extent of mis-classification. In our data of all Medicaid enrollees born before 1970, 33% had eligibility based on SSI receipt at the beginning of our sample period (1999–2001), compared to 30% at the end (2017–2019). To benchmark these estimates, we compared them with estimates from the Medical Expenditure Panel Survey (MEPS), restricting to individuals born before 1970 who reported being enrolled in Medicaid for any reason. In MEPS, 30% of all Medicaid enrollees reported also receiving SSI at the beginning of our period (1999-2001), while only 21% did at the end of our period (2017-2019). At face value, this comparison might suggest that we do not misclassify individuals early in the sample and may even over-classify them as SSI by the later years. However, this interpretation is complicated by the well-documented under-reporting of program participation in surveys: prior work estimates that between one-quarter and more than one-half of true recipients fail to report receipt, while false reports by non-recipients are rare (Celhay et al. 2024, 2025).

[17] Appendix B provides additional details on how we code these and other outcomes.

[18] To measure ED visits we combine information from the ED records on 'outpatient ED visits' (i.e. ED visits that do not result in an inpatient hospital admission) with information from the hospital records on 'inpatient ED visits' (i.e. ED visits that results in an inpatient hospital admission.)

[19] For the low income elderly individuals studied by Gross et al. (2022), co-pays ranged from \$2 for generic drugs to \$6 for branded drugs.

diagnosed conditions, where the timing of purchase more likely corresponds to the timing of consumption. Moreover, re-fills may be coordinated with other shopping trips, such as for the purchase of food or alcohol. We therefore focus on a subset of prescription drug fills that are more likely to temporally correspond to consumption. Specifically, following Gross et al. (2022), we examine first fills of a drug, where a "first fill" is defined as a prescription in a therapeutic class for which the recipient had no fills in the last six months; for such fills, the recipient does not have access to an existing stock pile of the drug, and so the timing of the filling likely indicates the beginning of actual consumption, rather than just the timing of purchase.

3.2 Analytic Samples

We make a number of sample restrictions to define our analysis samples. In our main analysis, we define a SNAP sample and an SSI sample. The SNAP sample consists of person-months on SNAP, while the SSI sample consists of two sub-samples: person-months on SSI and person-months likely not on SSI. For all samples, we use the death certificate data to drop person-months after the year of death. For the likely not on SSI sample, to reduce the chance of classifying someone as likely not on SSI who actually is on SSI, we exclude any individual who at any point from 1998-2019 belong to a household in which any individual was ever receiving SSI. For the SNAP and on SSI samples, we restrict person-months in each benefit category to spells in which the person is in that category for at least 12 months, so that we can interpret any response as a response to anticipated benefit receipt. For all three of the samples, we drop any person-month on TANF, so that we do not conflate the impact of SNAP or SSI receipt with that of TANF. For the SNAP sample, we make a number of other very minor sample restrictions; Appendix Table OA.4 shows the impact of each of these restrictions.

The first three columns of Table 1 report summary statistics for the SNAP sample (column 1) and the SSI sample (columns 2 and 3), showing statistics within the SSI sample separately for those on SSI (column 2) and those likely not on SSI (column 3). Because our analysis examines daily changes in outcomes within the month relative to the timing of benefit receipt, our effective sample size scales with the number of person-months. We observe about 29 million person-months (corresponding to about 380,000 individuals) on SNAP, about 19-million person months (about 200,000 individuals) on SSI, and about 109 million person-months (about 500,000 individuals) likely not on SSI. Compared to person-months on SSI (column 2), the person-months on SNAP (column 1) are slightly younger (mean age of 57 compared to 60), slightly more likely to be female (64 percent vs. 61 percent) and similar in terms of share black (about 44 percent). Because our analysis is conducted at the date (day-month-year) level, mean outcomes are expressed as such. Relative to the SSI sample (column 2), the SNAP sample (column 1) has slightly lower rates of ED visits per day overall (34.18 per 10,000 person-days compared to 39.25 per 10,000) as well as drug or alcohol related ED visits (1.90 per 10,000 compared to 2.36 per 10,000).

For the SSI analysis we also conduct a difference-in-differences analysis between person-months on SSI (column 2) and likely not on SSI (column 3). Compared to those likely not on SSI, those on SSI are older (average age of 60 compared to 57), less likely to be female (61 percent compared to 66 percent) and more likely to be black (43 percent compared to 33 percent). Most strikingly, compared to the likely not on SSI sample (column 3), the SSI sample (column 2) has notably higher rates of ED visits both overall (39.25 vs 15.65 per 10,000 person-days) as well as drug or alcohol related ED visits (2.36 per 10,000 compared to 0.53 per 10,000).

'Overlap' sample. A key focus of our analysis is testing whether we can reject that the response to SNAP benefits is the same as the response to SSI benefits. One challenge in this respect is that the SNAP sample (column 1), consists of person-months both on and not on SSI, and likewise the SSI sample (column 2) includes person-months both on and not on SNAP. This might lead us to incorrectly reject fungibility not because responses to the treatments (SSI vs SNAP) are different, but because responses are heterogeneous across people. We therefore also report analyses for the 'overlap sample' of person-months who are both on SNAP and on SSI. This sample has the advantage of testing differential impacts of SNAP and SSI *among the same individuals*, but at the cost of potentially lower power.

Columns (4) and (5) show summary statistics for the overlap samples of person-months on both SNAP and SSI (column 4) and the sample of person-months on SNAP and either on SSI or likely not on SSI (column 5).[20] Compared to the full sample, we retain about one-third of the person-months on SNAP, about half of the person-months on SSI, and only about 11 percent of the person-months likely not on SSI. ED outcomes for those on SSI and SNAP are thus, by construction, the same, while ED outcomes for person-months on SSI and likely not on SSI are now more similar (i.e. the difference between means in columns 4 and 5 is less than that between columns 2 and 3); whether this is a feature or a bug is not clear as it is possible that by requiring everyone to be on SNAP, our 'likely not on SSI' now has a higher share of people who are in fact on SSI whom we simply did not code as such.

Prescription drug sample. For any analyses where the outcome variable is a measure of prescription drug fills, we must further restrict the sample to person-months in which we can observe fills in the Medicaid prescription drug data. Unlike outcome variables that relate to ED visits, prescription drug fills are only observable for a subset of our data: person-months in which the individual is on Medicaid and Medicaid is the primary payer for their prescription drugs. In order to observe prescription drug fills, therefore, the person-month must both be on Medicaid and also not be covered by Medicare Part D prescription drug coverage.[21] This causes us to lose between

[20]Thus when we do the difference-in-differences analysis between those on SSI and those likely not on SSI in the overlap sample, both the on SSI and likely not on SSI samples are restricted to person-months on SNAP.

[21]If an individual is covered by both Medicare Part D and Medicaid, Medicare is the primary payer, so the prescription drug fill data in Medicaid will be extremely incomplete. Moreover, such individuals would not face

60 and 75 percent of our person-months.[22]

4 Empirical Results

4.1 Graphical Evidence

Consumption of Temptation Goods. Figure 1 shows the impact of receipt of SNAP and receipt of SSI on emergency department visits for drug and alcohol use, our proxy for (excessive) consumption of temptation goods. Panel (a) shows no evidence of an impact of receipt of SNAP on the number of drug or alcohol related ED visits. By contrast, panel (b) shows a sharp increase in the number of a drug-or-alcohol related ED visit immediately following receipt of SSI; more specifically, there is an increase of approximately 0.26 visits (standard error = 0.053) per 10,000 on the day of the SSI payout (day 0), rising to an increase of 0.86 (standard error = 0.055) by the day after receipt (day 1), that stays elevated for another several more days before gradually declining. On average over the week after receipt, we estimate that drug-or-alcohol related ED visits increase on average by 0.70 visits (standard error = 0.035) per 10,000 people per day; relative to an average number of ED visits for drug and alcohol use of about 2.36 per 10,000 people per day in this population (Table 1 column 2), this represents an approximately 30 percent increase in ED visits in the week following SSI receipt.

Evidence of an increase in ED visits for drug and alcohol use following receipt of cash benefits is consistent with an existing literature (reviewed in more detail in Appendix A) showing that receipt of cash benefits is followed by an increase in ED visits for substance abuse (e.g., Dobkin and Puller 2007; Shaner et al. 1995), and in substance abuse mortality (e.g., Phillips et al. 1999; Evans and Moore 2012); it is also consistent with evidence from tax rebates that on the extensive margin as well, receipt of cash transfers increase these proxies for consumption of temptation goods (Evans and Moore 2011; Gross and Tobacman 2014). Most closely related to our analysis is Dobkin and Puller (2007) who find that drug-or-alcohol related ED visits rise by about 20 percent following SSI receipt in California. In contrast to the prior evidence on the relationship between receipt of cash transfers and use of alcohol and drugs, we are not aware of prior work examining the impact the relationship between receipt of SNAP and use of alcohol and drugs.[23]

copays (Gross et al. 2022). Starting in 2006 - the year the Medicare Part D program was introduced - individuals on Medicaid may be covered by Medicare Part D if they are 65 and over, or they are under 65 but disabled. As a result, we exclude from the drug fills sample any person-month in 2006 or later who is 65 and over; we also exclude any person-months from 2006 on if the person was ever dually-eligible for Medicare from 2006-2019 when they were 64 and younger. Finally, we restrict our analysis to person-months in which the individual has been enrolled in Medicaid for the previous 6 months, so that we can accurately measure 'first fills.'

[22] The bottom panel of Appendix Table OA.4 shows the impact of each of these restriction and Appendix Table OA.5 shows a comparable set of summary statistics to Table 1, showing results both for the full prescription drug sample and the overlap sample subset of the prescription drug sample.

[23] Cotti et al. (2016) find that alcohol-related traffic fatalities decline on the day of food stamp receipt if that day is a weekday, but as we discuss in Appendix A they interpret this as reflecting a decline in driving rather than in

A concern with this analysis, however, is that, as we discussed in Section 2, the pattern of drug and alcohol use relative to SSI payout day in panel (b) may overstate the impact of SSI if there are other drivers of alcohol and drug use that are correlated with the day of SSI receipt. We therefore augment the typical timing strategy used in prior work with a difference-in-difference analysis of changes in outcomes around the timing of SSI benefit receipt for SSI recipients relative to changes in outcomes for a sample of low-income adults who are likely not on SSI. Panel (c) compares the estimated pattern of ED visits for drug and alcohol use relative to the timing of SSI receipt for those on SSI (green line) to those likely not on SSI (red line). Those likely not on SSI show some evidence of a small increase in ED visits for drug and alcohol use after the date of SSI benefit payout, but this increase is substantially smaller than that observed for those on SSI. As a result, the difference-in-differences approach (panel d) suggests only a slightly smaller impact of receipt of SSI on ED visits for drug and alcohol use: an average increase in visits per day in the week following SSI receipt of 0.64 (standard error = 0.042) per 10,000, or about 27 percent.

Consumption of non-labeled non-temptation goods. Figure 2 shows the impact of receipt of SNAP and receipt of SSI on fills of new prescription drugs, our proxy for non-labeled, non-temptation consumption. Once again, panel (a) shows no evidence that such fills increase following SNAP benefit receipt. In contrast, figures (b) through (d) indicate an increase in fills of new prescriptions following receipt of SSI. In particular, on the payout day for SSI there is an increase in new fills per 10,000 people of about 147 (standard error = 6.96) in the within-month analysis (panel b) and of about 97 (standard error = 5.98) in the difference in difference analysis (panel d). This higher rate of first fills persists - albeit at a lower level - in the subsequent days. Adding up the increase in first fills in the week following SSI receipt, the estimates imply an increase in first fills of 401 (standard error = 21.34) using the within-month variation and of 183 (standard error = 21.31) in the difference in difference analysis, representing between a 20 and 40 percent increase relative to the average weekly number of first fills of 984 per 10,000. The estimated impact of SSI is somewhat smaller in the difference-in-difference analysis (panel d) than the within-month analysis for SSI alone (panel b), reflecting an increase in new new prescription drug fills on the first of the month for the 'likely not on SSI' population; this might reflect liquidity effects due to the receipt of one's paycheck or other benefits, or to other 'first of the month' effects.

The evidence of an increase in first fills following the SSI payment day is consistent with evidence from Gross et al. (2022) who find the first fills of drugs among low-income elderly adults facing small co-pays increase by about 6 percent following the receipt of their Social Security check.[24] We follow Gross et al. (2022) and focus on fills of new prescription drugs to look for evidence of an impact on drug consumption, rather than merely the timing of purchase of a refill of a chronic medication

drinking.

[24] The population they study is older, sicker, and higher income than ours, which may contribute to the smaller estimated effects.

- whose consumption may be unaffected by when the refill occurs. Interestingly, Appendix Figure OA.1 shows that drug refills - which are about 85 percent of total fills - do experience a slight but statistically significant increase on the SNAP payout day of about 20 (standard error = 4.9) refills per 10,000 (or about 3 percent relative to the daily mean of 751 per Appendix Table OA.5), although they increase much more on the SSI payout day (by about 1,550 fills per 10,000, or about 167 percent relative to the mean of 923). We interpret the increase in refills as a shopping, or purchasing effect.

4.2 Fungibility tests

To test whether we can reject the null that a dollar of SNAP benefits is fungible with a dollar of SSI benefits, we make two adjustments to the analyses just shown. First, we adjust for the fact that SSI benefits tend to be higher than SNAP benefits. To do so, we use the fact that, between 2006 and 2019, the ratio of the legislated, maximum individual benefit for SSI relative to SNAP ranged from 2.8 to 4.0 depending on the year and whether we are considering an individual recipient or a couple (USDA, 2021). We therefore scale the estimates of the SSI effects by one-fourth and test whether we can reject the null hypothesis of equality of the (scaled) SSI impacts and SNAP impacts. Since the four-fold higher level of SSI benefits relative to SNAP benefits is a rough approximation, we also report how much higher SSI benefits would have to be relative to SNAP benefits to be unable to reject - at the 5 percent level - the null hypothesis of equality of impacts per dollar of SNAP and dollar of SSI benefits.[25] Second, to make sure that we are testing equality of responses for the *same* individuals, we also show estimates of impacts for the 'overlap' sample of individuals who receive both benefits. This reduces the sample size considerable (see Table 1) and therefore not reduces precision, but, as we will see, does not have much impact on point estimates.[26]

Figure 3 summarizes the average daily impact on ED visits for drug and alcohol use in the week (7 days) following payout. We report the estimated impact of SNAP (column 1), and the average impact for SSI based on two different estimates: the (slightly) larger estimates are based only on the within-month variation in outcomes for the SSI sample (column 2), and the (slightly) smaller estimates are based on the difference-in-difference analysis of changes in outcomes for this sample relative to low income adults likely not on SSI (column 3); as discussed, we suspect that these bound the impact of SSI. In the full sample, we estimate the average 7-day impact of SNAP on ED visits for drug and alcohol use is to decrease visits by a statistically insignificant -0.006

[25] Ideally we would use the benefit payments received by our participants. However, while we observe SNAP benefit payments directly in our data, unfortunately we do not observe SSI benefit payments. Looking in the MEPS data at people born before 1970 who are on Medicaid and whose household is receiving both SSI and SNAP, we estimate that at the beginning of our data (1991-2001) the ratio of average household SSI benefits to average household SNAP benefits is about 5.1; by the end of our data (2017-2019) it is about 4.6.

[26] Appendix Figures OA.2 and OA.3 report the analogous event studies for the overlap sample as those shown in the full sample for ED visits for drug and alcohol use (i.e. Figure 1) and first fills of a prescription for a new illness (i.e. Figure 2).

visits (standard error of 0.043) per day per 10,000. By comparison, the estimate of the average 7-day impact of SSI is a statistically significant increase of 0.703 (standard error = 0.035) visits per day per 10,000 people if we use the within-month variation in SSI receipt only (column 2), and an increase of 0.639 (standard error =0.042) if we use the difference-in-difference specification (column 3). We can reject that both estimates of one-fourth the impact of SSI are equal to the estimated impact of SNAP with p-values of < 0.001. Moreover, SSI benefits would have to be 8 to 9 times larger than SNAP benefits (rather than the 4 times larger that we assumed) before we were unable to reject the null of equality of response to a dollar of SSI and a dollar of SNAP at the 5 percent level. In the overlap sample, the point estimates are similar, but the p-values of the difference in estimates is slightly larger; specifically the p-value is 0.008 when comparing SNAP estimates to one-fourth of the within-SSI only estimates, and it is 0.030 when using the difference-in-differences variation in SSI. Overall, we interpret the evidence in Figure 3 as consistent with a higher marginal propensity to consume temptation goods out of cash than SNAP.

Figure 4 shows an analogous set of fungibility tests for the first fills of a prescription for a new illness. Once again, we report estimated impacts in the week following benefit receipt although here, given the nature of the outcome, we report the sum of impacts over the first seven days rather than the average. In the full sample, we estimate that the total SNAP impact on having a first fill of a new prescription over the first week is a statistically insignificant increase in first fulls of 9.07 per 10,000 (standard error = 7.99) or about 0.9 percent relative to the average weekly number of first fills of 1,004. By contrast, the SSI impact over the first week ranges from a statistically significant increase of 400.93 first fills per 10,000 (standard error = 21.34) to 182.60 first fills (standard error = 21.31). Once again, we can reject that the effect of SNAP and one-fourth the effect of SSI are the same for both estimates of SSI (p-value < 0.001); SSI benefits would have to be between 7 and 17 times larger than SNAP benefits before we were unable to reject the null of equality of response to a dollar of SSI and a dollar of SNAP at the 5 percent level. In the overlap sample, we can still reject equality of both SSI estimates and SNAP (p-values < 0.001). This evidence of a higher marginal propensity to consume new prescription drug fills out of SSI than SNAP highlights that cash provides the flexibilty not only to consume 'bads' (i.e. temptation goods) but also to optimize over 'goods' that are not provided by the in kind transfer.

Robustness We explored the robustness of our fungibility tests to a number of alternative specifications and found them to be generally robust. We summarize some of the main alternative specifications here; Appendix C.1 provides more details. In the overlap sample, we considered an alternative specification in which we control for SNAP payout day in the SSI analysis and we control for SSI payout day (rather than 'only' calendar day since SSI payout day is not always on the first of the month) in the SNAP analysis. We also tried, among other specifications, ones in which we imposed that the effects of all of the covariates in equation (2) did not vary by the SNAP assignment regime s; removed or added additional covariates to both analysis, limited SSI analysis to 2013 and later (when we know for sure that all benefits are paid electronically so received on the payment date); and estimated a proportional rather than a linear model of the effect of SNAP and SSI benefit receipt. For the prescription drug analysis, we also show that results are similar when we examined an alternative proxy for consumption (vs. refills) of prescription drugs. Specifically, instead of our 'first fills' measure from Gross and Tobacman (2014), we followed Einav et al. (2018) and examined fills for 'non-maintenance' drugs; these are drugs that are not associated with on-going, chronic conditions, and therefore again likely proxy for drugs that are being immediately consumed to address acute conditions. Finally, since decision-making within a two-adult household may violate fungibility for reasons other than mental accounting, we show that results look the same when we limit the sample to unmarried households.

4.3 Heterogeneity and Additional Outcomes

Heterogeneity In the normative framework below, we will interpret ED visits for drug and alcohol use as a proxy for the consumption of temptation goods, which increase in the extent of time-inconsistency (a.k.a. self-control) problems. Consistent with this interpretation, we show here that individuals who are more likely to have self-control problems also experience a greater increase in ED visits for drug and alcohol use following receipt of SSI.

We proxy for the extent of self-control issues by whether or not the individual has had prior ED visits related to behavioral health (which include mental illness and substance use disorder).[27] For this analysis, we limit the sample to individuals whom we can observe for at least 5 years, and use the data from the first four years to classify an individual based on whether or not they had an ED visit for behavioral health issues over these four years. About 13 percent of the on-SSI sample and about 10 percent of the SNAP sample are classified as having behavioral health issues. We then analyze the impact of SNAP receipt and SSI receipt in years 5 and later separately for these two groups of individuals.[28]

Figure 5 shows the results. The top two panels show no impact of SNAP receipt for either group of individuals, although the point estimates become quite noisy for the (considerably smaller) sample with no prior behavioral health issues. Strikingly however, the impact of SSI receipt is substantially bigger for those with prior behavioral issues. In the week following SSI receipt, individuals with prior behavioral health issues experience an average daily increase of 2.9 (standard error = 0.25) ED visits per 10,000 for drug and alcohol use, while individuals without prior behavioral health issues experience an average increase of only 0.36 (standard error = 0.037) visits; both estimates represent about a 30% increase relative to their (very different) baseline means (see

[27] See Appendix B for details. We are grateful to Sheena Tan for this suggestion.

[28] The restriction to observing the person for at least five years and then only analyzing person-months in years 5 and later reduces our on-SSI sample to about 11,742,028 person-months (about 61 percent of the baseline sample), our likely-not-on-SSI sample to about 85,556,735 person-months (about 78 percent of the baseline sample), and our on-SNAP sample to about 16,653,834 person-months (about 57 percent of the baseline sample).

Appendix Table OA.6). These differences are statistically distinguishable in both the within-SSI only analysis and the difference-in-difference analysis using those likely not on SSI as a control (see Appendix Table OA.6). They indicate that about 60% of the impact of SSI on ED visits for drug and alcohol use come from the 13% of the population with prior behavioral health issues. We view these results as consistent with interpreting the increase in ED visits for drug and alcohol use as reflective of self-control problems, as well as consistent with the existence of heterogeneity in the extent of self-control problems within our population.[29]

Additional Outcomes. In addition to our primary focus on consumption of temptation goods and consumption of non-labeled, non temptation goods, we also examine impacts of SSI and SNAP receipt on several other outcomes. First, motivated by existing evidence of a higher MPCf out of SNAP than case (Hastings and Shapiro 2018; Song 2022), as well as evidence of an increase in ED visits for nutrition sensitive conditions at the end of the SNAP benefit month (Seligman et al. (2014)), we examine the impact of SNAP and SSI receipt on ED visits for nutrition sensitive conditions, which may proxy for a (lack of) food consumption. Appendix C.2 describes our analyses which we view as largely uninformative; the available classifications of 'nutrition sensitive' conditions are either too small to provide power or too broad to be confident that they are proxying for food consumption per se rather than other underlying health issues.

In this spirit, we also explored SSI and SNAP impacts on 14 broad categories of primary diagnoses for ED visits identified by the National Center for Health Statistics; the largest category (21 percent in our data) is 'ill-defined', followed by injuries and poisonings (17 percent), respiratory diseases (11 percent), and musculoskeletal (10 percent). Appendix Tables OA.8 and OA.9 show the results. We see statistically significant SSI-induced increases in a number of conditions (including injuries and poisonings, mental conditions, respiratory diseases, and the 'ill-defined' category that make up 20 percent of admissions). Interestingly, we see the largest SSI-induced increases in admissions for mental disorders (a statistically significant increase of 0.41 visits) and injuries and poisonings (a statistically significant increase of 0.62 visits), suggesting that the impact on temptation goods and/or risky behavior may be broader than just drugs and alcohol. We also find statistically significant SNAP-induced declines in musculoskeletal conditions, suggesting that SNAP may be having beneficial health effects relative to SSI.

[29] Appendix Table OA.7 repeats our fungibility tests on the combined (smaller) sample as well as for the two subsamples separately. We continue to reject fungibility in the combined sample as well as in the sample that did not have prior behavioral health issues, but - given the substantial imprecision in the SNAP estimates for the (substantially smaller) sample with prior behavioral health issues seen in panel (a) of Figure 5 - we cannot reject fungibility of a dollar of SNAP and a dollar of SSI in this subsample, although the point estimates indicate substantial differences in responses.

5 Framework and Normative Implications

The empirical results indicate a lack of fungibility between cash and SNAP. Given the extensive existing evidence that SNAP benefits are inframarginal for food consumption (Trippe and Ewell 2007; Hoynes and Schanzenbach 2015; Hastings and Shapiro 2018), we follow Hastings and Shapiro (2018) and assume that individuals engage in mental accounting; this can generate the empirical findings of a higher marginal propensity to consume temptation goods and non-food goods out of cash than out of inframarginal SNAP. We then explore normative implications for a paternalistic social planner's optimal mix of in-kind and cash transfers when facing individuals with self-control problems that lead them to over-consume temptation goods such as drugs and alcohol, and we compare the use of in-kind transfers to other policy instruments such as a food subsidy or a Pigouvian tax on the temptation good.

5.1 Model setup

We consider a two-period model ($t = 1, 2$) in which, at the start of period 1, the social planner chooses how much of a fixed transfer budget ($\bar{y}$) she should allocate to cash (y_1), which can be used to consume anything, or to SNAP benefits (b_1), which can only be spent on food. The consumer can allocate their budget over total food consumption in both periods ($f \equiv f_1 + f_2$), total non-food consumption in both periods ($n \equiv n_1 + n_2$), and the "bad" temptation good that can only be consumed in the first period (c_1^b) and which has negative utility consequences in period two. The consumption (or lack of consumption) of non-food and the temptation good were proxied in the empirical work by purchases of prescription drug medication for new illnesses and emergency department visits for drug and alcohol use, respectively.

Normalizing the price of non-food to one ($p_n = 1$), the individual's budget constraints are:

$$\begin{aligned} p_f * f + n + p_b * c_1^b &\leq y_1 + b_1 \\ n + p_b * c_1^b &\leq y_1 \end{aligned}$$

where the second constraint follows from the fact that SNAP benefits (b_1) can only be spent on food (f), creating the familiar "kinked" budget set.

The consumer chooses consumption in each period to maximize her total utility across periods, subject to these budget constraints. We denote utility in each period by:

$$\begin{aligned} U_1 &= \alpha_g \alpha_f \log(f_1) + \alpha_g(1-\alpha_f)\log(n_1) + (1-\alpha_g)\log(c_1^b) \\ U_2 &= \alpha_g \alpha_f \log(f_2) + \alpha_g(1-\alpha_f)\log(n_2) - \gamma(1-\alpha_g)\log(c_1^b) \end{aligned}$$

where U_1 and U_2 are the utility functions in each period, α_g and α_f are Cobb-Douglas preference parameters that determine the budget shares for each good (with $0 < \alpha_g, \alpha_f < 1$), and $0 < \gamma < 1$

scales the negative health consequences in period two from consuming the temptation good in period one.[30]

We denote by ϕ_0 the share of the individual's budget that she would choose to spend on food in the absence of mental accounting (i.e., $\kappa = 0$), or, equivalently, if the entire transfer were made in cash (i.e., $y_1 = \bar{y}$ and $b_1 = 0$); ϕ_0 is a function of the other preference parameters (α_g, α_f, β, and γ). Total utility is then given by:

$$U = U_1 + \beta U_2 - \kappa[(\phi_0 y_1 + b_1) - p_f(f_1 + f_2)]^2.$$

This formulation for total utility extends Hastings and Shapiro (2018)'s model of mental accounting of SNAP benefits to allow for the presence of a temptation good with negative future health consequences. We denote by $0 < \beta \leq 1$ the individual's subjective discount factor between the two periods. We interpret the model as capturing consumption decisions in a relatively short time period, and we follow Hastings and Shapiro (2018) by defining $\beta = 1$ as the standard rational model benchmark and $\beta < 1$ as short-run hyperbolic discounting following Laibson (1997). The individual's optimal choice of the temptation good is decreasing in self-control (i.e., decreasing in β), while her optimal choice of food and non-food are increasing in self-control (see Appendix D.1 for derivations). Intuitively, a consumer with more self-control (i.e., higher β) spends more of their income on food (and non-food) and less of their income on the temptation good since the consumer more strongly internalizes the future negative health consequences from consuming the temptation good when β is higher.

The last term in the total utility function captures mental accounting, with the $\kappa \geq 0$ parameter governing the strength of the individual's mental accounting of SNAP benefits. Mental accounting is modeled as a quadratic utility cost associated with the gap between actual food consumption ($p_f(f_1 + f_2)$) and "target" food consumption ($\phi_0 y_1 + b_1$).[31] Target food consumption is determined by the sum of SNAP benefits (b_1) and the amount the consumer would choose to spend on food out of non-SNAP benefits in the absence of mental accounting (i.e., $\phi_0 y_1$). Intuitively, the individual psychologically treats SNAP income as "food money".

The following definitions will be useful for what follows:

Definition 1. Inframarginal SNAP benefits. *SNAP benefits (b_1) are* ***inframarginal*** *if they are below the amount that the consumer would have chosen to spend on food in the absence of mental accounting (or, equivalently, if the planner had allocated the entire transfer as cash): i.e.,* $b_1 < \frac{\phi_0}{1-\phi_0} y_1$.

[30] We assume $0 < \gamma < 1$ so that the individual consumes a strictly positive amount of the temptation good for all $\beta \in (0, 1]$, which avoids having to consider corner solutions in all of the derivations that follow.

[31] Although Hastings and Shapiro (2018) use an absolute value functional form instead of the quadratic functional form for the utility cost of departing from "target" food consumption, we choose a quadratic form for its analytical tractability in deriving our comparative statics, since it allows for a more straightforward first-order approach.

Definition 2. Marginal Propensities to Consume. *The consumer's marginal propensities to consume food ($MPCf$), non-food ($MPCn$), and the "bad" temptation good ($MPCb$) out of cash and out of SNAP are denoted by* $MPCx^{cash} \equiv \dfrac{d(x^*)}{dy_1}$ *and* $MPCx^{SNAP} \equiv \dfrac{d(x^*)}{db_1}$*, where x denotes f, n or b and x^* indicates the consumer's choice of expenditure on good x.*

The key fungibility (or non-fungibility) result from this model is that when SNAP benefits are inframarginal, mental accounting ($\kappa > 0$) is necessary and sufficient for SNAP and cash to be non-fungible:

Proposition 1. ***Mental accounting and non-fungibility****. For* $b_1 < \frac{\phi_0}{1-\phi_0} y_1$*:*

1. *If $\kappa = 0$, then $MPCf^{cash} = MPCf^{SNAP} = \phi_0$, $MPCb^{cash} = MPCb^{SNAP} = \theta_0$, and $MPCn^{cash} = MPCn^{SNAP} = 1 - \phi_0 - \theta_0$, where θ_0 denotes the share of the consumer's income she chooses to spend on the temptation good when $\kappa = 0$.*

2. *If $\kappa > 0$, then $MPCf^{cash} < MPCf^{SNAP}$, $MPCn^{cash} > MPCn^{SNAP}$, and $MPCb^{cash} > MPCb^{SNAP}$. The differences $(MPCf^{SNAP} - MPCf^{cash})$ and $(MPCb^{cash} - MPCb^{SNAP})$ are decreasing in β and increasing in κ, and the difference $(MPCn^{cash} - MPCn^{SNAP})$ is increasing in κ.*

Proof: See Appendix D.2.

Proposition 1 says that if SNAP is inframarginal, then in the absence of mental accounting ($\kappa = 0$), individuals' consumption responses to cash transfers and inframarginal SNAP benefit are the same. However, with mental accounting ($\kappa > 0$), individuals will respond differently to cash transfers and SNAP benefits, even if SNAP benefits are inframarginal; this leads to a lack of fungibility - i.e. to $MPCf$, $MPCn$, and $MPCb$ values that are no longer equal for cash and SNAP. Intuitively, with mental accounting, the marginal propensity to consume food is higher out of SNAP than cash, making all other marginal propensities lower out of SNAP. Moreover, as the individual's mental accounting behavior gets stronger (i.e., as κ increases), the individual's consumption responses to SNAP and cash diverge more. As the individual's self-control decreases (i.e., β decreases from 1), the consumption responses to SNAP and cash diverge for food and the temptation good, but could either converge or diverge for non-food depending on the budget share parameters.

Relation to empirical work.

Our key empirical results were the finding of a higher marginal propensity to consume temptation goods (b) and prescription drugs (n) out of cash than SNAP. Given the existing evidence that SNAP benefits are inframarginal for most consumers (Trippe and Ewell 2007; Hoynes et al. 2015; Hastings and Shapiro 2018), Proposition 1 indicates that these empirical results are consistent with individuals engaging in mental accounting of their SNAP benefits.

Liquidity constraints. A natural rejoinder is that our empirical results could reflect severe liquidity constraints rather than mental accounting. In particular, if people have no cash on hand when they receive their SNAP benefits, it is possible that they could treat SNAP and cash as fungible over the course of the month, but our within-month strategy would detect what looks like non-fungibility because on the day SNAP arrives, people have no cash on hand. Consistent with some role for liquidity effects, Atwood et al. (2025) find that individuals who receive their SNAP payout around the same time as their TANF payout have a higher rate of drug overdoses than individuals whose SNAP payouts are further away in time from their TANF payout. However, it appears implausible that our non-fungibility result can be entirely explained by a lack of liquidity when SNAP benefits are received. First, among individuals in the 1998-2009 Survey of Consumer Finances who received some social assistance (SNAP, SSI, TANF, or other), only about one-fifth report having no liquid assets. Moreover, when we limit our analysis to the individuals in our overlap sample (i.e. they receive both SSI and SNAP) who receive SNAP within the first 10 days of the month (so that they are more likely to still have cash-on-hand from SSI), we continue to find no impact of SNAP receipt on either of our main outcomes (see Appendix Figure OA.4); this is inconsistent with a complete lack of liquidity explaining our results.[32]

Permanent vs. inter-temporal responses. Even without severe liquidity constraints, another concern with the mapping from the model to the empirical results is that the theoretical results concern the uncompensated responses to permanent changes in transfers, while our empirical results estimate individuals' within-month responses to anticipated, intertemporal fluctuations in the timing of benefit receipt. In Appendix D.4, therefore, we develop a simple dynamic model with anticipated transfers, hyperbolic discounting, and mental accounting in which the individual can save and borrow at a constant real interest rate.[33] We show that in this model, our empirical evidence of non-fungibility in response to the within-month timing of anticipated benefit receipt implies non-fungibility in response to permanent benefit receipt. This gives a formal justification for interpreting our empirical results as valid tests of fungibility (i.e., tests of $\kappa = 0$).

Specifically, we first show that intertemporal responses to anticipated transfers weakly understate uncompensated responses.[34] We then show that the difference between the marginal propen-

[32] A related concern is the possibility that increased ED visits for drug and alcohol use following the receipt of SSI reflect a general increase in the recipient's ability to afford to seek care once she has cash, for example because she can now pay for transportation to the ED. In practice, however, we find no increase in ED visits for 'placebo' outcomes such as visits for neoplasms (tumors) or infectious diseases, which might be planned based on affordability. We also find similar effects of SSI if we limit our analysis of ED visits for drugs or alcohol to visits which involve an ICU stay, which may be less likely to reflect planned visits to the ED based on affordability; see Appendix Figures OA.5 through OA.8 and Appendix Table OA.10.

[33] We use constant interest rates to simplify the presentation of the results, but we conjecture that our results readily generalize to allowing for convex borrowing costs that create a "soft borrowing constraint" following Maxted (2025) which would capture more realistic liquidity constraints alongside present bias. Naturally with hard borrowing constraints that bind (i.e. hand to mouth consumers) the intertemporal response is the same as the uncompensated response.

[34] To see this, consider first the case in which $\beta = 1$ and $\kappa = 0$, so there is no consumption response to anticipated

sity to consume the bad out of within-month receipt of cash compared to out of within-month receipt of SNAP *understates* the magnitude of the difference in marginal propensities to consume the bad out of a permanent change in cash compared to out of a permanent change in SNAP, with the difference between the intertemporal and permanent differences in MPCs increasing (in absolute value) in the degree of mental accounting κ. Intuitively, in response to a permanent increase in SNAP a consumer who engages in mental accounting will want to increase food consumption in all periods, while the intertemporal response to the receipt of SNAP reflects the difference in the increase in food consumption in the period of SNAP receipt relative to a period without SNAP receipt, thus "differencing out" part of the permanent response.

5.2 Benefit Design: Optimal Mix of SNAP vs Cash

We now consider the problem faced by a paternalistic social planner choosing y_1 and b_1, subject to a total available transfer budget $\bar{y}$, to maximize the consumer's utility evaluated at $\beta = 1$ and $\kappa = 0$:

$$\begin{aligned} \max_{y_1, b_1} \quad & U^{SP}(\beta = 1, \kappa = 0) \\ \text{s.t.} \quad & y_1 + b_1 \leq \bar{y} \\ & \text{consumer maximizes } U \text{ given } y_1 \text{ and } b_1 \end{aligned} \tag{3}$$

where U^{SP} denotes the individual's utility evaluated at the social planner's (SP's) preferences $\beta = 1$ and $\kappa = 0$ and the individual's privately optimal consumption choices that are made after the planner chooses transfers y_1 and b_1. Intuitively, the planner is trying to choose b_1^* so that the individual's optimal choices (given y_1^* and b_1^*) coincide with the planner's social optimum.

Our first result is that in the absence of self control problems ($\beta = 1$), the planner will never choose a positive amount of SNAP, while in the presence of self-control problems ($\beta < 1$), the planner will always choose a strictly positive amount of SNAP. This is summarized in the following theorem:

Theorem 1. *If* $\beta = 1$*, then the social planner maximizes* (3) *by choosing* $y_1^* = \bar{y}$ *and* $b_1^* = 0$*. If* $\beta < 1$*, then the social planner maximizes* (3) *by choosing* $0 < y_1^* < \bar{y}$ *and* $0 < b_1^* < \bar{y}$*, with* $y_1^* + b_1^* = \bar{y}$*.*
Proof: See Appendix D.2.

Note that the theorem indicates that self-control problems are both necessary and sufficient for the social planner to optimally choose to use SNAP benefits, but that mental accounting is neither

transfers while the uncompensated response to an increase in transfers would be positive due to the increase in permanent income. At the other extreme, if $\beta << 1$ and borrowing is sufficiently expensive, then the consumer will be (endogenously) "hand to mouth" as a result of their present bias and the intertemporal and uncompensated responses are identical. In between these extremes, the intertemporal responses are smaller in magnitude than the uncompensated responses, with present bias working to bring the two magnitudes closer together.

necessary nor sufficient for this.[35] Intuitively, if the consumer has no self-control problems, so there is no reason for the planner to use SNAP benefits to try to distort the consumer's consumption choices. However, when individuals have self-control problems ($\beta < 1$), they over-consume the temptation good relative to the social planner's $\beta = 1$ benchmark, and the social planner therefore uses SNAP benefits to reduce the individual's over-consumption of the temptation good.

With self-control problems it is useful to consider two cases. The first case is when the planner keeps the SNAP share sufficiently low that it is inframarginal, and the planner exploits mental accounting - and the resultant higher marginal propensity to consume the bad out of cash than out of SNAP (recall proposition 1) - to help address the consumer's self-control problems; specifically, by "swapping" some of the cash transfer for SNAP benefits (starting from $b_1 = 0$), the planner is able to get the individual to make consumption choices closer to the paternalistic planner's social optimum. The second case is when the planner uses SNAP to increase food consumption directly by increasing the amount of SNAP above the inframarginal amount, hence decreasing consumption of the bad. Which case we end up in depends on the strength of the mental accounting parameter κ.

Specifically, in the presence of self control problems ($\beta < 1$), we now show that the optimal SNAP share of the planner's total transfer is weakly decreasing in the strength of mental accounting (κ) and weakly increasing in the individual's self-control problems (i.e., decreasing in β):

Theorem 2. *When $\beta < 1$, the optimal SNAP share $\frac{b_1^*}{\bar{y}}$ is constant for all $0 \leq \kappa < \kappa^*$ and is strictly decreasing in κ and β for all $\kappa^* \leq \kappa < \infty$, with κ^* defined as the lowest value of κ where the optimal SNAP share is such that SNAP benefits are inframarginal.*
Proof: See Appendix D.2.

Intuitively, the optimal SNAP share is weakly increasing in the extent of self-control problems because the farther β is from 1, the farther the individual's consumption choices are from what the planner would choose; the planner therefore chooses a larger SNAP benefit share in order to move consumption in the direction the planner prefers. The optimal SNAP share is decreasing in the strength of the consumer's mental accounting because the more that consumers engage in mental accounting, the smaller the SNAP benefit needed to induce a given increase in food consumption. In other words, if the individual's mental accounting behavior is very strong (i.e. κ is large), then SNAP is very effective at increasing food consumption to the level desired by the social planner; but as κ decreases from a large value, the planner needs to increase SNAP benefits to achieve the same increase in food consumption. More subtly, when κ becomes sufficiently small, the planner hits the inframarginality constraint (at $\kappa = \kappa^*$) – i.e., the amount of SNAP benefits becomes larger than the amount of food the individual would have chosen to consume if the entire

[35] The fact that, for any value of κ, the planner chooses a positive amount of cash transfers is not a general result, but merely a consequence of our assumption (for convenience) that the consumer has no resources other than the cash and SNAP transfers provided by the government; as a result, choosing only SNAP benefits would force consumption of non-food goods to zero which cannot be optimal.

transfer were in cash; below this level of κ, the planner switches from using mental accounting to increase food consumption to increasing food consumption directly by using the kink in the budget constraint created by SNAP benefits. The planner's optimal SNAP share is therefore constant and independent of κ and $\beta < 1$ for $0 \leq \kappa \leq \kappa^*$ because in this range, the planner is setting food spending directly at the level of SNAP because the planner's choice of SNAP is above the food consumption the individual would have chosen had the entire transfer been in cash. An implication of this result is that if mental accounting is strong enough, the planner will choose a SNAP benefit share that preserves the inframarginality of SNAP benefits.

Alternative normative benchmarks. We have assumed a particular normative benchmark in which the planner evaluates the individual's utility at $\beta = 1$ and $\kappa = 0$ rather than at the individual's actual β and κ parameters. This is known as the long-run utility criterion (O'Donoghue and Rabin 1999). Naturally, one could choose other normative benchmarks. In Appendix D.3 we show that the above theoretical results continue to hold under an alternative normative benchmark in which the planner maximizes a weighted sum of consumer welfare, with weight ω on the time-inconsistent consumer's actual utility based on their β and κ, and weight $(1-\omega)$ on the consumer's utility evaluated at $\beta = 1$ and $\kappa = 0$ (see e.g. Kroft (2011) and Naik and Reck (2024) for potential rationales for this alternative normative benchmark).[36] In this case, we show that the planner's problem is identical to simply evaluating the individual's utility at $\beta' = 1 + (\beta - 1)\omega$ and $\kappa' = \omega\kappa$, and as a result the planner continues to choose a strictly positive amount of both SNAP and cash as long as $0 \leq \omega < 1$.

Alternative paternalistic models. We can also relax the assumption that the social planner is interested in correcting time-inconsistent behavior and instead allow for a non-welfarist social planner who prefers that the consumer choose a level of food consumption that exceeds what the consumer would choose herself. In Appendix D.3 we show that the main result in Theorem 1 that the social planner will choose a a strictly positive SNAP share still applies. Thus if one wants to interpret the increase in ED visits for drug and alcohol use in response to the receipt of a cash transfer – and the greater increase in these visits for those with prior behavioral health issues – as consistent with the behavior of fully rational, time-consistent optimizing consumers, the theoretical result that the social planner will optimally choose a positive amount of SNAP still follows from our empirical non-fungibility result as long as the planner wants the consumer to choose a higher level

[36] We generalize this "weighted sum of selves" planner problem further to allow for the planner to put different weights on the time-inconsistency and the mental accounting behavior using weights ω_β and ω_κ, and we show that the planner problem in this case is identical to evaluating the individual's utility at $\beta' = 1 + (\beta - 1)\omega_\beta$ and $\kappa' = \omega_\kappa \kappa$. Yet another normative benchmark in the literature is in Laibson (1997), which proposes a Pareto criterion under which a policy is said to increase welfare only if both the time-consistent and time-inconsistent selves are weakly better off.

of food consumption than she chooses for herself.[37] Moreover, similar to the comparative statics on the optimal SNAP share in Theorem 2, we show that the optimal SNAP share is increasing in the "wedge" between the food consumption the individual would choose and the food consumption that the social planner would choose

5.3 Alternative policy instruments

Thus far we have restricted the social planner to choosing between transferring cash income and SNAP benefits for a representative agent. We now consider two other policy instruments: the optimal Pigouvian tax on the temptation good, which provides a direct way to correct the "internality" of over-consumption of the temptation good due to self-control problems, and an optimal (linear) food subsidy.[38] We consider how these instruments perform relative to SNAP, both under a representative agent model and when we allow for heterogeneity in the extent of agent's self-control problems (β) and their mental accounting (κ). Appendix D.5 contains the proofs.

Representative agent. If $\beta < 1$, the optimal Pigouvian tax on the temptation good is positive, and in a representative agent model, the government would not use subsidies on other goods or SNAP if a Pigouvian tax on the temptation good is available.[39] We also show equivalence between the optimal use of a linear food subsidy and SNAP; specifically, if instead of allocating a fixed budget between SNAP and cash transfers, the planner has to allocate that same fixed budget between a linear food subsidy and cash transfers, for any $\beta < 1$, the optimal food subsidy (which is positive) will result in the individual making the same consumption choices - and the planner spending the same share of their budget on the in-kind food transfer- as when the planner optimally chooses SNAP.

Heterogeneous agents. If we allow for (unobserved by the social planner) heterogeneity across consumers in both self-control (β) and the extent of mental accounting (κ), a mix of SNAP and cash may now outperform the optimal Pigouvian tax on the temptation good, which was not possible in the case of a representative agent. The key insight is that the optimal (uniform) Pigouvian tax on the temptation good can no longer achieve the first best, since in the presence of heterogeneity across individuals in the extent of self-control problems, the optimal Pigouvian tax differs across individuals; this is simply the "internality" version of the classic Diamond (1973) result that in

[37]Potential paternalistic desires to reduce consumption of unhealthy food such as sugary beverages (Allcott et al. 2019a) are outside of the scope of our model and data.

[38]One can think of an inframarginal SNAP benefit b_1 as providing a non-linear food subsidy: 100% of food costs are covered up to b_1, and 0% beyond that.

[39]Technically, the social planner can do even better with time-dependent taxes since the planner also prefers that the individual allocate more total consumption to second period, which could be achieved by a general tax on first-period consumption, but we abstract from this throughout our analysis.

the presence of heterogenous agents, the optimal (uniform) Pigouvian tax for externalities can no longer achieve the first best.

To see the intuition for how SNAP can outperform the Pigouvian tax, consider an extreme example in which there are only two types of individuals: type A engages in neither mental accounting nor hyperbolic discounting ($\kappa = 0, \beta = 1$), while type B engages in both ($\kappa > 0, \beta < 1$).[40] The first best therefore would be to leave the consumption choices of type A unchanged, but to reduce the consumption of the bad for type B. Proposition 1 tells us that provision of SNAP will not distort the consumption bundle of type A as long as SNAP benefits are inframarginal. Moreover, Theorem 2 tells us that if, for the type B individuals, if κ is sufficiently large, the optimal SNAP share for these individuals would preserve inframarginality of SNAP and thus the planner can optimize the safety net to achieve the first best consumption level for the B types, without distorting the consumption of the A types.[41]

In addition, with heterogeneous agents, giving a planner with a fixed budget access to a mix of cash and SNAP transfers is no longer equivalent to giving them access to cash transfers and a linear food subsidy. In the above example, SNAP will outperform the food subsidy for the same reason it can outperform the optimal uniform Pigouvian tax on the temptation good: it only distorts consumption for the individuals with self-control problems. Of course, for the same reason, if type A individuals have $\beta = 1$ and $\kappa > 0$ while type B individuals have $\beta < 1$ and $\kappa = 0$ - so that agents with self control problems do not engage in mental accounting and agents without self control problems do, then SNAP will do worse than the optimal linear food subsidy since it only distorts the behavior of individuals with $\beta = 1$, which is counter-productive. This type of result is reminiscent of the Allcott et al. (2019a) findings that whether or not the redistribution and corrective properties of sin taxes work in tandem or are in tension depends on whether self-control problems are decreasing or increasing with income.

5.4 Calibrations

We calibrate the model parameters to provide a rough sense of the model's quantitative implications. Appendix D.6 provides the full details, which we briefly summarize here.

Representative agent. We calibrate $\beta = 0.7$ based on a large literature estimating hyperbolic discounting in the lab (see, e.g., Frederick et al. (2002) and Andreoni and Sprenger (2012)), and we calibrate the Cobb-Douglas preference parameters (α_g and α_f) to match an assumed share of spending on food and temptation goods of 20 percent and 3 percent, respectively, based on the expendi-

[40] In this case, the individuals with self-control problems ($\beta < 1$) are the only ones who engage in mental accounting ($\kappa > 0$); this would be consistent with some of the original thinking about mental accounting as a way for agents to mitigate their own self-control problems (Thaler 1985).

[41] Kaplow (2015) provides a similar intuition for how Social Security can outperform capital subsidies when myopic individuals under-save and only some individuals in the population are myopic.

ture shares of food (both at home and away from home) and temptation goods (alcohol, tobacco and lotteries) of individuals on both SNAP and SSI in the pooled 2008, 2010 and 2012 Consumer Expenditure Surveys (Bureau of Labor Statistics 2008, 2010, 2012). We calibrate the κ parameter to match the range of estimates from Hastings and Shapiro (2018) of a $0.5 \leq MPCf^{SNAP} \leq 0.6$; this gives a range of $0.042 \leq \kappa \leq 0.79$. Lastly, we calibrate γ to match a 7.5-fold higher rate of spending on temptation goods for individuals with $\beta = 0.7$ compared to those with $\beta = 1$;[42] this results in an implied value of $\gamma = 0.950$.[43]

Given these parameters, we find that it is optimal for the planner to make SNAP inframarginal (as it is in practice). Specifically, we solve for κ^*, the value of κ above which the planner's optimal SNAP choice of SNAP is an amount that makes SNAP inframarginal to the consumer (recall Theorem 2) and find that $\kappa^* = 0.0025$; this is below our assumed range of values of κ ($0.042 \leq \kappa \leq 0.79$). We calculate an optimal SNAP share of food spending between 8.9 and 11.6 percent of food spending, which is below the actual SNAP share of food spending of roughly 40 percent of food spending (Hastings and Shapiro 2018). This implies that under our calibrated parameters, SNAP benefits are "overly paternalistic." To rationalize the current SNAP share of food spending as optimal, we would need to increase γ from 0.950 to 0.9905; at this value, $\beta = 0.7$ leads consumers to over-consume temptation goods by a factor of 30 relative to what the planner would prefer.[44]

Heterogeneous agents. We consider a "two-by-two" heterogeneity structure, with individuals either having $\beta = 1$ or $\beta = \bar{\beta}$ (with $\bar{\beta} < 1$) and either having $\kappa = 0$ or $\kappa = \bar{\kappa}$ (with $\bar{\kappa} > 0$). We set $\bar{\beta} = 0.4$ and assume that half the population has $\beta = \bar{\beta} = 0.4$ so that the average β in the population stays at 0.7 to match the representation agent calibration above. We use the same consumption share parameters and γ used in the representative agent calibration, and we set $\bar{\kappa} = 0.042$.

The optimal SNAP share is decreasing in the correlation (ρ) between β and κ. To see the intuition, consider two cases. If $\rho = -1$, then we are in a "two type" case in which half the population is neither time inconsistent nor engages in mental accounting ($\beta = 1, \kappa = 0$), and the other half is both time inconsistent and engages in mental accounting ($\beta = \bar{\beta} = 0.4$, $\kappa = \bar{\kappa} = 0.042$);

[42]The 7.5 higher rate of consumption of temptation goods comes from the ratio of the average rate of drug and alcohol ED visits for individuals on SSI with prior behavioral health issues relative to the those on SSI without prior behavioral health issues, as shown in Panel A of Appendix Table OA.6.

[43]Note that α_g and α_f are pinned down by the assumed expenditure shares and an assumed value of γ; using $\gamma = 0.950$ we calculate $\alpha_g = 0.779$ and $\alpha_f = 0.211$.

[44]We also explored the sensitivity of our calibration results to allow for a richer model of consumer demand where, instead of our baseline Cobb-Douglas utility function, the utility function is Cobb-Doublas in the temptation good and an CES aggregate of food and non-food (so that food and non-food are in the "inner nest" with an elasticity of substitution parameter $\sigma = \frac{1}{1-\epsilon}$). The optimal SNAP share is decreasing in ϵ until eventually ϵ is sufficiently large that the optimal SNAP share is driven down to zero; intuitively, at higher values of ϵ, food and non-food become stronger demand substitutes, which means that increased food spending due to SNAP will primarily substitute for non-food spending rather than spending on the temptation good. To rationalize the current SNAP share of food spending with CES demand, we would need a value of ϵ of approximately -0.425, which corresponds to an elasticity of substitution between food and non-food of 0.70.

in this case, the optimal SNAP share is the same as in a representative agent model in which everyone has everyone having $\beta = 0.4$ and $\kappa = 0.042$. Intuitively, the planner is able to choose the optimal SNAP share for the $\beta = \bar{\beta}$ type at no cost to the "rational" types. In the other extreme, if $\rho = 1$ then we are in the opposite "two type" case in which half the population is time inconsistent but does not engage in mental accounting ($\beta = \bar{\beta} = 0.4$, $\kappa = 0$), and half the population is time consistent but does engage in mental accounting ($\beta = 1$, $\kappa = \bar{\kappa} = 0.042$); in this case, the optimal SNAP share is zero. Intuitively, if the only individuals who engage in mental accounting are the $\beta = 1$ types, then the planner cannot choose an inframarginal SNAP transfer to increase social welfare.[45] Regardless of the value of ρ that we assume, we generally calculate an optimal SNAP share of food spending that is below the actual SNAP share of food spending, suggesting that - under our assumptions regarding all the other parameters - SNAP is "overly paternalistic" unless γ is very large, as in the representative agent calibration.

6 Conclusion

We consider, both empirically and theoretically, a paternalistic rationale for providing transfers in-kind rather than in cash based on their different impacts on consumption of temptation goods. Empirically, we find evidence of non-fungibility between cash (SSI) and in-kind (SNAP) transfers for adults in South Carolina. In particular, we estimate that ED visits for drugs and alcohol increase by 20 to 30 percent immediately following receipt of SSI but do not respond to SNAP receipt. We also find that fills of prescriptions for new illnesses increase substantially following SSI receipt but not SNAP receipt. We consider the normative implications in a model in which individuals engage in mental accounting (which generates higher marginal propensities to consume food out of SNAP than cash) and over-consume temptation goods (like alcohol and drugs) due to self control problems. The social planner's problem is how to split a fixed transfer budget between SNAP and cash. We show that when individuals have self-control problems, the paternalistic social planner will choose to provide a strictly positive amount of its total transfer in SNAP, in order to reduce over-consumption of temptation goods; the optimal SNAP share of the transfer is weakly increasing in the amount of self-control problems and weakly decreasing in the strength of mental accounting. Moreover, with heterogeneous agents, the optimal mix of SNAP and cash transfers may outperform an optimal Pigouvian tax on the temptation good if self-control problems and mental accounting are positively correlated.

While our empirical focus was on paternalistic social policy in the United States, similar policies exist worldwide. For instance, in Brazil concerns that a large share of a cash transfer program for

[45] Given our parameter values, the social planner does not want to set the SNAP share at a non-inframarginal level but this is of course possible for other parameters; for example, if $\bar{\beta}$ were sufficiently low and the share of the population with $\beta = 1$ was sufficiently small, then the social planner could still prefer to use the kinked budget set to get the "behavioral" types to consume more food even at the cost of distorting the food consumption of the $\beta = 1$ "rational" types.

the poor (Bolsa Familia) was being spent on on-line gambling recently prompted the government to prohibit use of cash transfer program cards for on-line betting (Reuters (2024); Pereira (2024); iGamblingToday (2025)). Our normative model could readily be adapted to analyze this decision if online betting reflects self-control problems (as suggested by Brown et al. (2025)) and if mental accounting causes individuals to reduce betting by more than would be predicted under a fully rational model with fungible money.

We conclude by highlighting several directions that we believe would be fruitful for future research. First, our theoretical analysis revealed several empirical parameters needed to calibrate our new formulas for the optimal SNAP share that, to our knowledge, have not yet been estimated. For example, we showed that the correlation between present bias and mental accounting is critical for how well SNAP can perform relative to a Pigouvian tax on the temptation good, yet we know of little evidence on the within-person correlation between present bias and mental accounting, even though the early literature on mental accounting motivated it as a way of overcoming self control problems (e.g. Thaler (1985)).

Second, our analysis has treated all food consumption as identical from the paternalistic social planner's perspective. This simplification allowed us to focus on the tradeoff between food and temptation goods, but in practice it seems likely that policymakers and voters also care about the kinds of food purchased with SNAP and similar transfers. Many cities and states, for example, have adopted soda taxes to discourage sugar-sweetened beverages (Allcott et al. 2019b; Global Food Research Center 2020). More recently, several states have obtained waivers to exclude soda and candy from SNAP-eligible items (Tansing and Matz 2025; Food and Nutrition Service 2025). Our framework could be naturally extended to study these types of policies, shifting the focus from "SNAP or cash?" to "what foods should be SNAP-eligible?"

Finally, much remains to be learned about the nature and origins of paternalistic preferences among policymakers and voters. For example, are these preferences motivated primarily by a desire to correct internalities — such as the over-consumption of temptation goods emphasized in this paper—or by non-welfarist concerns? While our main theoretical results are robust to alternative models of paternalism – as long as we can identify the "gaps" between individuals' choices and those preferred by the planner – reliably estimating these gaps and evaluating alternative paternalistic policy interventions ultimately requires a deeper understanding of paternalistic preferences.

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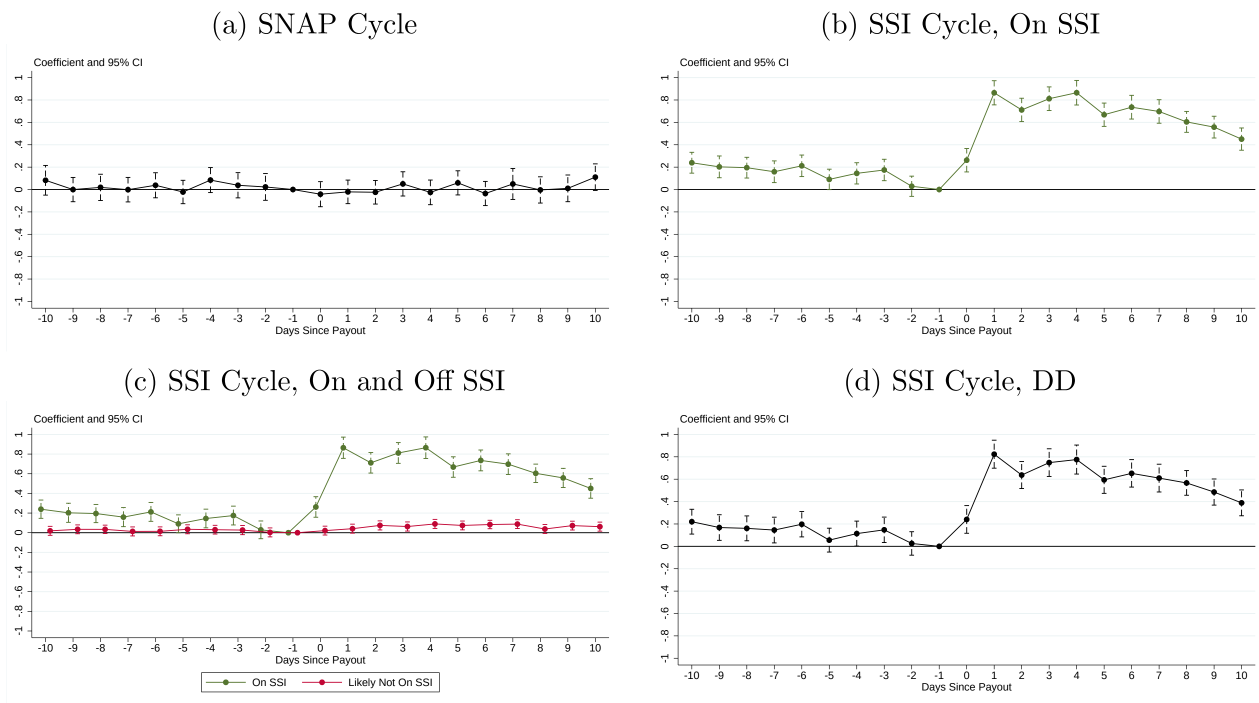
7 Figures

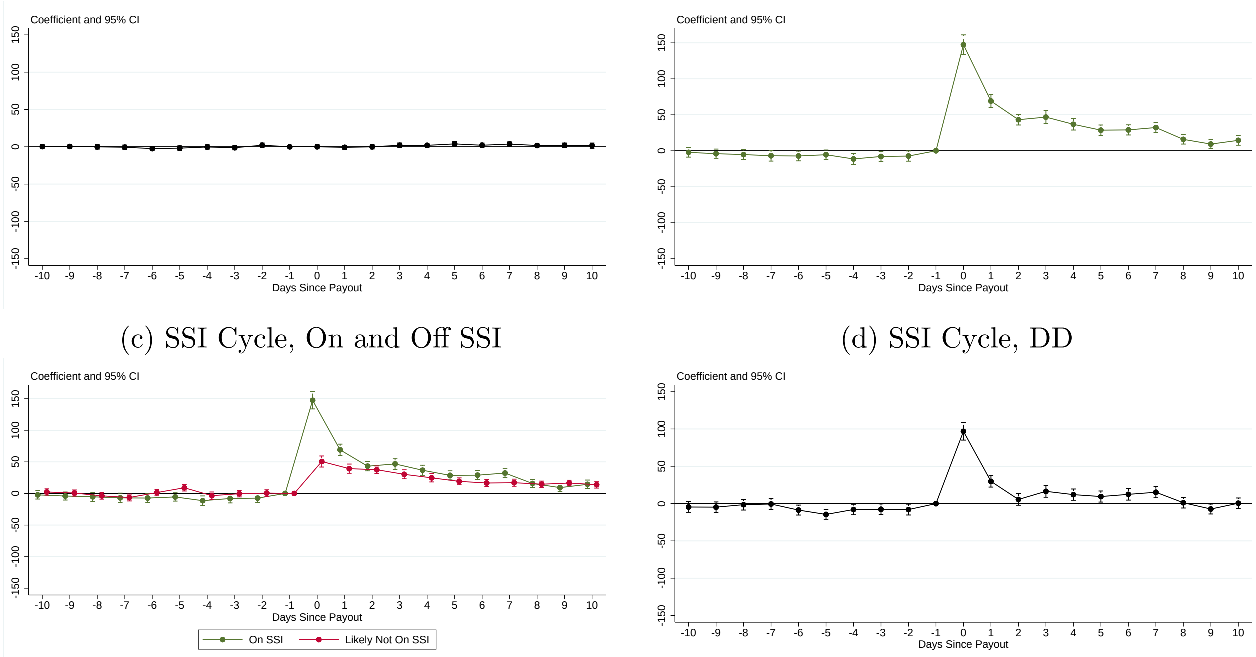
Figure 1: Effects of SNAP and SSI on Drug and Alcohol ED Visits



Notes: The outcome variable is ED visits for drug-and-alcohol-related conditions per day per 10,000. Panel (a) shows estimates of (a) β_r from equation (2); panel (b) shows estimates of $\alpha_{r'} + \beta_{r'}$ from equation (1); panel (c) reproduces (in green) the estimates of $\alpha_{r'} + \beta_{r'}$ from equation (1) and overlays the estimates of $\alpha_{r'}$ from equation (1) (in red); panel (d) shows the estimates of $\beta_{r'}$ from equation (1). In panel (a), N person-months on SNAP = 29,016,217. In panels (b)-(d), N person-months on SSI = 19,236,048, and N person-months likely not on SSI = 109,240,417. Standard errors are clustered at the date (day-month-year) level.

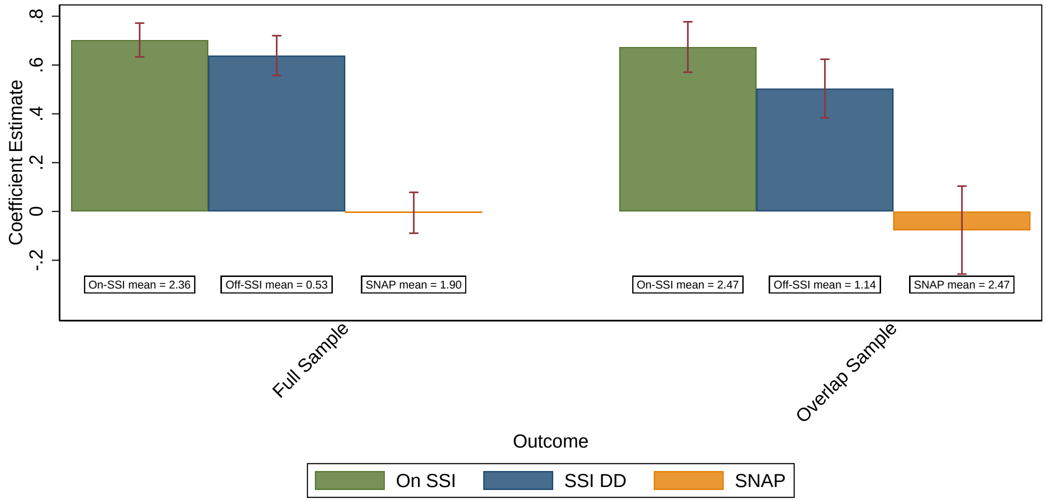
Figure 2: Effects of SNAP and SSI on First Fills

(a) SNAP Cycle — (b) SSI Cycle, On SSI — (c) SSI Cycle, On and Off SSI — (d) SSI Cycle, DD



Notes: The outcome variable is first fills per day per 10,000. Panel (a) shows estimates of (a) β_r from equation (2); panel (b) shows estimates of $\alpha_{r'} + \beta_{r'}$ from equation (1); panel (c) reproduces (in green) the estimates of $\alpha_{r'} + \beta_{r'}$ from equation (1) and overlays the estimates of $\alpha_{r'}$ from equation (1) (in red); panel (d) shows the estimates of $\beta_{r'}$ from equation (1). In panel (a), N person-months on SNAP = 7,877,590. In panels (b)-(d), N person-months on SSI = 9,288,812, and N person-months likely not on SSI = 7,377,659. Standard errors are clustered at the date (day-month-year) level.

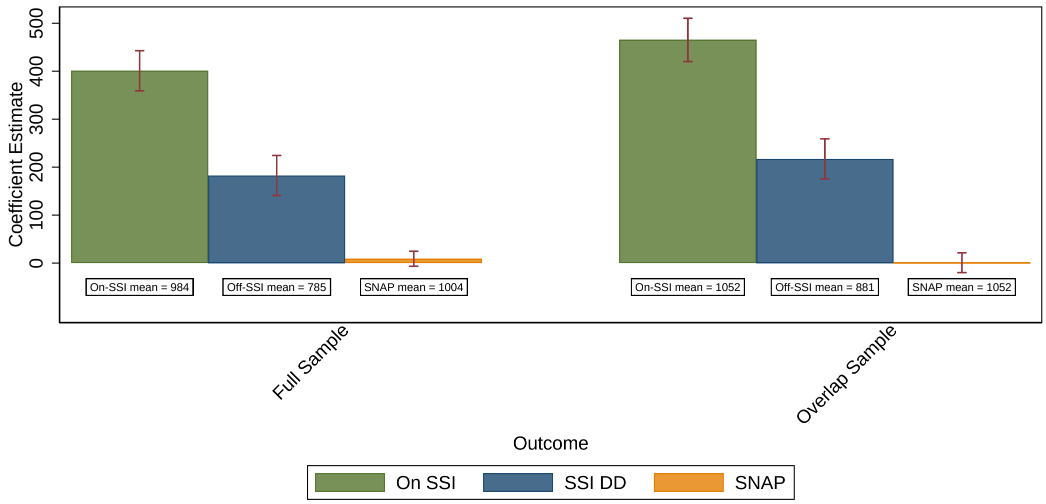
Figure 3: Examining Fungibility, Drug and Alcohol ED Visits



		(1) SNAP Estimate	(2) SSI Estimate On SSI	(3) SSI Estimate SSI DD
Full Samples	Estimate	-0.006	0.703	0.639
		(0.043)	(0.035)	(0.042)
	Difference, $\frac{1}{4}$SSI - SNAP	-	0.181	0.165
		-	(0.044)	(0.044)
	P-value of difference between $\frac{1}{4}$SSI and SNAP	-	< 0.001	< 0.001
	Scaling factor		9.09	8.33
Overlap Samples	Estimate	-0.076	0.674	0.504
		(0.092)	(0.053)	(0.061)
	Difference, $\frac{1}{4}$SSI - SNAP	-	0.245	0.202
		-	(0.093)	(0.093)
	P-value of difference between $\frac{1}{4}$SSI and SNAP	-	0.008	0.030
	Scaling factor		6.67	5.00

Notes: Exhibit shows fungibility test results for drug-and-alcohol-related ED visits. Figure shows point estimates and confidence intervals for the average daily effects of SNAP receipt and SSI receipt over the first week (relative days 0 through 6) following equations (1) and (2) respectively. Green bars show the average first week on-SSI effect from equation (1). Navy bars show the average first week SSI DD effect from equation (1). Orange bars show the average first week SNAP effect from equation (2). "Means" in figure represent mean number of drug-and-alcohol-related ED visits per day per 10,000 individuals in a given sample. Table shows the corresponding point estimates and confidence intervals for the average first week effect of SNAP receipt and SSI receipt, as well as the difference in one-fourth of the SSI estimate and the SNAP estimate. "Scaling factor" refers to the number of times larger SSI payments would have to be than SNAP payments such that, under the effect size we calculate, the effect per dollar of SSI and the effect per dollar of SNAP would be statistically indistinguishable at the 5 percent level. Standard errors are in parentheses. All estimates shown are from estimation of the regression equations (1) and (2), stacked in block diagonal form to allow for correlation between the error terms of the two equations; standard errors are clustered at the date (day-month-year) level.

Figure 4: Examining Fungibility, First Fills



		(1) SNAP Estimate	(2) SSI Estimate On SSI	(3) SSI Estimate SSI DD
Full Samples	Estimate	9.066 (7.985)	400.931 (21.342)	182.597 (21.305)
	Difference, $\frac{1}{4}$SSI - SNAP	- -	91.167 (9.628)	36.583 (9.641)
	P-value of difference between $\frac{1}{4}$SSI and SNAP	-	< 0.001	< 0.001
	Scaling factor		16.67	7.14
Overlap Samples	Estimate	0.807 (10.537)	465.319 (23.041)	217.149 (21.355)
	Difference, $\frac{1}{4}$SSI - SNAP	- -	115.523 (12.081)	53.480 (11.891)
	P-value of difference between $\frac{1}{4}$SSI and SNAP	-	< 0.001	< 0.001
	Scaling factor		25.00	10.00

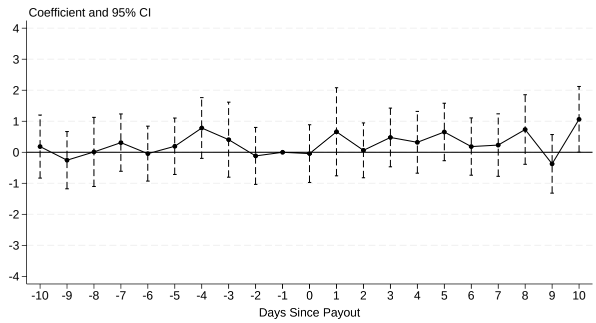
Notes: Exhibit shows fungibility test results for first fills. Figure shows point estimates and confidence intervals for the sum of effects of SNAP receipt and SSI receipt on first fills over the first week (relative days 0 through 6) following equations (1) and (2) respectively. Green bars show the sum of first week on-SSI effects from equation (1). Navy bars show the sum of first week SSI DD effects from equation (1). Orange bars show the sum of first week SNAP effects from equation (2). "Means" in figure represent mean number of first fills per week per 10,000 individuals in a given sample. Table shows the corresponding point estimates and confidence intervals for the sum of first week effects of SNAP receipt and SSI receipt, as well as the difference in one-fourth of the SSI estimate and the SNAP estimate. "Scaling factor" refers to the number of times larger SSI payments would have to be than SNAP payments such that, under the effect size we calculate, the effect per dollar of SSI and the effect per dollar of SNAP would be statistically indistinguishable at the 5 percent level. Standard errors are in parentheses. All estimates shown are from estimation of the two regression equations (2) and (1) stacked in block diagonal form to allow for correlation between the error terms of the two equations; standard errors are clustered at the date (day-month-year) level.

Figure 5: Effects of SNAP and SSI on Drug and Alcohol ED visits, by Prior Behavioral Health Issues

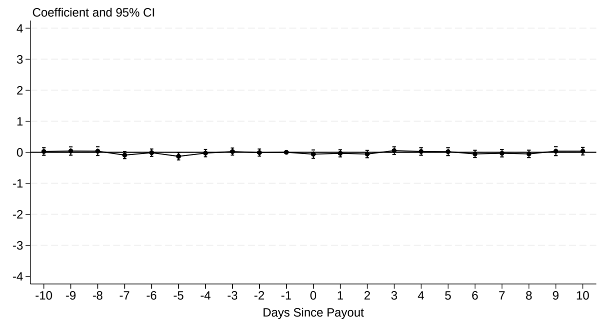
Prior Behavioral Health Issues

No Prior Behavioral Health Issues

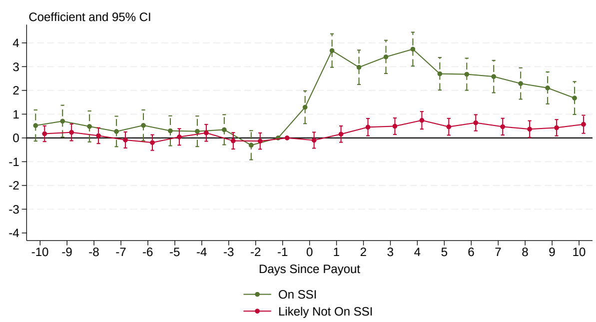
(a) SNAP Cycle



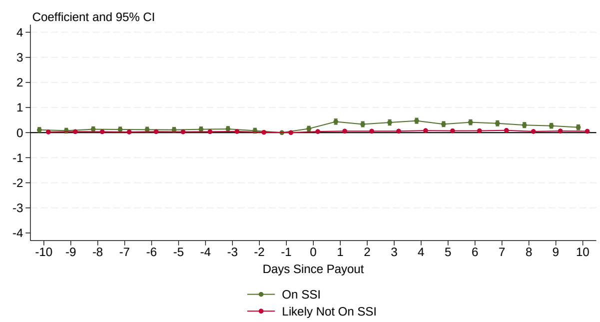
(b) SNAP Cycle



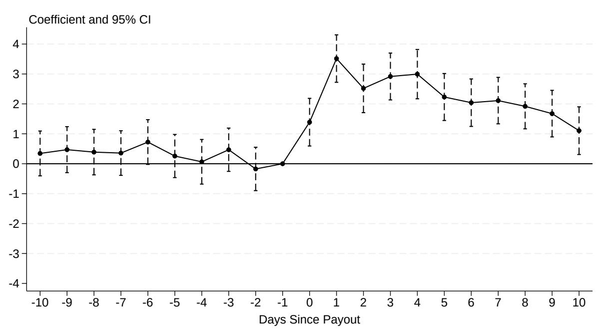
(c) SSI Cycle, On and Off SSI



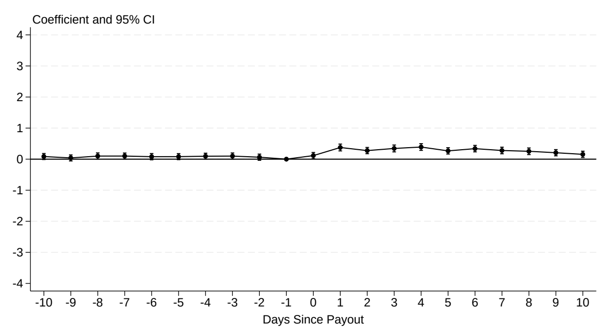
(d) SSI Cycle, On and Off SSI



(e) SSI Cycle, DD



(f) SSI Cycle, DD



Notes: The outcome variable is ED visits for drug-and-alcohol-related conditions per day per 10,000. Left-hand-panels are restricted to the 10 to 15 percent of individuals who have behavioral health issues in the first four years they are observed in the data; right-hand-panels are restricted to individuals who do not have behavioral health issues in the first four years in the data. The analysis then uses all person-months for these individuals observed in years five and later. Panels (a) and (b) show estimates of β_r from equation (2); panels (c) and (d) show estimates of $\alpha_l + \beta_l$ from equation (1) (in green) overlaid with α_l from equation (1) (in red); panels (e) and (f) show estimates of β_l from equation (1). In panel (a), N person-months on SNAP = 1,637,081. In panel (b), N person-months on SNAP = 15,016,753. In panels (c) and (e), N person-months on SSI = 1,515,591 and N person-months likely not on SSI = 2,809,981. In panels (d) and (f), N person-months on SSI = 10,226,437 and N person-months likely not on SSI = 82,746,754. Standard errors are clustered at the date (day-month-year) level.

8 Tables

Table 1: Summary Statistics, ED Samples

	SNAP Sample	SSI Sample		Overlap Sample	
	(1)	(2)	(3)	(4)	(5)
	On SNAP	On SSI	Likely Not On SSI	On SNAP & On SSI	On SNAP & Likely Not On SSI
Panel A: Demographics					
Mean Age	56.6	60.4	56.7	61.2	54.6
Share 65+	0.26	0.35	0.31	0.36	0.24
Share 40-64	0.66	0.59	0.54	0.61	0.65
Share less than 40	0.08	0.05	0.15	0.03	0.12
Share Female	0.64	0.61	0.66	0.63	0.67
Share White	0.39	0.33	0.50	0.32	0.44
Share Black	0.44	0.43	0.33	0.44	0.44
Share Other	0.17	0.24	0.16	0.25	0.11
Share Missing	0.01	0.00	0.02	0.00	0.01
Panel B: ED Visits Per Day (Per 10,000)					
Drug/alcohol-related	1.90	2.36	0.53	2.47	1.14
Any cause	34.18	39.25	15.65	42.18	27.19
Panel C: Share Receiving Benefits					
Person-months on SNAP	1.00	0.54	0.14	1.00	1.00
Person-months on SSI	0.34	1.00	0.00	1.00	0.00
People ever on SNAP	1.00	0.75	0.51	1.00	1.00
People ever on SSI	0.42	1.00	0.00	1.00	0.00
N person-months	29,016,217	19,236,048	109,240,417	9,794,149	12,815,630
N unique individuals	380,533	197,917	507,464	136,132	199,346

Notes: This table presents descriptive statistics for the SNAP sample (column (1)), the SSI sample (columns (2) and (3)), and the overlap sample (columns (4)-(5)), derived from the Medicaid data. Mean age is calculated as the average age across person-months in each sample defined by the column headers. ED visits per day per 10,000 are calculated by averaging the number of ED visits in a given category to the day level, multiplying by 10,000, then averaging across all days. "Other" nests all non-Black, non-white, and non-missing racial categories. As of 2014, filling out the race field was no longer required on the South Carolina Medicaid application form.

Appendices

A Impacts of Cash and In-Kind Transfers

A.1 Impacts on Temptation Goods

A.1.1 Cash transfers

In the U.S., a growing body of evidence suggests that cash transfers are associated with adverse health outcomes from substance abuse. Most closely related to our work is evidence in other U.S. contexts of the cyclicality of substance abuse based on cash-transfer benefit cycles that we replicate in our setting. For example, Dobkin and Puller (2007) use patient-level data on admissions to California hospitals between 1994 and 2000 and find that drug-related admissions spike for SSI recipients after they receive their benefits on the first of the month; likewise, Shaner et al. (1995) find that low-income individuals with schizophrenia and cocaine dependence receiving disability benefits (paid on the first of the month) experienced an increase in cocaine use, psychiatric symptoms and hospital admissions during the first week of the month. In highly-related work, Phillips et al. (1999) and Evans and Moore (2012) document that U.S. mortality - and particularly mortality from substance abuse - peaks in the first week of the month; Evans and Moore (2012) also show that this pattern is larger among individuals of lower SES, a finding they attribute to increased liquidity around the first of the month, while Evans and Moore (2011) document mortality spikes - including substance-abuse mortality - following the arrival of monthly Social Security payments or regular wage payments for military personnel. These findings are consistent with evidence of an increase in 'instantaneous consumption' – which includes food and alcohol consumed away from home - following receipt of a social security check (Stephens Jr 2003). They have been interpreted as evidence of liquidity (or "full wallet") effects (e.g., Dobkin and Puller 2007; Evans and Moore 2012) and as a potential reason to spread transfer payments over multiple payouts over the month; consistent with this interpretation, Atwood et al. (2025) find that individuals who receive their benefits spread out across multiple transfers in the month experience less of a rise of drug overdoses than those who receive them all around the same time.

There is also evidence on the extensive margin of the impact of new or increased cash transfers on temptation goods in the United States. Substance abuse mortality (Evans and Moore 2011) and emergency department visits for drug and alcohol use (Gross and Tobacman 2014) increased following the 2001 and 2008 tax rebates, respectively.[46]

By contrast, a large body of evidence from developing countries has failed to find evidence that cash transfers increase consumption of temptation goods such as alcohol and tobacco. Evans and Popova (2017) review a large number of studies and conclude that there is no evidence for an impact of cash transfers (either conditional or unconditional ones) on temptation goods in Latin America, Africa, and Asia; more recent papers have reached similar conclusions (e.g., Haushofer and Shapiro 2016). One potential reason for these ostensibly conflicting findings is that, as Evans and Popova (2017) note, the cash transfer programs they study often come with strong social messaging, which may make them more akin to 'labeled cash'; this is not the case for the US programs. Another potential explanation is that the U.S.-based literature tends to measure (arguably more welfare-relevant) extreme consumption of temptation goods that manifests itself in mortality or

[46] Likewise, evidence from Australia indicates that when individuals were allowed early pension withdrawals during the COVID-19 pandemic, there was a high marginal propensity to spend on gambling (Hamilton et al. 2023).

ED admissions, rather than mean consumption levels, and to use administrative data on health outcomes rather than self-reported consumption of temptation goods. There is evidence, at least in the United States, that individuals under-report consumption of temptation goods (such as gambling and alcohol) in the Consumer Expenditure Survey (Bee et al. 2015). Consistent with the hypothesis that estimates of the impact of cash transfers on consumption of temptation goods may looking different when using self-reported data on consumption, the one U.S. study we are aware of that looked at the impact of cash transfers on self-reported consumption of temptation goods (using data from the National Survey of Drug Use and Health to study the impact of the 2021 advanced child tax credit) also found no evidence of impacts (Donahoe et al. 2025).

A.1.2 In-kind transfers

There is relatively little work in the US on the impact of in-kind transfers on temptation goods. The closest we have found is Cotti et al. (2016) who find that alcohol-related traffic fatalities in the U.S. decline on the day of food stamp receipt, but only if the food stamps are received on a weekday; they hypothesize that this result is due to families being more likely to eat at home on weekdays on which they received SNAP benefits. In addition, Castellari et al. (2017) find that in months in which food stamps are paid on a weekend rather than a weekday, monthly purchases of beer are higher.

However, several studies in developing countries - all randomized trials - have compared the impact on temptation goods of cash transfers relative to in-kind food transfers. In contrast to our findings, they found no evidence that cash increased consumption of temptation goods (specifically alcohol or tobacco) relative to in-kind food transfers (Cunha 2014; Gilligan and Roy 2013). In closely related work, Banerjee et al. (2023a) find no evidence that moving from an (inframarginal) in-kind food transfer to a food voucher increases consumption of temptation goods.

A.2 Adult Health Impacts

We are not aware of any direct comparisons in the U.S. or other developed countries of the impact of cash and in-kind transfers on health outcomes.[47] However, there are distinct literatures looking separately at the impact of cash and of in-kind transfers on adult health outcomes in the U.S.

A.2.1 Cash Transfers

The evidence on the impact of cash outcomes on health in the U.S. is mixed. As discussed above, there is considerable evidence of deleterious health consequences of an injection of cash liquidity operating through induced over-consumption of drugs or alcohol (Dobkin and Puller 2007; Evans and Moore 2011, 2012; Shaner et al. 1995; Phillips et al. 1999; Gross and Tobacman 2014). However, several recent papers have also found a cash benefit cycle that could have positive health benefits in which low-income individuals increase their prescription drug fills upon benefit receipt; these

[47] In the U.S., the only direct comparison of the impact of cash and in-kind food transfers on health outcomes that we know of is Bitler et al. (2022). In a difference-in-differences design, they find that when Wisconsin reduced the cash payment to SSI recipients and replaced it with an equivalent amount of food stamps in 1992, food stamp use increased; they also find 'suggestive evidence' that hospitalizations for food-related diagnoses decreased among a population that was likely covered by SSI. However, the authors caution that there is also evidence of compositional changes in their 'likely SSI' sample associated with Wisconsin's policy change, which may be contributing to their estimates.

include including new fill (vs. refills) and fills for drugs used to treat acute conditions, where timely treatment may be essential (Lyngse 2020; Gross et al. 2022).

Looking beyond the literature on benefit cycles, a much larger literature has examined the causal impact of income on health in the US, with very mixed results across studies; Lleras-Muney (2022) and Miller et al. (2024) provide useful reviews. Once again, the evidence is mixed. For example, a randomized evaluation of providing substantial monthly cash benefits for three-quarters of a year to low-income individuals in Chelsea, MA during the pandemic indicated that receipt of cash reduced emergency department visits, including reductions in visits related to behavioral health and substance use (Agarwal et al. 2024). However, impacts on health have been more muted or mixed from other recent randomized cash transfers to a low-income populations such as a guaranteed income (Miller et al. 2024) or the extension of the earned income tax credit to adults without dependent children (Courtin et al. 2020, 2022; Muennig et al. 2024).

A.2.2 SNAP

Most closely related to our work is the literature on SNAP benefit cycles and health.[48] Several (although not all) papers find evidence consistent with receipt of SNAP reducing hospital or ED visits for hypoglycemia or other potentially-nutrition sensitive conditions. Seligman et al. (2014) find that admissions for hypoglycemia in California increase in low-income populations toward the end of the month, a result they interpret as reflecting an exhaustion of the month's food budget, particularly SNAP benefits which are paid in California in the first 10 days of the month. However, exploiting random variation across individuals in the day of the month of receipt of SNAP benefits in Missouri, Heflin et al. (2017) find no evidence that the probability of ED visits covered by Medicaid for hypoglycemia declines with receipt of SNAP. Using the same data and empirical strategy, Arteaga et al. (2018) find that SNAP receipt is associated with a decline in the probability of a pregnancy-related ED visit (and note that dietary quality is considered an important component of health for pregnant women) while Ojinnaka and Heflin (2018) find that SNAP receipt is associated with a decline in hypertension-related ED visits, visits that they argue can be affected by food insecurity.

Some of this existing evidence comes from South Carolina and exploits the same within-month variation in SNAP benefit receipt that we do to document that Medicaid-covered emergency department use overall falls on the day of SNAP benefit receipt (Cotti et al. 2020) and student test scores decline when the exam falls late in the SNAP benefit cycle (Cotti et al. 2018), a result that they interpret as indicative of poor nutrition.[49] Our findings that SNAP receipt is associated with an immediate but short lived decline in ED visits for nutrition-sensitive conditions complements this existing evidence base, and is consistent with other studies finding a substantial decline in caloric intake among SNAP recipients at the end of the benefit month (Wilde and Ranney 2000; Shapiro 2005; Todd 2015; Gassman-Pines and Schenck-Fontaine 2019; Kuhn 2018; Hamrick and Andrews 2016) and that SNAP recipients redeem a large share of their month's benefit immediately upon receipt (Castner and Henke 2011; Wilde and Ranney 2000).

[48] In addition, several papers examining the roll out of the introduction of food stamps across counties in the 1960s and early 1970s have found that this was associated with both short-run and longer-run health improvements (Almond et al. 2011; Hoynes et al. 2016).

[49] In a similar vein, Bond et al. (2022) using data from several states find that low-income students who take the SAT in the last two weeks of the SNAP benefit cycle do worse than those who take it in the two weeks following disbursement.

B Outcome Definitions

Drug and Alcohol Related ED Visits. Our coding of drug and alcohol related ED visits follows Dobkin and Puller (2007). Specifically, we include the following drug- and alcohol-related (primary or secondary) diagnoses (and corresponding ICD-9 codes): cocaine (3042*, 3056*), opioid (3040*, 3047*, 3055*), amphetamine (3044*, 3057*), residual drug dependence (admissions for dependence on other drugs) (292*, 304* excluding admissions for cocaine, amphetamines, and opioids), and alcohol only (291*, 303*, 3050*).[50]

ED Visits for Behavioral Health Issues. We follow Agarwal et al. (2024)'s definition of ED visits for behavioral health issues. These are defined as a union of three categories of ED visits identified in Johnston et al. (2017): mental-health-related, drug-related, and alcohol-related ED visits.

There is naturally considerable overlap with our measure of ED visits for drug and alcohol use, but the overlap is not complete as the behavioral health measure includes other types of visits than drug and alcohol, and the coding of drug and alcohol visits differs across the two (primarily because our definition follows Dobkin and Puller (2007) and includes ED visits with primary or secondary diagnoses for drugs or alcohol, while the Agarwal et al. (2024) uses only primary diagnoses). We estimate that about three-fifths of the visits we would classify as ED visits for drug or alcohol use would be classified by the Agarwal et al. (2024) algorithm as ED visits for behavioral health issues, and that only two-fifths of the ED visits that Agarwal et al. (2024) would classify as for behavioral health issues are ones we would classify as visits for drug and alcohol use.

Non-Maintenance Drug Fills. Einav et al. (2018) classify NDC-11 drug codes as maintenance or non-maintenance using the classification from First Databank, a drug classification company. Maintenance drugs reflect drugs that are associated with treating ongoing, chronic conditions, while non-maintenance drugs reflect drugs that are not. To classify the drugs in our data, we merge the dataset of NDC-11 classifications from the replication files of Einav et al. (2018). We are able to successfully classify 87.95% of drug fill events in our data as maintenance or non-maintenance, and code the rest as "unclassified".

Nutrition-Sensitive ED Visits. We code ED visits as attributed to "nutrition-sensitive" conditions if they were prompted by hypoglycemia, metabolic diabetes-related complications, or hypertension, three sets of conditions chosen based on the literature, which we examine individually and in combination.

Our inclusion of hypoglycemia is motivated by Seligman et al. (2014), who study the impacts of exhaustion of food budgets on hospital admissions for hypoglycemia. We define hypoglycemia ED visits using an algorithm developed in Ginde et al. (2008). The algorithm defines hypoglycemia ED visits as those associated with a primary or secondary ICD-9 diagnosis code taking any of the following values: 2510-2512, 2703, 7750, 7756, 9623. A diagnosis code of 2508 is also included, *only if* it is not accompanied by diagnosis codes 2598, 2727, 681*, 682*, 6869*, 7071*-7079*, 7093*, 7300*-7302*, or 7318*.

[50]Note that all of our measures of ED visits use both the ED data and the hospital data since the latter are the way we can measure ED visits if they ended up triggering an inpatient admission. The ED data itself only contains records of outpatient ED visits.

Our inclusion of metabolic diabetes-related complications is motivated by Wharam et al. (2017). We adapt their published ICD-9 codes to proxy for acute complications of diabetes or related comorbidities in an emergency department setting. We define ED visits related to diabetes complications as those with values of the primary or secondary ICD-9 diagnosis codes matching any of those on the list.

Our inclusion of hypertension is motivated by Ojinnaka and Heflin (2018), who study the impact of SNAP on hypertension-related ED claims, arguing that it is an indication of food insecurity. We follow their definition of ED visits for hypertension: the first 3 digits of any primary or secondary ICD-9 diagnosis code are 401 through 405, inclusive, or the value of any primary or secondary ICD-9 diagnosis code is 4372.

The last column of Appendix Table OA.11 shows the share of ED visits which correspond to each component of nutrition-sensitive ED visits, as well as the full category. As can be seen there, a challenge with measures of nutrition-sensitive conditions is that the definitions are either sufficiently narrow as to involve essentially no sample (e.g. hypoglycemia which involves less than 0.1 percent of admissions) or sufficiently broad - i.e. hypertension and diabetes-related complications - that is is hard to be confident that they are picking up effects of nutritional intake per se.

Major Causes of ED Visits. R Rui and K Kang (2015) from the National Center for Health Statistics identify 14 broad categories under which primary diagnoses (defined by ICD-9 codes) at emergency department visits may be classified. These categories serve as high-level classifications of outcomes which may be impacted by the SSI and SNAP cycles. The outcomes are infectious and parasitic diseases, neoplasms (tumors), metabolic/immunity disorders, mental disorders, diseases of the nervous, circulatory, respiratory, digestive, genitourinary, skin, and musculoskeletal systems, "ill-defined" conditions, injuries and poisonings, and "supplementary classifications". If an ED visit has a primary diagnosis code falling into any of the above groups, we code it as such. Any ED visit with a primary diagnosis code which cannot be sorted into one of the above categories are sorted into a residual category.

The last column of Appendix Tables OA.8 and OA.9 shows the share of ED visits which correspond to each major cause of ED visits.

ED Visits for 'Placebo' Causes: Neoplasms and Infectious Diseases. We define 'placebo' outcomes as ED visits for neoplasms (tumors) or infectious diseases, as such visits may be planned based on affordability. Neoplasms and infectious diseases are included in the "major causes of ED visits" defined by R Rui and K Kang (2015), as described in the previous section. Specifically, we classify an ED visit as being for neoplasms if the ED record contains any of the following ICD-9 primary diagnosis codes: 140*-239*. Infectious diseases correspond to the following ICD-9 primary diagnosis codes: 001*-139*.

Drug-and-alcohol-related ED visits that involve an ICU stay. We also look separately at drug-and-alcohol-related ED visits which involve an ICU stay, as these visits may be less likely to be planned based on affordability. To define drug-and-alcohol-related ED visits which involve an ICU stay, we begin with the set of drug-and-alcohol-related ED visits, then code visits as additionally involving an ICU stay if any of the following charge variables in the Uniform Billing data have a value greater than 0: CHG200 (ICU), CHG203 (ICU pediatric), CHG204 (ICU psych), CHG206 (intermediate ICU), CHG207 (ICU - burn unit), CHG210 (coronary care), and CHG214 (coronary care-intermediate ICU).

C Additional Results

C.1 Robustness

We explored the robustness of our fungibility tests to a number of alternative specifications. In each table we first replicate the baseline specification and then report results from specific alternative specifications; we report both the direct estimates of SNAP receipt and one-fourth of the estimates of SSI receipt (both using only the within-month variation in SSI as well as the DD variation), as well as the tests of fungibility (i.e. equality of impact) between a dollar of SNAP and a dollar of SSI. Where applicable, we report these for both the full and overlap samples. The estimates are largely unaffected.

Appendix Tables OA.12 and OA.13 summarize the results for, respectively, ED visits for drug and alcohol use and for first fills. We first consider the sensitivity of the results to whether and how we control for various covariates. The second row shows the results of an alternative specification in which we add indicators for SNAP payout day to the baseline SSI analysis and using indicators for day relative to SSI payout day rather than calendar day for the SNAP analysis.[51] We focus this test on the overlap sample where controlling for the other benefit's payout day is most relevant. In the third row, we relax the assumption in the baseline SNAP analysis in equation (2) that the fixed effects Ω_d and κ_k can vary with the SNAP assignment regime s. We did this in the baseline specification because SNAP payout day (which is based on the last digit of the case number) is random conditional on the assignment regime (s) - i.e. the period before or after September 2012, as the assignment of case numbers to payout dates changed at that point (see Appendix Table OA.1). We also explored the sensitivity of results to including the fixed effects Ω_d in equations (1) and (2). Specifically, we sequentially (and cumulatively) drop the indicators for 'special days', for calendar year, for calendar month, and day of the week from both analyses; we also then dropped the day of the month indicators κ from the SNAP analysis; the results remain virtually the same (see Appendix Tables OA.14 and OA.15).

We next consider the sensitivity of our results to various sample restrictions. These results are shown in rows 4 through 6, and Appendix Table OA.16 shows the (quite substantial) reductions in sample size associated with each specification. In the fourth row we limit the SSI analysis to 2013 and later, since in that period we know for sure that all benefits are paid electronically and therefore received on the payment date. In the fifth row we limit the sample to people under age 62 so that they are not likely to be receiving Social Security with its own payment cycle based on the day of the month they were born (Gross et al. 2022). In the the sixth row we limit the SNAP sample to people who received their SNAP payouts on the first ten days of the month, so that if they are receiving SSI as well they likely still have cash-on-hand when they receive SNAP.

Row 7 shows robustness to a proportional (i.e. Poisson) rather than linear specification. For ease of comparison to the baseline we report in {curly brackets} the implied proportional effect from the baseline linear specification.

In addition, in the prescription drug analysis, row 8 shows that results are similar when we

[51] Controls for calendar day are not quite the same as controls for SSI payout day because the SSI payout day falls before the first of the month if the first of the month is a weekend of federal holiday (so about 2/7ths of the time).

examine an alternative proxy for consumption (vs. refills) of prescription drugs instead of our 'first fills' measure; specifically, following Einav et al. (2018), we examine fills for "non-maintenance" drugs, which are drugs that are not associated with on-going, chronic conditions, and therefore again likely proxy for drugs that are being immediately consumed to address acute conditions. Appendix B provides details on how we code these "non-maintenance" drugs and Appendix Figures OA.9 and OA.10 show the underlying event studies.

In addition, since since decision-making within a two-adult household may violate fungibility for reasons other than mental accounting, Appendix Figures OA.20 and OA.21 show that results look similar when we limit the overlap sample to person-spells that are not married (based on the DSS data's variable on marital status). About half of the person-months are not married.

Finally, we note that throughout our analyses we have computed standard errors clustered at the date (day-month-year) level. However, because the "treatment" of SNAP occurs at the individual level, it would be appropriate to cluster standard errors at the individual level. Clustering at this level, however, is computationally intensive. In Appendix Figure OA.11, we conduct an exercise comparing estimates of the effect of SNAP on first fills using standard errors clustered at the date (day-month-year) level compared to bootstrapped standard errors which simulate individual level clustering, showing that confidence intervals are basically the same as those in our main set of estimates.

C.2 Analysis of 'Nutrition Sensitive' Conditions

We attempt to proxy for ED visits that are attributed to 'nutrition sensitive' conditions, since this may be a proxy for (lack of) food consumption. We follow several approaches that have been used by the existing literature, including coding ED visits for hypoglycemia, diabetes-related complications and hypertension; Appendix B provides more details on the sources and exact codings for each of these approaches. In practice, hypoglycemia is the condition that most obviously reflects (lack of) food consumption, but is quite rare (less than 0.1 percent of ED visits in our data); the other conditions are much more common, but interpretation of impacts on them is complicated by the fact that their causes are multifaceted.

Appendix Table OA.11 shows the impact of SSI and SNAP on ED visits for nutrition sensitive conditions using the union of the three definitions used in previous studies (top row) as well as for each measure separately (following three rows); Appendix Figures OA.12 through OA.19 show the underlying event studies. Appendix Table OA.11 Column (1) shows evidence that, for all definitions, nutrition-sensitive ED visits decline following receipt of SNAP.[52] Columns (2) and (3) show evidence that, by contrast, ED visits for nutrition sensitive conditions increase following receipt of SSI. The estimates in columns (4) and (5) indicate that - for all of the definitions of nutrition-sensitive conditions but hypoglycemia - we can reject fungibility. While the contrasting effects of SNAP (column 1) and SSI (columns 2 or 3) on ED visits for nutrition sensitive conditions

[52] This is consistent with an existing literature (reviewed in more detail in Appendix A) that SNAP recipients redeem a large share of their month's benefit immediately upon receipt (Castner and Henke 2011; Wilde and Ranney 2000), and that their caloric intake declines over the benefit month (Wilde and Ranney 2000; Shapiro 2005; Todd 2015; Gassman-Pines and Schenck-Fontaine 2019; Kuhn 2018; Hamrick and Andrews 2016); there is also prior evidence of a decline in ED visits for nutrition-sensitive conditions following receipt of SNAP (e.g., Ojinnaka and Heflin 2018; Arteaga et al. 2018). Most closely related to our work, Cotti et al. (2020) and Cotti et al. (2018) exploit the within-month variation in SNAP benefit receipt in South Carolina to document, respectively, that Medicaid-covered emergency department use overall falls following SNAP benefit receipt and student test scores decline when the exam falls late in the SNAP benefit cycle, a result that they interpret as indicative of poor nutrition.

are consistent with prior findings that the marginal propensity to consume food out of SNAP is higher than out of cash (Hastings and Shapiro 2018; Song 2022), we hesitate to put too much weight on them since, as noted in section B, the measures of nutrition sensitive conditions are either incredibly narrow (less than 0.1% of ED visits in the case of hypoglycemia) and hence quite underpowered, or are sufficiently broad (e.g. hypertension or diabetes-related complications) that we cannot be confident that they are proxying for (lack of) food consumption rather than some other underlying health issue.

D Proofs and Derivations

D.1 Preliminaries: Set up, definitions, and intermediate results

Set up. To simplify the derivations, we re-cast the individual's optimization problem as being over three variables: f (total food consumption), n (total non-food consumption), and c_1^b (consumption of temptation good). This transforms the individual's utility function from the model in the main text, U, into the following:

$$
\begin{aligned}
U = \quad & \alpha_g \alpha_f \left[\log\left(\frac{f}{1+\beta}\right) + \beta \log\left(\frac{\beta f}{1+\beta}\right)\right] + \alpha_g(1-\alpha_f)\left[\log\left(\frac{n}{1+\beta}\right) + \beta \log\left(\frac{\beta n}{1+\beta}\right)\right] \\
& + (1-\alpha_g)(1-\beta\gamma)\log(c_1^b) - \kappa(\phi_0 y_1 + b_1 - p_f f)^2
\end{aligned}
$$

which comes from the definitions $f = f_1 + f_2$ and $n = n_1 + n_2$ and the optimal decisions:

$$
\begin{aligned}
f_1 &= \frac{f}{1+\beta}, \qquad f_2 = \frac{\beta f}{1+\beta} \\
n_1 &= \frac{n}{1+\beta}, \qquad n_2 = \frac{\beta n}{1+\beta}
\end{aligned}
$$

We normalize the price of n to one and use p_f and p_b to denote the relative prices of food and the temptation good, respectively.

Definitions. The following definitions will be useful for the analysis, where x^* indicates the optimal choice of good x made by the consumer:

- ϕ denotes the share of the individual's income she chooses to spend on food, with $\phi(\alpha_g, \alpha_f, \beta, \gamma, \kappa) \equiv \frac{p_f f}{y_1 + b_1}$.
- θ denotes the share of the individual's income she chooses to spend on the temptation good, with $\theta(\alpha_g, \alpha_f, \beta, \gamma, \kappa) \equiv \frac{p_b(c_1^{b*})}{y_1+b_1}$.
- ϕ_0 and θ_0 denote the values of ϕ and θ (respectively) when $\kappa = 0$ (i.e., there is no mental accounting). Thus, $\phi_0 \equiv \phi(\alpha_g, \alpha_f \beta, \gamma, \kappa = 0)$ and $\theta_0 \equiv \theta(\alpha_g, \alpha_f, \beta, \gamma, \kappa = 0)$.
- We define SNAP benefits (b_1) as ***inframarginal*** if they are below the amount that the consumer would have chosen to spend on food in the absence of mental accounting (or if the planner had allocated the entire transfer as cash): i.e., $b_1 < \frac{\phi_0}{1-\phi_0} y_1$.
- The marginal propensities to consume food ($MPCf$), non-food ($MPCn$), and the "bad" temptation good ($MPCb$) out of cash and SNAP are:

$$MPCf^{cash} \equiv \frac{d(p_f f^*)}{dy_1} \qquad MPCf^{SNAP} \equiv \frac{d(p_f f^*)}{db_1}$$

$$MPCn^{cash} \equiv \frac{d(n^*)}{dy_1} \qquad MPCn^{SNAP} \equiv \frac{d(n^*)}{db_1}$$

$$MPCb^{cash} \equiv \frac{d(p_b(c_1^{b*}))}{dy_1} \qquad MPCb^{SNAP} \equiv \frac{d(p_b(c_1^{b*}))}{db_1}$$

Deriving differences between the $MPCf$, $MPCn$, and $MPCb$ out of SNAP and cash. We derive expressions for the differences between the marginal propensities to consume food, non-food, and the temptation good out of SNAP relative to cash. These expressions are used in the proofs of the main theorems below. The expressions are collected in the following lemma:

Lemma 1. *The differences between the MPCs out of SNAP and cash for the three goods are given by the following expressions:*

$$\begin{aligned} MPCf^{SNAP} - MPCf^{cash} &= \left(\frac{d\phi}{db_1} - \frac{d\phi}{dy_1}\right)(y_1 + b_1) \\ &= \frac{2\kappa(1-\phi)(1-\phi_0)(y_1+b_1)}{\frac{(1+\beta)\alpha_g\alpha_f}{\phi^2} + 2\kappa(y_1+b_1)[(1+\phi_0-2\phi)y_1 + 2(1-\phi)b]} \\ MPCn^{SNAP} - MPCn^{cash} &= \frac{-(1+\beta)\alpha_g(1-\alpha_f)}{(1+\beta)\alpha_g(1-\alpha_f) + (1-\alpha_g)(1-\beta\gamma)}(MPCf^{SNAP} - MPCf^{cash}) \\ MPCb^{SNAP} - MPCb^{cash} &= \frac{-(1-\alpha_g)(1-\beta\gamma)}{(1+\beta)\alpha_g(1-\alpha_f) + (1-\alpha_g)(1-\beta\gamma)}(MPCf^{SNAP} - MPCf^{cash}) \end{aligned}$$

Proof:

At an interior optimum, the individual equalizes the ratios of marginal utility to price:

$$\frac{MU_f}{p_f} = MU_n = \frac{MU_b}{p_b}$$

Differentiating the utility function gives the following marginal utilities:

$$\begin{aligned} MU_f &= \frac{(1+\beta)\alpha_g\alpha_f}{f} + 2\kappa p_f(\phi_0 y_1 + b - p_f f) \\ MU_n &= \frac{(1+\beta)\alpha_g(1-\alpha_f)}{n} \\ MU_b &= \frac{(1-\alpha_g)(1-\beta\gamma)}{c_1^b} \end{aligned}$$

Using the definitions of ϕ and θ above, we can then re-write the individual's consumption decisions as follows:

$$\begin{aligned} f &= \frac{\phi(y_1+b_1)}{p_f} \\ c_1^b &= \frac{\theta(y_1+b_1)}{p_b} \\ n &= (1-\phi-\theta)(y_1+b_1) \end{aligned}$$

We next re-write the marginal utilites in terms of θ and ϕ, noting that ϕ_0 is the constant function of the individual's preference parameters defined above:

$$\begin{aligned} \frac{MU_f}{p_f}(\phi) &= \frac{(1+\beta)\alpha_g\alpha_f}{\phi(y_1+b_1)} + 2\kappa[(\phi_0-\phi)y_1+(1-\phi)b] \\ \frac{MU_b}{p_b}(\theta) &= \frac{(1-\alpha_g)(1-\beta\gamma)}{\theta(y_1+b_1)} \\ MU_n(\theta,\phi) &= \frac{(1+\beta)\alpha_g(1-\alpha_f)}{(1-\phi-\theta)(y_1+b_1)} \end{aligned}$$

Setting the last two equal gives:

$$\theta = \frac{(1-\phi)(1-\alpha_g)(1-\beta\gamma)}{(1+\beta)\alpha_g(1-\alpha_f)+(1-\alpha_g)(1-\beta\gamma)}$$

Plugging this into $\frac{MU_b}{p_b}(\theta)$ gives:

$$\frac{MU_b}{p_b}(\phi) = \frac{(1+\beta)\alpha_g(1-\alpha_f)+(1-\alpha_g)(1-\beta\gamma)}{(1-\phi)(y_1+b_1)}$$

Setting this equal to $MU_f(\phi)/p_f$ gives:

$$\frac{(1+\beta)\alpha_g\alpha_f}{\phi(y_1+b_1)} + 2\kappa[(\phi_0-\phi)y_1+(1-\phi)b] = \frac{(1+\beta)\alpha_g(1-\alpha_f)+(1-\alpha_g)(1-\beta\gamma)}{(1-\phi)(y_1+b_1)}$$

Rearranging gives the following

$$\begin{aligned} \frac{(1+\beta)(1-\phi)\alpha_g\alpha_f}{\phi} + 2(1-\phi)(y_1+b_1)\kappa[(\phi_0-\phi)y_1+(1-\phi)b] - \\ (1+\beta)\alpha_g(1-\alpha_f)-(1-\alpha_g)(1-\beta\gamma) &= 0 \end{aligned} \quad (4)$$

We define the equation (4) above as $G(\phi, y, b) = 0$ from now on, and we implicitly differentiate this function to derive expressions for $MPCf$ and $MPCb$:

$$\begin{aligned} \frac{\partial G}{\partial \phi} &= \frac{-(1+\beta)\phi a_g a_f - (1+\beta)(1-\phi)a_g a_f}{\phi^2} - 2[(\phi_0-\phi)y_1+(1-\phi)b](y_1+b_1)\kappa - 2\kappa(1-\phi)(y_1+b_1)^2 \\ &= \frac{-(1+\beta)\alpha_g\alpha_f}{\phi^2} - 2\kappa(y_1+b_1)[(1+\phi_0-2\phi)y_1+2(1-\phi)b] \end{aligned}$$

The optimal choice for food is always bounded by $f < \phi_0 y_1 + b_1$, because as $\kappa \to \infty$ the individual's optimal food spending approaches the mental account $f = \phi_0 y_1 + b_1$ from below (see section E.3 below for details). Plugging in this upper bound, we then know:

$$\frac{\partial G}{\partial \phi} < -\frac{(1+\beta)\alpha_g \alpha_f}{\phi^2} - 2\kappa(y_1+b_1)(1-\phi_0)y_1 < 0$$

Differentiating G with respect to y_1:

$$\frac{\partial G}{\partial y_1} = 2\kappa(1-\phi)[(\phi_0-\phi)y_1 + (1-\phi)b] + 2\kappa(\phi_0-\phi)(1-\phi)(y_1+b_1)$$

Differentiating G with respect to b_1:

$$\frac{\partial G}{\partial b_1} = 2\kappa(1-\phi)[(\phi_0-\phi)y_1 + (1-\phi)b] + 2\kappa(1-\phi)^2(y_1+b_1)$$

From here, we can derive how expenditure shares change with changes in b_1 or y_1. We can translate these into the difference in the $MPCf$ out of SNAP and cash in the following way:

$$\begin{aligned} f &= \phi(y_1,b_1)(y_1+b_1) \\ \frac{df}{dy_1} &= \frac{d\phi}{dy_1}(y_1+b_1) + \phi \\ \frac{df}{db_1} &= \frac{d\phi}{db_1}(y_1+b_1) + \phi \\ MPCf^{SNAP} - MPCf^{cash} &= \left(\frac{d\phi}{db_1} - \frac{d\phi}{dy_1}\right)(y_1+b_1) \end{aligned}$$

We can derive $(\frac{d\phi}{db_1} - \frac{d\phi}{dy_1})$ as follows:

$$\frac{d\phi}{db_1} - \frac{d\phi}{dy_1} = -\frac{\frac{\partial G}{\partial b_1} - \frac{\partial G}{\partial y_1}}{\frac{\partial G}{\partial \phi}} = \frac{2\kappa(1-\phi)(1-\phi_0)(y_1+b_1)}{\frac{(1+\beta)\alpha_g\alpha_f}{\phi^2} + 2\kappa(y_1+b_1)[(1+\phi_0-2\phi)y_1 + 2(1-\phi)b]}$$

Recall the relationship derived between ϕ and θ:

$$\theta(y,b) = \frac{(1-\alpha_g)(1-\beta\gamma)}{(1+\beta)\alpha_g(1-\alpha_f) + (1-\alpha_g)(1-\beta\gamma)}(1-\phi(y_1,b_1))$$

Taking the derivative with respect to y_1:

$$\frac{d\theta}{dy_1} = -\frac{d\phi}{dy_1}\frac{(1-\alpha_g)(1-\gamma)}{(1+\beta)\alpha_g(1-\alpha_f) + (1-\alpha_g)(1-\gamma)}.$$

We have an analogous result when we differentiate with respect to b_1:

$$\frac{d\theta}{db_1} - \frac{d\theta}{dy_1} = \frac{(1-\alpha_g)(1-\beta\gamma)}{(1+\beta)\alpha_g(1-\alpha_f) + (1-\alpha_g)(1-\beta\gamma)}\left(\frac{d\phi}{dy_1} - \frac{d\phi}{db_1}\right)$$

This can be translated to the difference in $MPCb$ expressions as follows:

$$MPCb^{SNAP} - MPCb^{cash} = \left(\frac{d\theta}{db_1} - \frac{d\theta}{dy_1}\right)(y_1 + b_1)$$
$$= \frac{-(1-\alpha_g)(1-\beta\gamma)}{(1+\beta)\alpha_g(1-\alpha_f) + (1-\alpha_g)(1-\beta\gamma)}(MPCf^{SNAP} - MPCf^{cash}) \quad (5)$$

Finally, we use the results above to solve for the difference in $MPCn$:

$$MPCn^{SNAP} - MPCn^{cash} = (1 - MPCf^{SNAP} - MPCb^{SNAP}) - (1 - MPCf^{cash} - MPCb^{cash})$$
$$= -(MPCf^{SNAP} - MPCf^{cash}) - (MPCb^{SNAP} - MPCb^{cash})$$
$$= -(MPCf^{SNAP} - MPCf^{cash}) + \frac{(1-\alpha_g)(1-\beta\gamma)}{(1+\beta)\alpha_g(1-\alpha_f) + (1-\alpha_g)(1-\beta\gamma)}(MPCf^{SNAP} - MPCf^{cash})$$
$$= \frac{-(1+\beta)\alpha_g(1-\alpha_f)}{(1+\beta)\alpha_g(1-\alpha_f) + (1-\alpha_g)(1-\beta\gamma)}(MPCf^{SNAP} - MPCf^{cash}) \quad \blacksquare$$

Comparative statics of the optimal food share with respect to SNAP and cash. Using the results above, we can also derive the signs of $\frac{d\phi}{db_1}$, $\frac{d\phi}{dy_1}$, and $\frac{d\phi}{db_1} - \frac{d\phi}{dy_1}$:

$$\frac{d\phi}{db_1} = -\frac{d^2U}{d\phi db_1} / \frac{d^2U}{d\phi^2},$$
$$\frac{d\phi}{dy_1} = -\frac{d^2U}{d\phi dy_1} / \frac{d^2U}{d\phi^2}$$

$$\frac{d^2U}{d\phi db_1} = \kappa\frac{dU_B}{db_1} = 2\kappa[(1+\phi_0-2\phi)y_1 + 2(1-\phi)b] > 0$$

$$\frac{d^2U}{d\phi dy_1} = \kappa\frac{dU_B}{dy_1} = 2\kappa[(\phi_0-\phi)(y_1+b_1) + (\phi_0 y_1 + b - \phi(y_1+b_1))] \lesseqgtr 0$$

Therefore, $\frac{d\phi}{db_1} > 0$, but $\frac{d\phi}{dy_1}$ could be positive or negative. However, $\frac{d\phi}{db_1} - \frac{d\phi}{dy_1} = 2\kappa(1-\phi_0)(y_1+b_1) > 0$ if $\kappa > 0$ so that an increase in SNAP always increases ϕ more than an increase in cash if $\kappa > 0$.

Comparative statics of the optimal food consumption (f^*) with respect to κ. We prove the following lemma as an intermediate result that we use below:

Lemma 2. *Optimal food consumption increases monotonically in κ (i.e., $\partial f^*/\partial\kappa > 0$), and $f^* \in [\phi_0(y_1+b_1), \phi_0 y_1 + b_1)$ for $\kappa \in [0,\infty)$.*

Proof: The individual's optimal food spending for any $\kappa \geq 0$ is always between the food spending at $\kappa = 0$ and the food spending in the limit as $\kappa \to \infty$. When $\kappa = 0$, the individual chooses the optimal food consumption absent mental accounting. This turn out to be the lower bound on the individual's food consumption of $f^*_{\kappa=0} = \phi_0(y_1+b)$. As $\kappa \to \infty$, the individual's optimal food consumption approaches exactly the "target" in the mental accounting term in the utility function. This is the upper bound on food consumption: $f^*_{(\kappa\to\infty)} = \phi_0 y_1 + b$. We prove that optimal food consumption increases monotonically in κ, so that κ pins down a unique food consumption in between these two bounds; i.e., $f^* \in [\phi_0(y_1+b_1), \phi_0 y_1 + b_1)$, with $\frac{\partial f}{\partial\kappa} > 0$.

Begin with the case where $\kappa = 0$ so there is no mental accounting. Food consumption is exactly the Cobb-Douglas share multiplied by total income:

$$f^* = \frac{(1+\beta)\alpha_g\alpha_f}{(1+\beta)\alpha_g + (1-\alpha_g)(1-\beta\gamma)}(y_1 + b_1) = \phi_0(y_1 + b_1)$$

For the $\kappa \to \infty$ case, recall the following:

$$\begin{aligned}
\frac{MU_{\bar{f}}}{p_f}(\phi) &= \frac{(1+\beta)\alpha_g\alpha_f}{\phi(y_1+b_1)} + 2\kappa[(\phi_0 - \phi)y_1 + (1-\phi)b] \\
\frac{MU_{b_1}}{p_b}(\phi) &= \frac{(1+\beta)\alpha_g(1-\alpha_f) + (1-\alpha_g)(1-\beta\gamma)}{(1-\phi)(y_1+b_1)}
\end{aligned}$$

Since $\frac{MU_{\bar{f}}}{p_f} = \frac{MU_b}{p_b}$, we can divide both sides by κ and use $\frac{MU_{\bar{f}}}{p_f\kappa} = \frac{MU_b}{\kappa p_b}$:

$$\begin{aligned}
\frac{MU_F}{p_f\kappa} &= \frac{MU_b}{\kappa p_b} \\
\frac{(1+\beta)\alpha_g\alpha_f}{\kappa\phi(y_1+b_1)} + 2[(\phi_0 - \phi)y_1 + (1-\phi)b] &= \frac{(1+\beta)\alpha_g(1-\alpha_f) + (1-\alpha_g)(1-\beta\gamma)}{(1-\phi)(y_1+b_1)\kappa}
\end{aligned}$$

As $\kappa \to \infty$, this collapses to

$$2[(\phi_0 - \phi)y_1 + (1-\phi)b_1] = 0 \implies \phi = \frac{\phi_0 y_1 + b_1}{y_1 + b_1}$$

Note that food consumption when $\kappa \to \infty$ is always greater than that when $\kappa = 0$, since

$$f^*_{\kappa\to\infty} - f^*_{\kappa=0} = \phi_0 y_1 + b_1 - \phi_0(y_1 + b_1) = (1-\phi_0)b_1 > 0.$$

We now show that food consumption will never be higher than $f^*_{\kappa\to\infty}$ and never be lower than $f^*_{\kappa=0}$. Recall that the consumer's "simplified" utility function is:

$$\begin{aligned}
U(f, n, c_1^b) &= \alpha_g\alpha_f\left[\log\left(\frac{f}{1+\beta}\right) + \beta\log\left(\frac{\beta f}{1+\beta}\right)\right] + \\
&\quad \alpha_g(1-\alpha_f)\left[\log\left(\frac{n}{1+\beta}\right) + \beta\log\left(\frac{\beta n}{1+\beta}\right)\right] + \\
&\quad (1-\alpha_g)(1-\beta\gamma)\log(c_1^b) - \kappa(\phi_0 y_1 + b - p_f f)^2
\end{aligned}$$

We can define two helpful (partially optimized) sub-utility functions, U_A and U_B:

$$\begin{aligned}U_A(f) \equiv \max_{n,c_1^b} \Bigg\{ & \alpha_g\alpha_f \left[\log\left(\frac{\bar{f}}{1+\beta}\right) + \beta\log\left(\frac{\beta\bar{f}}{1+\beta}\right)\right] + \\ & \alpha_g(1-\alpha_f)\left[\log\left(\frac{\bar{n}}{1+\beta}\right) + \beta\log\left(\frac{\beta\bar{n}}{1+\beta}\right)\right] + \\ & (1-\alpha_g)(1-\beta\gamma)\log(c_1^b)\Bigg\} \\ & \text{subject to } p_f f + n + p_b c_1^b = y_1 + b_1\end{aligned}$$

The sub-utility $U_A(f)$ takes in a value of f, and returns the maximum possible utility (over all possible choices of n and c_1^b) that the consumer can achieve given that choice of f and no mental accounting. That is, $U_A(f)$ is the utility achieved if the consumer chooses (the possibly non-optimal) f, then makes the optimal (n, c_1^b) choices conditional on f, all when there is no mental accounting.

The optimal n and c_1^b conditional on f are the choices which allocate the share of the budget not spent on f such that the ratio of the marginal utilities of c_1^b and n is equal to the price ratio p_b (since p_n normalized to 1). Since utility is additively separable in food and other consumption, this is equivalent to finding the (n, c_b^1) that maximizes the following:

$$\alpha_g(1-\alpha_f)\left[\log\left(\frac{n}{1+\beta}\right) + \beta\log\left(\frac{\beta n}{1+\beta}\right)\right] + (1-\alpha_g)(1-\beta\gamma)\log(c_1^b)$$

subject to $p_b c_1^b + n = (1-\phi)(y_1+b_1)$. Solving this gives the following optimal choices of $p_b c_1^b$ and n:

$$\begin{aligned}p_b c_1^b &= \frac{(1-\alpha_g)(1-\beta\gamma)(y_1+b_1)(1-\phi)}{(1-\alpha_g)(1-\beta\gamma)+\alpha_g(1-\alpha_f)(1+\beta)} = \frac{\theta_0(1-\phi)(y_1+b_1)}{(1-\phi_0)} \\ n &= \frac{\alpha_g(1-\alpha_f)(1+\beta)(y_1+b_1)(1-\phi)}{(1-\alpha_g)(1-\beta\gamma)+\alpha_g(1-\alpha_f)(1+\beta)} = \frac{(1-\phi_0-\theta_0)(1-\phi)(y_1+b_1)}{(1-\phi_0)}\end{aligned}$$

We can now write U_A fully in terms of (the possibly non-optimal) ϕ:

$$\begin{aligned}U_A(\phi) = \quad & \alpha_g\alpha_f\left[\log\left(\frac{\phi(y_1+b_1)}{p_f(1+\beta)}\right) + \beta\log\left(\frac{\beta\phi(y_1+b_1)}{p_f(1+\beta)}\right)\right] + \\ & \alpha_g(1-\alpha_f)\left[\log\left(\frac{(1-\phi)(1-\phi_0-\theta_0)(y_1+b_1)}{(1-\phi_0)(1+\beta)}\right) + \right. \\ & \left.\beta\log\left(\beta\frac{(1-\phi)(1-\phi_0-\theta_0)(y_1+b_1)}{(1-\phi_0)(1+\beta)}\right)\right] + \\ & (1-\alpha_g)(1-\beta\gamma)\log\left(\frac{(1-\phi)\theta_0(y_1+b_1)}{(1-\phi_0)p_b}\right)\end{aligned}$$

Next, we define $U_B(f) \equiv -(\phi_0 y_1 + b - p_f f)^2$, which is simply the mental accounting term without the κ term multiplying the quadratic utility cost. This can also be written in terms of ϕ:

$$U_B(\phi) = -(\phi_0 y_1 + b - \phi(y_1+b_1))^2$$

Then, for a given ϕ (or equivalently, a given f), a consumer who makes choices that are utility-maximizing conditional on (the possibly non-optimal) ϕ has utility:

$$U(\phi) = U_A(\phi) + \kappa U_B(\phi)$$

Differentiating U_A with respect to ϕ:

$$\frac{\partial U_A}{\partial \phi} = \frac{\alpha_g \alpha_f (1+\beta)}{\phi} - \frac{\alpha_g (1-\alpha_f)(1+\beta)}{1-\phi} - \frac{(1-\alpha_g)(1-\beta\gamma)}{1-\phi}$$

This shows that $\frac{dU_A}{d\phi} = 0$ (i.e., U_A is maximized) at $\phi = \phi_0$. For $\phi < \phi_0$, $\frac{dU_A}{d\phi} > 0$, and for $\phi > \phi_0$, $\frac{dU_A}{d\phi} < 0$.

Writing U_B in terms of ϕ and differentiating:

$$\begin{aligned}\frac{dU_B}{d\phi} &= 2(\phi_0 y_1 + b - \phi(y_1 + b_1))(y_1 + b_1) \\ &= 2((\phi_0 - \phi)y_1 + (1-\phi)b)(y_1 + b_1)\end{aligned}$$

So U_B is maximized at $\phi = \frac{\phi_0 y_1 + b_1}{y_1 + b_1}$. For $\phi < \frac{\phi_0 y_1 + b_1}{y_1 + b_1}$, $\frac{dU_B}{d\phi} > 0$, and for $\phi > \frac{\phi_0 y_1 + b_1}{y_1 + b_1}$, $\frac{dU_B}{d\phi} < 0$.

For $\phi < \phi_0$, both $dU_A/d\phi > 0$ and $dU_B/d\phi > 0$. It will never be optimal to choose $\phi < \phi_0$ because the consumer can instead increase food consumption (i.e., increase ϕ) and achieve higher utility from both U_A and U_B. Similarly, for any choice of $\phi > \frac{\phi_0 y_1 + b_1}{y_1 + b_1}$, both $dU_A/d\phi < 0$ and $dU_B/d\phi < 0$ and the consumer is made strictly better off by choosing $\phi = \frac{\phi_0 y_1 + b_1}{y_1 + b_1}$. This shows that for any $\kappa \geq 0$, the optimal food expenditure falls within the interval: $\phi \in [\phi_0, \frac{\phi_0 y_1 + b_1}{y_1 + b_1})$. Determining where food expenditure lies within that interval requires evaluating the tradeoff between lower U_A and higher U_B. Note that when $b_1 = 0$ there is no trade-off: the optimum for U_A is at $\phi = \phi_0$, and the optimum for U_B is $\phi = \phi_0$.

Differentiating the overall utility function and evaluating at the optimum ϕ:

$$\frac{\partial U}{d\phi}(\phi) = \frac{\partial U_A}{\partial \phi}(\phi) + \kappa \frac{\partial U_B}{\partial \phi}(\phi) = 0$$

Since $\phi \in [\phi_0, \frac{\phi_0 y_1 + b_1}{y_1 + b_1}]$, $\frac{dU_A}{d\phi}(\phi) \leq 0$ and $\frac{dU_B}{d\phi}(\phi) \geq 0$. We can also show that ϕ is strictly increasing in κ, using implicit differentiation on the first order condition on U:

$$\frac{d\phi}{d\kappa} = -\frac{d^2 U}{d\phi d\kappa} / \frac{d^2 U}{d\phi^2}$$

The numerator is given by

$$\frac{d^2 U}{d\phi d\kappa} = \frac{dU_B}{d\phi} > 0$$

The denominator is given by

$$\begin{aligned}\frac{d^2 U}{d\phi^2} &= \frac{d^2 U_A}{d\phi^2} + \kappa \frac{d^2 U_B}{d\phi^2} \\ &= -\frac{(1+\beta)\alpha_g \alpha_f}{\phi^2} - \frac{\alpha_g(1-\alpha_f)(1+\beta) + (1-\alpha_g)(1-\beta\gamma)}{(1-\phi)^2} - 2\kappa(y_1 + b_1)^2 < 0\end{aligned}$$

Putting these two together gives $\frac{d\phi}{d\kappa} > 0$, completing the proof. ■

Comparative statics of the optimal consumption choices with respect to β We prove the following lemma since we state this result in the main text and we also use it as an intermediate result in the results below:

Lemma 3. *The individual's optimal choice of the temptation good is strictly decreasing in β, and the optimal choice of food and non-food are strictly increasing in β.*

Proof:

We can restate the results in the lemma as follows: $\frac{\partial\theta}{\partial\beta} < 0$, $\frac{\partial\phi}{\partial\beta} > 0$, and $\frac{\partial(1-\phi-\theta)}{\partial\beta} > 0$. To prove these results, we use the fact that $d\phi/d\beta = -\frac{d^2U}{d\phi d\beta}/\frac{d^2U}{d\phi^2}$. Since $\frac{d^2U}{d\phi^2} < 0$, then this means that we need to prove $\frac{d^2U}{d\phi d\beta} > 0$. Using the expression for $\frac{dU}{d\phi}$ above and differentiating that expression with respect to β we have the following:

$$
\begin{aligned}
\frac{d^2U}{d\phi d\beta} &= \frac{\alpha_g\alpha_f}{\phi} - \frac{\alpha(1-\alpha_f)}{1-\phi} + \frac{\gamma(1-\alpha_g)}{1-\phi} \\
&= \frac{\alpha_g\alpha_f(1-\phi)}{\phi(1-\phi)} - \frac{\phi\alpha_g(1-\alpha_f)}{\phi(1-\phi)} + \frac{\phi\gamma(1-\alpha_g)}{\phi(1-\phi)} \\
&= \frac{\alpha_g\alpha_f(1-\phi) - \phi\alpha_g(1-\alpha_f) + \phi\gamma(1-\alpha_g)}{\phi(1-\phi)} \\
&= \frac{\alpha_g\alpha_f - \phi\alpha_g + \phi\gamma(1-\alpha_g)}{\phi(1-\phi)} \\
&= \frac{\alpha_g(\alpha_f - \phi) + \phi\gamma(1-\alpha_g)}{\phi(1-\phi)} \\
&> 0
\end{aligned}
$$

Recall the relationship derived between ϕ and θ:

$$\theta(y,b) = \frac{(1-\alpha_g)(1-\beta\gamma)}{(1+\beta)\alpha_g(1-\alpha_f) + (1-\alpha_g)(1-\beta\gamma)}(1-\phi(y_1,b_1))$$

The equation above implies that $d\phi/d\beta > 0$ implies that $d\theta/d\beta < 0$. Additionally, since the magnitude of $d\phi/d\beta$ is larger than the magnitude of $d\theta/d\beta$ this implies that $d(1-\phi-\theta)/d\beta > 0$. ■

D.2 Proofs of Results in Main Text

Proposition 1. *Mental accounting and non-fungibility*. *For $b_1 < \frac{\phi_0}{1-\phi_0}y_1$:*

1. *If $\kappa = 0$, then $MPCf^{cash} = MPCf^{SNAP} = \phi_0$, $MPCb^{cash} = MPCb^{SNAP} = \theta_0$, and $MPCn^{cash} = MPCn^{SNAP} = 1 - \phi_0 - \theta_0$, where θ_0 denotes the share of the consumer's income she chooses to spend on the temptation good when $\kappa = 0$.*

2. *If $\kappa > 0$, then $MPCf^{cash} < MPCf^{SNAP}$, $MPCn^{cash} > MPCn^{SNAP}$, and $MPCb^{cash} > MPCb^{SNAP}$. The differences $(MPCf^{SNAP} - MPCf^{cash})$ and $(MPCb^{cash} - MPCb^{SNAP})$*

are decreasing in β and increasing in κ, and the difference $(MPCn^{cash} - MPCn^{SNAP})$ is increasing in κ.

Proof:

To prove part 1 of the Proposition, we use the fact that when $b_1 < \frac{\phi_0}{1-\phi_0} y_1$, SNAP benefits are ***inframarginal***, which means that we can use the first-order approach to solve for the optimal consumption choices. When $\kappa = 0$ (in part 1), we can equate the marginal utilities and find optimal choices of ϕ and θ:

$$\begin{aligned}\phi = \phi_0 &= \frac{(1+\beta)\alpha_g\alpha_f}{\alpha_g(1+\beta) + (1-\alpha_g)(1-\beta\gamma)} > 0 \\ \theta = \theta_0 &= \frac{(1-\alpha_g)(1-\beta\gamma)}{\alpha_g(1+\beta) + (1-\alpha_g)(1-\beta\gamma)} > 0\end{aligned}$$

Since ϕ does not depend on y_1 or b_1, then

$$\frac{d\phi}{db_1} - \frac{d\phi}{dy_1} = 0$$

Thus $MPCf^{SNAP} - MPCf^{cash} = 0$ and $MPCb^{SNAP} - MPCb^{cash} = 0$, which implies that $MPCf^{SNAP} = MPCf^{cash}$ and $MPCb^{SNAP} = MPCb^{cash}$.

We can solve for the $MPCf$ and $MPCb$ terms immediately:

$$MPCf^{SNAP} = \frac{d\phi^*(y_1 + b_1)}{db_1} = \frac{d\phi^*}{db_1}(y_1 + b_1) + \phi^*$$

Since $\phi^* = \phi_0$, which is a constant, then we have $MPCf^{SNAP} = \phi_0$. Therefore, $MPCf^{SNAP} = MPCf^{cash} = \phi_0$.

Similarly,

$$MPCb^{SNAP} = \frac{d\theta^*(y_1 + b_1)}{db_1} + \theta^* = \frac{d\theta^*}{db_1}(y_1 + b_1) + \theta^*$$

Since $\theta^* = \theta_0$, which is a constant, then we have $MPCb^{SNAP} = \theta_0$. Therefore, $MPCb^{SNAP} = MPCb^{cash} = \theta_0$.

Lastly, since $MPCf + MPCn + MPCb = 1$, then $MPCn = 1 - MPCf - MPCfB$, which implies that $MPCn^{cash} = MPCn^{SNAP} = (1 - \phi_0 - \theta_0)$.

To prove part 2 of the Proposition, we again use the fact that since $b_1 < \frac{\phi_0}{1-\phi_0} y_1$, then SNAP benefits are ***inframarginal***, which means that we can use the first-order approach to solve for the optimal consumption choices. As a result, for $\kappa > 0$, we have the following:

$$\frac{d\phi}{db} - \frac{d\phi}{dy} = -\frac{\frac{\partial G}{\partial b_1} - \frac{\partial G}{\partial y_1}}{\frac{\partial G}{\partial \phi}} = \frac{2\kappa(1-\phi)(1-\phi_0)(y_1 + b_1)}{\frac{(1+\beta)\alpha_g\alpha_f}{\phi^2} + 2\kappa(y_1 + b_1)[(1 + \phi_0 - 2\phi)y + 2(1-\phi)b]} > 0$$

This implies that $MPCf^{SNAP} - MPCf^{cash} > 0$, or $MPCf^{SNAP} > MPCf^{cash}$. From equation (5) above, we also have that $MPCb^{SNAP} - MPCb^{cash} < 0$, which implies that $MPCb^{SNAP} < MPCb^{cash}$. This proves the first half of the proposition.

To prove that $(MPCf^{SNAP} - MPCf^{cash})$ is decreasing in β, we differentiate with respect to

β:

$$\frac{d}{d\beta}(MPCf^{SNAP} - MPCf^{cash}) = \frac{-2\alpha_g\alpha_f\kappa(1-\phi)(1-\phi_0)(y_1+b_1)}{\phi^2\left(\frac{(1+\beta)\alpha_g\alpha_f}{\phi^2} + 2\kappa(y_1+b_1)[(1+\phi_0-2\phi)y + 2(1-\phi)b]\right)^2} < 0$$

Thus, as β increases towards 1, the gap between $MPCf^{SNAP}$ and $MPCf^{cash}$ decreases.

To prove that $(MPCb^{SNAP} - MPCb^{cash})$ is decreasing in β, we use equation (5):

$$\begin{aligned} & MPCb^{SNAP} - MPCb^{cash} \\ & = \frac{-(1-\alpha_g)(1-\beta\gamma)}{(1+\beta)\alpha_g(1-\alpha_f) + (1-\alpha_g)(1-\beta\gamma)}(MPCf^{SNAP} - MPCf^{cash}) \end{aligned}$$

We then differentiate with respect to β:

$$\begin{aligned} & \frac{d}{d\beta}(MPCb^{SNAP} - MPCb^{cash}) \\ = \quad & \frac{-(1-\alpha_g)(1-\beta\gamma)}{(1+\beta)\alpha_g(1-\alpha_f) + (1-\alpha_g)(1-\beta\gamma)} \frac{d}{d\beta}(MPCf^{SNAP} - MPCf^{cash}) + \\ & (MPCf^{SNAP} - MPCf^{cash}) \frac{d}{d\beta}\left(\frac{-(1-\alpha_g)(1-\beta\gamma)}{(1+\beta)\alpha_g(1-\alpha_f) + (1-\alpha_g)(1-\beta\gamma)}\right) \end{aligned}$$

We can sign each of the terms in the previous expression:

$$\begin{aligned} \frac{-(1-\alpha_g)(1-\beta\gamma)}{(1+\beta)\alpha_g(1-\alpha_f) + (1-\alpha_g)(1-\beta\gamma)} &< 0 \\ \frac{d}{d\beta}(MPCf^{SNAP} - MPCf^{cash}) &< 0 \\ \frac{d}{d\beta}\left(\frac{-(1-\alpha_g)(1-\beta\gamma)}{(1+\beta)\alpha_g(1-\alpha_f) + (1-\alpha_g)(1-\beta\gamma)}\right) &= \\ \frac{\alpha_g(1-\alpha_g)(1-\alpha_f)(\gamma+1)}{((1+\beta)\alpha_g(1-\alpha_f) + (1-\alpha_g)(1-\beta\gamma))^2} &> 0 \\ (MPCf^{SNAP} - MPCf^{cash}) &> 0 \end{aligned}$$

This gives:

$$\frac{d}{d\beta}(MPCb^{SNAP} - MPCb^{cash}) > 0$$

To prove that $MPCn^{cash} > MPCn^{SNAP}$, we use the expressions above to solve for the following:

$$\begin{aligned} MPCn^{cash} - MPCn^{SNAP} &= (1 - MPCf^{cash} - MPCb^{cash}) - (1 - MPCf^{SNAP} - MPCb^{SNAP}) \\ &= (MPCf^{SNAP} - MPCf^{cash}) + (MPCb^{SNAP} - MPCb^{cash}) \\ &= (MPCf^{SNAP} - MPCf^{cash}) \\ &\quad + \frac{-(1-\alpha_g)(1-\beta\gamma)}{(1+\beta)\alpha_g(1-\alpha_f) + (1-\alpha_g)(1-\beta\gamma)}(MPCf^{SNAP} - MPCf^{cash}) \\ &= \frac{(1+\beta)\alpha_g(1-\alpha_f)}{(1+\beta)\alpha_g(1-\alpha_f) + (1-\alpha_g)(1-\beta\gamma)}(MPCf^{SNAP} - MPCf^{cash}) \end{aligned}$$

Since $MPCf^{SNAP} > MPCf^{cash}$, then this implies that $MPCn^{cash} > MPCn^{SNAP}$.

To prove that $(MPCf^{SNAP} - MPCf^{cash})$ is increasing in κ, we differentiate with respect to κ:

$$\frac{d}{d\kappa}(MPCf^{SNAP} - MPCf^{cash}) =$$
$$\frac{d}{d\kappa}\left(-\frac{\frac{\partial G}{\partial b_1} - \frac{\partial G}{\partial y_1}}{\frac{\partial G}{\partial \phi}}\right) = \frac{2(1-\phi)(1-\phi_0)(y_1+b_1)\cdot \frac{(1+\beta)\alpha_g\alpha_f}{\phi^2}}{\left(\frac{(1+\beta)\alpha_g\alpha_f}{\phi^2} + 2\kappa(y_1+b_1)\left[(1+\phi_0-2\phi)y + 2(1-\phi)b\right]\right)^2} > 0$$

Lastly, to prove that $(MPCb^{cash} - MPCb^{SNAP})$ is increasing in κ, we use equation (5) again and differentiate with respect to κ:

$$\begin{aligned} &MPCb^{SNAP} - MPCb^{cash} \\ &= \frac{-(1-\alpha_g)(1-\beta\gamma)}{(1+\beta)\alpha_g(1-\alpha_f) + (1-\alpha_g)(1-\beta\gamma)}(MPCf^{SNAP} - MPCf^{cash}) \end{aligned}$$

We then differentiate with respect to κ:

$$\begin{aligned} &\frac{d}{d\kappa}(MPCb^{SNAP} - MPCb^{cash}) \\ =\quad & \frac{-(1-\alpha_g)(1-\beta\gamma)}{(1+\beta)\alpha_g(1-\alpha_f) + (1-\alpha_g)(1-\beta\gamma)}\frac{d}{d\kappa}(MPCf^{SNAP} - MPCf^{cash}) + \\ & (MPCf^{SNAP} - MPCf^{cash})\frac{d}{d\kappa}\left(\frac{-(1-\alpha_g)(1-\beta\gamma)}{(1+\beta)\alpha_g(1-\alpha_f) + (1-\alpha_g)(1-\beta\gamma)}\right) \\ =\quad & \frac{-(1-\alpha_g)(1-\beta\gamma)}{(1+\beta)\alpha_g(1-\alpha_f) + (1-\alpha_g)(1-\beta\gamma)}\frac{d}{d\kappa}(MPCf^{SNAP} - MPCf^{cash}) \end{aligned}$$

In the last line above, the first term is negative, and the second term is positive, so the entire term is negative, which means that $\frac{d}{d\kappa}(MPCb^{cash} - MPCb^{SNAP}) > 0$.

Lastly, it is straightforward to see that $(MPCn^{cash} - MPCn^{SNAP}$ is increasing in κ since $(MPCf^{SNAP} - MPCf^{cash})$ is increasing in κ, and we have the following relationship:

$$MPCn^{cash} - MPCn^{SNAP} = \frac{(1+\beta)\alpha_g(1-\alpha_f)}{(1+\beta)\alpha_g(1-\alpha_f) + (1-\alpha_g)(1-\beta\gamma)}(MPCf^{SNAP} - MPCf^{cash})$$

This completes all of the parts of the proof. ■

Theorem 1. *If $\beta = 1$, then the social planner maximizes (3) by choosing $y_1^* = \bar{y}$ and $b_1^* = 0$. If $\beta < 1$, then the social planner maximizes (3) by choosing $0 < y_1^* < \bar{y}$ and $0 < b_1^* < \bar{y}$, with $y_1^* + b_1^* = \bar{y}$.*

Proof:

We prove the Theorem in two parts, first considering the $\beta = 1$ case and then considering $\beta < 1$ case.

Case 1: $\beta = 1$

This case proceeds by considering two separate sub-cases: $\kappa = 0$ and $\kappa > 0$. In the $\kappa = 0$ case, the social planner's objective and the individual's objective are identical, so there is no reason for the planner to use SNAP. When $\kappa = 0$, SNAP is fungible with cash if SNAP benefits are inframarginal, so SNAP and cash have the same effects on consumption, which means there is no reason for the planner to prefer to use SNAP. If SNAP benefits are not inframarginal, then they generate a kink in the individual's budget constraint which cannot increase the individual's utility. Therefore, the planner can do no better by substituting cash for SNAP when $\kappa = 0$.

If $\kappa > 0$, then the consumer engages in mental accounting, which means that SNAP benefits will lead to different consumption responses than cash even when SNAP benefits are inframarginal. However, the planner still prefers cash to SNAP in this case because SNAP leads to larger increases in food spending compared to cash, but when $\beta = 1$, the consumer does not under-consume food from the planner's perspective. So, again, there is no reason for the planner to prefer to use SNAP instead of cash.

Formally, our proof proceeds by defining the following changes in utility:

$$\begin{aligned} dU^{SNAP} &= \frac{dU}{db_1} \\ dU^{cash} &= \frac{dU}{dy_1} \\ dU(\beta = 1, \kappa = 0)^{SNAP} &= \frac{dU_{\beta=1,\kappa=0}}{db_1} \\ dU(\beta = 1, \kappa = 0)^{cash} &= \frac{dU_{\beta=1,\kappa=0}}{dy_1} \end{aligned}$$

We previously showed that the optimal n and c_1^b conditional on the consumer's share of income spent on food ϕ are:

$$\begin{aligned} c_1^b &= \frac{\theta_0(1-\phi)(y+b)}{(1-\phi_0)p_b} \\ \bar{n} &= \frac{(1-\phi_0-\theta_0)(1-\phi)(y+b)}{(1-\phi_0)} \end{aligned}$$

Substituting these into the utility function, we can write the consumer's decision utility in terms of ϕ:

$$\begin{aligned} U(\phi) = \quad & \alpha_g \alpha_f \left[\log\left(\frac{\phi(y+b)}{p_f(1+\beta)}\right) + \beta \log\left(\frac{\beta\phi(y+b)}{p_f(1+\beta)}\right)\right] \\ & + \alpha_g(1-\alpha_f)\left[\log\left(\frac{(1-\phi)(1-\phi_0-\theta_0)(y+b)}{(1-\phi_0)(1+\beta)}\right) + \beta\log\left(\beta\frac{(1-\phi)(1-\phi_0-\theta_0)(y+b)}{(1-\phi_0)(1+\beta)}\right)\right] \\ & + (1-\alpha_g)(1-\beta\gamma)\log\left(\frac{(1-\phi)\theta_0(y+b)}{(1-\phi_0)p_b}\right) - \kappa(\phi_0 y + b - \phi(y+b))^2 \end{aligned}$$

Let ϕ denote the consumer's decision utility-maximizing choice of ϕ given (κ, β, y, b):

$$\phi(\kappa, \beta, y, b) = \arg\max_{\phi} U(\phi; \kappa, \beta, y, b)$$

From the envelope theorem, we only need to focus on the direct effects on utility from marginal changes in b and y and not indirect effects through changes in ϕ:

$$\begin{aligned} dU^{SNAP} = \frac{dU}{db} &= \frac{\partial U}{\partial b_1} \\ dU^{cash} = \frac{dU}{dy} &= \frac{\partial U}{\partial y_1} \end{aligned}$$

As a result, we can derive the following expressions:

$$\begin{aligned} dU^{SNAP}(\phi) &= \frac{\alpha_g(1+\beta) + (1-\alpha_g)(1-\beta\gamma)}{y+b} - 2\kappa((\phi_0-\phi)y + (1-\phi)b)(1-\phi) \\ dU^{cash}(\phi) &= \frac{\alpha_g(1+\beta) + (1-\alpha_g)(1-\beta\gamma)}{y+b} - 2\kappa((\phi_0-\phi)y + (1-\phi)b)(\phi_0-\phi) \end{aligned}$$

However, we cannot use the same envelope theorem argument when it comes to evaluating the social planner's utility, because ϕ is not optimally chosen given the social planner's objective function, so the social planner *does* care about changes in ϕ and the resulting effects on utility.

$$\begin{aligned} dU^{SNAP}(\kappa=0,\beta=1) = \frac{dU_{(\kappa=0,\beta=1)}}{db} &= \frac{\partial U_{(\kappa=0,\beta=1)}}{\partial b_1} + \frac{\partial U_{(\kappa=0,\beta=1)}}{\partial \phi}\frac{d\phi}{db} \\ dU^{cash}(\kappa=0,\beta=1)\frac{dU_{(\kappa=0,\beta=1)}}{dy} &= \frac{\partial U_{(\kappa=0,\beta=1)}}{\partial y_1} + \frac{\partial U_{(\kappa=0,\beta=1)}}{\partial \phi}\frac{d\phi}{dy} \end{aligned}$$

From before, when $\kappa > 0$:

$$\frac{\partial\phi}{\partial b_1} > 0, \;\; \frac{\partial\phi}{\partial b_1} - \frac{\partial\phi}{\partial y_1} > 0$$

We can now complete the proof for the two subcases: $\kappa = 0$ and $\kappa > 0$.

Case 1a: $\kappa = 0$

When $\kappa = 0$ and $\beta = 1$, we have the following:

$$dU^{SNAP} = dU(\beta = 1, \kappa = 0)^{SNAP}$$
$$dU^{cash} = dU(\beta = 1, \kappa = 0)^{cash}$$

Additionally, when $\kappa = 0$ we have the following:

$$dU^{SNAP} = dU^{cash} = \frac{\alpha_g(1+\beta) + (1-\alpha_g)(1-\beta\gamma)}{y_1 + b_1}$$

Because changes in y_1 and b_1 have the same effects on the individual's utility and the social planner's objective function, the social planner cannot do better by choosing SNAP instead of cash.

Case 1b: $\kappa > 0$

First, we can show $dU^{SNAP} < dU^{cash}$ as follows:

$$dU^{SNAP} - dU^{cash} = -2\kappa((\phi_0 - \phi)y + (1-\phi)b)(1-\phi_0) < 0.$$

Second, We can show that $dU(\beta = 1, \kappa = 0)^{SNAP} < dU(\beta = 1, \kappa = 0)^{cash}$:

$$dU(\beta = 1, \kappa = 0)^{SNAP} - dU(\beta = 1, \kappa = 0)^{cash}$$
$$= \frac{\partial U_{\kappa=0,\beta=1}}{\partial b_1} - \frac{\partial U_{\kappa=0,\beta=1}}{\partial y_1} + \frac{\partial U_{\kappa=0,\beta=1}}{\partial \phi}\left(\frac{\partial \phi}{\partial b_1} - \frac{\partial \phi}{\partial y_1}\right).$$

When $\kappa = 0$, y and b enter symmetrically in the utility function, so

$$\frac{\partial U_{\kappa=0,\beta=1}}{\partial b_1} = \frac{\partial U_{\kappa=0,\beta=1}}{\partial y_1}$$

and the first two terms cancel out. Earlier, we showed:

$$\frac{\partial \phi}{\partial b_1} - \frac{\partial \phi}{\partial y_1} > 0$$

The only thing remaining is to find the sign of $\frac{\partial U_{\kappa=0,\beta=1}}{\partial \phi}$. We can prove that for $\kappa > 0$ and $\beta = 1$, $\frac{\partial U_{\kappa=0,\beta=1}}{\partial \phi} < 0$.

We can prove this by comparing the first-order conditions between the consumer's decision utility and social planner's utility. Rewriting utility in terms of U_A and U_B sub-utility functions as we did before, at the individual's optimum we have:

$$\frac{\partial U}{\partial \phi}(\phi) = \frac{\partial U_A}{\partial \phi}(\phi) + \kappa \frac{\partial U_B}{\partial \phi}(\phi) = 0$$

For the social planner, $\kappa = 0$, so

$$\frac{\partial U_{\kappa=0,\beta=1}}{\partial \phi}(\phi) = \frac{\partial U_{A\beta=1}}{\partial \phi}(\phi)$$

The social planner's first-order condition in general will not equal 0 since ϕ is not chosen at the social planner's optimum. Helpfully, however, U_A is the same for both the social planner and the consumer since $\beta = 1$ for both, and U_A does not involve κ. Since $\frac{\partial U_B}{\partial \phi} > 0$ for any ϕ (show above), the individual's first -order condition gives:

$$\frac{\partial U_A}{\partial \phi}(\phi) = -\kappa \frac{\partial U_B}{\partial \phi}(\phi) < 0$$

This implies that $\frac{\partial U_{\kappa=0,\beta=1}}{\partial \phi}(\phi) < 0$. Putting this all together:

$$\begin{aligned} &dU(\beta = 1, \kappa = 0)^{SNAP} - dU(\beta = 1, \kappa = 0)^{cash} \\ &= \frac{\partial U_{\kappa=0,\beta=1}}{\partial \phi} \left(\frac{\partial \phi}{\partial b_1} - \frac{\partial \phi}{\partial y_1} \right) < 0 \end{aligned}$$

So, $dU(\beta = 1, \kappa = 0)^{SNAP} < dU(\beta = 1, \kappa = 0)^{cash}$. This implies that if the individual engages in mental accounting ($\kappa > 0$) but the planner evaluates the individual's utility at $\kappa = 0$, then the planner will strictly prefer cash to SNAP. ■

The intuition for this result is that while SNAP and cash enter the planner's utility function identically, they differ in their indirect effects on utility through the individual's mental accounting behavior. When $\kappa > 0$, the individual's U_A (consumption sub-utility) pulls ϕ lower, while U_B (the mental accounting term) pulls ϕ higher. When $\beta = 1$, U_A does not pull ϕ below what the social planner would prefer. The only divergence between the social planner and the individual comes from the individual's mental accounting, which pulls ϕ higher than what the planner would prefer. An increase in SNAP therefore increases ϕ through mental accounting more than an increase in cash does, and the increase in ϕ from SNAP is worse for the planner than an increase in cash.

Case 2: $\beta < 1$

We prove this case by setting up the planner's problem as choosing y_1, b_1 such that:

$$y_1^*, b_1^* = \arg\max_{y_1, b_1} U^{SP}(\phi, y, b)$$

subject to:

$$\phi = \arg\max_{\phi} U(\phi, y^*, b^*)$$

and

$$y_1^* + b_1^* = \bar{y}$$

where U^{SP} is the individual's optimized utility evaluated at $\kappa = 0$ and $\beta = 1$. This can be re-written as

$$0 < \frac{b_1^*}{\bar{y}} < 1$$

We solve the planner's problem using the following three first-order conditions. First, we have the standard first-order condition for ϕ being the consumer's optimal choice:

$$\frac{\partial U}{\partial \phi}(\phi) = \frac{\alpha_g \alpha_f (1 + \beta)}{\phi} - \frac{\alpha_g (1 - \alpha_f)(1 + \beta) + (1 - \alpha_g)(1 - \beta\gamma)}{1 - \phi} + 2\kappa\bar{y}(\phi_0 y^* + b^* - \phi\bar{y}) = 0$$

Second, we have that the social planner must choose y_1 and b_1 to maximize their own utility. Note that in any place in which the planner cares about $(y_1 + b_1)$ together (rather than just y_1 or just b_1 separately), the choice of y_1^* versus b_1^* does not matter because we are holding $y_1 + b_1 = \bar{y}$ fixed.[53]

Given this, we can re-write the planner's utility to make this more explicit:

$$\begin{aligned} U^{SP} &= 2\alpha_g\alpha_f\left(\log\frac{\phi\bar{y}}{2p_f}\right) + 2\alpha_g(1-\alpha_f)\left(\log\frac{(1-\phi)(1-\phi_0-\theta_0)\bar{y}}{2(1-\phi_0)}\right) \\ &\quad +(1-\alpha_g)(1-\gamma)\log\left(\frac{(1-\phi)\theta_0\bar{y}}{(1-\phi_0)p_b}\right) \end{aligned}$$

The expression above shows that y_1 and b_1 never appear separately from $\bar{y}$ in the planner's problem, which implies that the choice of y_1 versus b_1 does not have a direct effect on the social planner's utility. The social planner only cares about the choice of (y_1, b_1) indirectly through the effects on the consumer's chosen consumption ϕ. As before, we *cannot* use the envelope theorem to ignore these indirect effects because ϕ is not optimally chosen from the planner's perspective. Differentiating the planner's utility with respect to y and b, respectively, gives:

$$\frac{\partial U_{(\beta=1,\kappa=0)}}{\partial y_1}(y^*) = \left(\frac{2\alpha_g\alpha_f}{\phi} - \frac{2\alpha_g(1-\alpha_f) + (1-\alpha_g)(1-\gamma)}{1-\phi}\right)\frac{\partial\phi}{\partial y_1} = 0$$

$$\frac{\partial U_{(\beta=1,\kappa=0)}}{\partial b_1}(b^*) = \left(\frac{2\alpha_g\alpha_f}{\phi} - \frac{2\alpha_g(1-\alpha_f) + (1-\alpha_g)(1-\gamma)}{1-\phi}\right)\frac{\partial\phi}{\partial b_1} = 0$$

With $\kappa > 0$, $\frac{\partial\phi}{\partial y_1} \neq \frac{\partial\phi}{\partial b_1}$ (since $MPCf^{SNAP} > MPCf^{cash}$). Therefore, the only way these two first-order conditions can both hold is if:

$$\frac{2\alpha_g\alpha_f}{\phi} - \frac{2\alpha_g(1-\alpha_f) + (1-\alpha_g)(1-\gamma)}{1-\phi} = 0$$

Rearranging:

$$\phi = \frac{2\alpha_g\alpha_f}{2\alpha_g + (1-\alpha_g)(1-\gamma)} = \phi^{SP}$$

Intuitively, the planner is choosing y_1^* and b_1^* such that the optimal choice for the individual is to choose the planner's optimal food consumption. Given this, we can find the conditions under which the individual's chosen food consumption ϕ is equal to the planner's preferred consumption ϕ^{SP}. Plugging ϕ^{SP} into the first-order condition for the consumer:

$$\frac{\alpha_g\alpha_f(1+\beta)}{\phi_{SP}} - \frac{\alpha_g(1-\alpha_f)(1+\beta) + (1-\alpha_g)(1-\beta\gamma)}{1-\phi_{SP}} + 2\kappa\bar{y}\left(\phi_0(\bar{y}-b^*) + b^* - \phi_{SP}\bar{y}\right) = 0$$

Dividing through by $\bar{y}$ and rearranging:

$$\frac{\alpha_g\alpha_f(1+\beta)}{\phi_{SP}\bar{y}} - \frac{\alpha_g(1-\alpha_f)(1+\beta) + (1-\alpha_g)(1-\beta\gamma)}{(1-\phi_{SP})\bar{y}} + 2\kappa\bar{y}\left(\phi_0 - \phi_{SP} + \frac{b^*}{\bar{y}}(1-\phi_0)\right) = 0$$

[53] Another way to put this is that $\frac{\partial\bar{y}}{\partial y_1} = \frac{\partial\bar{y}}{\partial b_1} = 0$, since the conceptual experiment is to replace cash with SNAP dollar-for-dollar without reducing the overall resource level of the consumer $\bar{y}$.

To simplify further, divide by $\alpha_g(1+\beta)+(1-\alpha_g)(1-\beta\gamma)$ and shift terms to the other side:

$$\frac{2\kappa\bar{y}}{\alpha_g(1+\beta)+(1-\alpha_g)(1-\beta\gamma)}\left(\phi_0-\phi_{SP}+\frac{b^*}{\bar{y}}(1-\phi_0)\right)=\frac{1-\phi_0}{(1-\phi_{SP})\bar{y}}-\frac{\phi_0}{\phi_{SP}\bar{y}}$$

Which gives the following expression for $\frac{b^*}{\bar{y}}$:

$$\frac{b^*}{\bar{y}}=\frac{\alpha_g(1+\beta)+(1-\alpha_g)(1-\beta\gamma)}{2\kappa\bar{y}^2(1-\phi_0)}\left[\frac{1-\phi_0}{1-\phi_{SP}}-\frac{\phi_0}{\phi_{SP}}\right]+\frac{\phi_{SP}-\phi_0}{1-\phi_0} \tag{6}$$

Using the expression above, we can prove that for any $\beta<1$ that $\frac{b^*}{\bar{y}}>0$. To see this, note that for any $\beta<1$, $\phi_0<\phi_{SP}$. This implies $\frac{1-\phi_0}{1-\phi_{SP}}>1$ and $\frac{\phi_0}{\phi_{SP}}<1$, so $[\frac{1-\phi_0}{1-\phi_{SP}}-\frac{\phi_0}{\phi_{SP}}]>0$. In addition, $\frac{\alpha_g(1+\beta)+(1-\alpha_g)(1-\beta\gamma)}{2\kappa\bar{y}(1-\phi_0)}>0$, and since $1>\phi_{SP}>\phi_0$, $\frac{\phi_{SP}-\phi_0}{1-\phi_0}>0$. Therefore, $\frac{b^*}{\bar{y}}>0$.

The final part of the proof is to prove that $\frac{b^*}{\bar{y}}<1$. This can be reasoned through contradiction. If the planner converts all income to SNAP, then the consumer can only purchase food, but this cannot be optimal choice for planner because $n=0$ leads to $U=-\infty$, and the planner can do strictly better by reducing SNAP and transferring at least some small positive amount of cash.

In fact, the first-order approach assumes that the individual is not making choices at kinks in the budget constraint. Since SNAP can only be spent on food, the consumer is restricted to $\phi\geq\frac{b_1^*}{\bar{y}}$. Suppose the planner is unable to achieve $\phi=\phi_{SP}$ by using the individual's mental accounting behavior. Then, the planner can still set $\frac{b_1^*}{\bar{y}}=\phi_{SP}$ and therefore achieve the planner's preferred allocation directly by manipulating the kink in the budget constraint so that when the individual chooses to locate on the kink this matches the planner's preferred food consumption.

To see this formally, suppose the planner cannot choose $\frac{b^*}{\bar{y}}$ that leverages mental accounting to achieve $\phi=\phi^{SP}$. Then, $\phi=\arg\max U(\phi,y^*,b^*)<\phi_{SP}$ for all $\frac{b^*}{\bar{y}}\in[0,1]$. Since $0<\phi^{SP}<1$, at $\frac{b^*}{\bar{y}}=\phi^{SP}$, $\phi<\phi^{SP}$. Setting $\frac{b^*}{\bar{y}}=\phi^{SP}$ forces the consumer to consume $\phi\geq\phi_{SP}$. Because the individual's preferred $\phi<\phi^{SP}$, this restriction on the budget set forces $\phi=\phi^{SP}$. Because the individual is already over-consuming food from their own perspective, the split the remaining $(1-\phi^{SP})$ of their income between non-food and the bad such that the ratio of their marginal utilities equals the price ratio. This is exactly the allocation the social planner *would have achieved* were it feasible to leverage mental accounting to achieve $\phi=\phi^{SP}$.

This completes the proof because it shows that $0<\frac{b^*}{\bar{y}}<1$ whether the planner uses the first-order approach or manipulates the individual's food consumption directly through kink in the budget constraint. ■

Theorem 2. *When $\beta<1$, the optimal SNAP share $\frac{b_1^*}{\bar{y}}$ is constant for all $0\leq\kappa<\kappa^*$ and is strictly decreasing in κ and β for all $\kappa^*\leq\kappa<\infty$, with κ^* defined as the lowest value of κ where the optimal SNAP share is such that SNAP benefits are inframarginal.*

Proof:

When SNAP benefits are inframarginal, we have found that the optimal SNAP share is given by

$$\frac{b^*}{\bar{y}}=\frac{\alpha_g(1+\beta)+(1-\alpha_g)(1-\beta\gamma)}{2\kappa\bar{y}^2(1-\phi_0)}\left[\frac{1-\phi_0}{1-\phi_{SP}}-\frac{\phi_0}{\phi_{SP}}\right]+\frac{\phi_{SP}-\phi_0}{1-\phi_0} \tag{7}$$

where $\phi_{SP} = \frac{2\alpha_g\alpha_f}{2\alpha_g+(1-\alpha_g)(1-\gamma)}$. This induces the consumer to choose $\phi(b^*, \bar{y}-b^*) = \phi_{SP}$. This equality will hold for all values of κ such that the "SNAP is inframarginal" constraint does not bind (i.e., where $\kappa > \kappa^*$).

If the SNAP inframarginality constraint binds, then the social planner will use b^* to exactly choose the food consumption for the consumer. Conditional on this level of food consumption, $f^* = b^*$, the consumer still chooses between c_1^b and $\bar{n}$ optimally given their "forced" food consumption of b^*. This results in optimal choices given by:

$$n_1 = \frac{\alpha_g(1-\alpha_f)}{\alpha_g(1-\alpha_f)(1+\beta)+(1-\alpha_g)(1-\beta\gamma)}(\bar{y}-b^*)$$
$$n_2 = \frac{\beta\alpha_g(1-\alpha_f)}{\alpha_g(1-\alpha_f)(1+\beta)+(1-\alpha_g)(1-\beta\gamma)}(\bar{y}-b^*)$$
$$c_1^b = \frac{(1-\alpha_g)(1-\beta\gamma)}{\alpha_g(1-\alpha_f)(1+\beta)+(1-\alpha_g)(1-\beta\gamma)}(\bar{y}-b^*)$$

The consumer also splits between f_1 and f_2 according to their preferences:

$$f_1 = \frac{b^*}{1+\beta},\ f_2 = \frac{\beta b^*}{1+\beta}$$

The social planner now just chooses b^* to maximize the social planner's utility function:

$$\begin{aligned}
U_{SP} = \quad & \alpha_g\alpha_f(\log f_1 + \log f_2) + \alpha_g(1-\alpha_f)(\log n_1 + \log n_2) + (1-\alpha_g)(1-\gamma)\log(c_1^b) \\
= \quad & \alpha_g\alpha_f\left(\log\frac{b^*}{1+\beta} + \log\frac{\beta b^*}{1+\beta}\right) \\
& +\alpha_g(1-\alpha_f)\left(\log\frac{\alpha_g(1-\alpha_f)(\bar{y}-b^*)}{\alpha_g(1-\alpha_f)(1+\beta)+(1-\alpha_g)(1-\beta\gamma)} + \log\frac{\beta\alpha_g(1-\alpha_f)(\bar{y}-b^*)}{\alpha_g(1-\alpha_f)(1+\beta)+(1-\alpha_g)(1-\beta\gamma)}\right) \\
& +(1-\alpha_g)(1-\gamma)\log\left(\frac{(1-\alpha_g)(1-\beta\gamma)(\bar{y}-b^*)}{\alpha_g(1-\alpha_f)(1+\beta)+(1-\alpha_g)(1-\beta\gamma)}\right)
\end{aligned}$$

Differentiating with respect to b^* gives:

$$0 = \frac{2\alpha_g\alpha_f}{b^*} - \frac{2\alpha_g(1-\alpha_f)}{\bar{y}-b^*} - \frac{(1-\alpha_g)(1-\gamma)}{\bar{y}-b^*}$$

Which gives optimal SNAP share:

$$\frac{b^*}{\bar{y}} = \frac{2\alpha_g\alpha_f}{2\alpha_g+(1-\alpha_g)(1-\gamma)}$$

Thus, for any $\kappa \in [0, \kappa^*)$, the social planner will choose exactly $\frac{b^*}{\bar{y}} = \frac{2\alpha_g\alpha_f}{2\alpha_g+(1-\alpha_g)(1-\gamma)} = \phi_{SP}$. Note that ϕ_{SP} is exactly the level of food consumption implemented in the optimal SNAP share in Equation (7). Over the full range of κ, the social planner would implement the exact same allocation for the consumer.

Over the range $0 \le \kappa < \kappa^*$, we can also rule out the possibility that the consumer, in response to the social planner choosing SNAP share $\frac{b^*}{\bar{y}}$ chooses an even higher ϕ such that $\phi > \frac{b^*}{\bar{y}}$. This is ruled out by focusing our attention to $\kappa \in [0, \bar{\kappa})$ over which 'SNAP is inframarginal' was binding. Towards a contradiction, suppose that the consumer facing $\frac{b^*}{\bar{y}} = \phi_{SP}$ would choose a $\phi(b^*, \bar{y} - b^*) > \phi_{SP}$ that is 'too high', even from the perspective of the social planner. If they did, then we would have that $\frac{b^*}{\bar{y}} \leq \phi(b^*, \bar{y} - b^*)$. That would imply that the planner's choice of SNAP actually satisfies 'SNAP is inframarginal' constraint, a contradiction to $0 \leq \kappa < \bar{\kappa}$.

At $\kappa = \kappa^*$, the 'SNAP is inframarginal' constraint holds with equality. This is exactly the point where the 'SNAP is inframarginal' constraint aligns with a solution to the consumer's optimization problem.

$$\frac{b^*}{\bar{y}} = \phi(b^*, \bar{y} - b^*) = \phi_{SP}$$

The level of SNAP benefits chosen at this kink is exactly the level of SNAP benefits chosen for all $\kappa < \bar{\kappa}$. Using the equation above, we solve for κ^* analytically as follows:

$$\begin{aligned} \frac{b^*}{\bar{y}} &= \frac{\alpha_g(1+\beta) + (1-\alpha_g)(1-\beta\gamma)}{2\kappa\bar{y}^2(1-\phi_0)}\left[\frac{1-\phi_0}{1-\phi_{SP}} - \frac{\phi_0}{\phi_{SP}}\right] + \frac{\phi_{SP}-\phi_0}{1-\phi_0} \\ \phi_{SP} &= \frac{\alpha_g(1+\beta) + (1-\alpha_g)(1-\beta\gamma)}{2\kappa^*\bar{y}^2(1-\phi_0)}\left[\frac{1-\phi_0}{1-\phi_{SP}} - \frac{\phi_0}{\phi_{SP}}\right] + \frac{\phi_{SP}-\phi_0}{1-\phi_0} \\ \kappa^* &= \frac{\alpha_g(1+\beta) + (1-\alpha_g)(1-\beta\gamma)}{2\bar{y}^2\phi_0(1-\phi_{SP})}\left(\frac{1-\phi_0}{(1-\phi_{SP})\phi_{SP}}\right) > 0 \end{aligned}$$

For $\kappa > \kappa^*$, the social planner's preferred food consumption is implemented by the "interior" value $\frac{b^*}{\bar{y}}$ given by equation (7). In this case, the "SNAP is inframarginal" constraint is not binding, and $\frac{b^*}{\bar{y}} < \phi(b^*, \bar{y} - b^*)$. If the social planner were instead to try and set $\frac{b^*}{\bar{y}} = \phi_{SP}$ as was the solution for $\kappa \in [0, \bar{\kappa}]$, then the consumer would choose $\phi(b^*, \bar{y} - b^*) > \frac{b^*}{\bar{y}} = \phi_{SP}$, which is "too high" a food consumption from the perspective of the social planner. The social planner prefers to choose the interior optimum in accordance with equation (7).

Summarizing the results:

- For $\kappa \in [0, \kappa^*]$, the social planner chooses $\frac{b^*}{\bar{y}} = \phi_{SP} = \frac{2\alpha_g\alpha_f}{2\alpha_g + (1-\alpha_g)(1-\gamma)}$. The consumer choose food consumption $\phi_{SP} * \bar{y}$.

- When $\kappa \in [\kappa^*, \infty)$, the social planner prefers to implement $\phi = \phi_{SP}$. The social planner can do this by setting SNAP share in accordance with equation (7).

- At $\kappa = \kappa^*$, the two approaches align exactly. $\frac{b^*}{\bar{y}} = \phi_{SP} = \phi(b^*, \bar{y} - b^*)$. κ^* is the threshold at which the behavioral mental accounting response to receiving $\frac{b^*}{\bar{y}} = \phi_{SP}$ causes over-consumption of food from the social planner's perspective. When $\kappa < \kappa^*$, the behavioral response is 'too weak' and so the social planner leverages the budget constraint. When $\kappa > \kappa^*$, the behavioral response is 'too strong' and so SNAP share is reduced to the interior solution.

- Using the results above, we therefore have that the optimal SNAP share is both continuous in κ and weakly monotonic as κ increases from $\kappa = 0$: flat over $(0, \kappa^*)$, and strictly decreasing over (κ^*, ∞). The strictly decreasing in κ for $\kappa > \kappa^*$ follows immediately from equation (7), which is strictly decreasing in κ.

The final part of the proof is to show that $\frac{b^*}{\bar{y}}$ is strictly decreasing in β for $\kappa > \kappa^*$. Since SNAP benefits are inframarginal when $\kappa > \kappa^*$, we need to show that the $b^*/\bar{y}$ defined in equation (7) is strictly decreasing in β. To do this we use the first-order condition that holds for all $\kappa > \kappa^*$:

$$\frac{\alpha_g\alpha_f(1+\beta)}{\phi_{SP}} - \frac{\alpha_g(1-\alpha_f)(1+\beta)+(1-\alpha_g)(1-\beta\gamma)}{1-\phi_{SP}} + 2\kappa\bar{y}\bigg(\phi_0(\bar{y}-b^*)+b^*-\phi_{SP}\bar{y}\bigg) = 0$$

We can then implicitly differentiate the expression above with respect to β. Note that ϕ_{SP} does not depend on β, but ϕ_0 does. We then have the following:

$$\begin{aligned}
\frac{\alpha_g\alpha_f}{\phi_{SP}} - \frac{\alpha_g(1-\alpha_f)-\gamma(1-\alpha_g)}{1-\phi_{SP}} + 2\kappa\bar{y}\bigg(\frac{d\phi_0}{d\beta}(\bar{y}-b^*)+\frac{db^*}{d\beta}-\phi_0\frac{db^*}{d\beta}\bigg) &= 0 \\
\frac{db^*}{d\beta}(1-\phi_0) = \frac{\alpha_g(1-\alpha_f)-\gamma(1-\alpha_g)}{1-\phi_{SP}} - \frac{\alpha_g\alpha_f}{\phi_{SP}} - 2\kappa\bar{y}\bigg(\frac{d\phi_0}{d\beta}(\bar{y}-b^*)\bigg)&
\end{aligned}$$

Since $\frac{d\phi_0}{d\beta} > 0$, then $\frac{db^*}{d\beta} < 0$ if $\frac{\alpha_g(1-\alpha_f)-\gamma(1-\alpha_g)}{1-\phi_{SP}} - \frac{\alpha_g\alpha_f}{\phi_{SP}} < 0$. To show this is true we can simplify as follows:

$$\begin{aligned}
\frac{\alpha_g(1-\alpha_f)-\gamma(1-\alpha_g)}{1-\phi_{SP}} - \frac{\alpha_g\alpha_f}{\phi_{SP}} &< 0 \\
\alpha_g(\phi_{SP}-\alpha_f) - \gamma(1-\alpha_g)\phi_{SP} &< 0
\end{aligned}$$

To complete the proof, we need to show that $\phi_{SP} - \alpha_f < 0$:

$$\begin{aligned}
\frac{2\alpha_g\alpha_f}{2\alpha_g+(1-\alpha_g)} &< \alpha_f \\
2\alpha_g\alpha_f &< 2\alpha_f\alpha_g + \alpha_f(1-\alpha_g) \\
0 &< \alpha_f(1-\alpha_g)
\end{aligned}$$

This completes the proof that b^* and $\frac{b^*}{\bar{y}}$ are strictly decreasing in β when $\kappa > \kappa^*$. ■

D.3 Alternative Normative Benchmarks: Weighted Sum of Selves and Non-Welfarist Planner

Welfare as a Weighted Sum of Selves

In the main model in the main text, the planner evaluates the consumer's utility at $\beta = 1$ and $\kappa = 0$:

$$U_{\beta=1,\kappa=0} = \alpha_g\alpha_f(\log f_1 + \log f_2) + \alpha_g(1-\alpha_f)(\log n_1 + \log n_2) + (1-\alpha_g)(1-\gamma)\log c_1^b$$

The consumer, by contrast, is assumed to be "naive" and makes decisions based on their actual utility function:

$$\begin{aligned}
U_{Naive} &= \alpha_g\alpha_f(\log f_1 + \beta\log f_2) + \alpha_g(1-\alpha_f)(\log n_1 + \beta\log n_2) + (1-\alpha_g)(1-\beta\gamma)\log c_1^b \\
&- \kappa(\phi_0 y + b - p_f(f_1+f_2))^2
\end{aligned}$$

We now assume the social planner uses weights ω_β and ω_κ to construct a welfare measure that can be interpreted as a weighted sum of selves. Using these two weights, we combine the two utility functions above as follows:

$$
\begin{aligned}
U_{Planner} &= \alpha_g\alpha_f \log f_1 + \alpha_g(1-\alpha_f)\log n_1 + (1-\alpha_g)\log c_1^b \\
&+ (1-\omega_\beta)\Big[\alpha_g\alpha_f \log f_2 + \alpha_g(1-\alpha_f)\log n_2 - \gamma(1-\alpha_g)\log c_1^b\Big] \\
&+ \omega_\beta\beta\Big[\alpha_g\alpha_f \log f_2 + \alpha_g(1-\alpha_f)\log n_2 - \gamma(1-\alpha_g)\log c_1^b\Big] \\
&- \omega_\kappa\kappa(\phi_0 y + b - p_f(f_1+f_2))^2
\end{aligned}
$$

Careful consideration of the expression above shows that this expression is "as if" identical to a model where the consumer makes optimal choices with $\beta' = 1 - \omega_\beta + \beta\omega_\beta$ and $\kappa' = \omega_\kappa\kappa$.

In the proofs of the theorems above, we showed that any consumer with $0 < \beta < 1$ and $\kappa > 0$ has a unique optimal food expenditure share, which we can denote with $\phi_{Planner}$. As a result, the social planner is then interested in maximizing welfare in the "weighted sum of selves" model by choosing the optimal SNAP and cash shares such that the consumer chooses $\phi_{Planner}$.

Non-Welfarist Social Planner

Now we assume that the social planner is not interested in correcting behavioral internalities due to β-δ time-inconsistency, but instead the planner wants to manipulate consumption for non-welfarist reasons.

We showed above that the social planner who wants to correct the internality from $\beta < 1$ chooses an optimal food share that can be derived by calculating the optimal food share for the consumer's utility funciton evaluated at $\beta = 1$ and $\kappa = 0$. This is given by:

$$\phi_{SP} = \frac{2\alpha_g\alpha_f}{2\alpha_g + (1-\alpha_g)(1-\gamma)}$$

We now consider a non-welfarist social planner who simply has their own Cobb-Douglas coefficients of their non-welfarist "utility" function, and we then use this function to find the implied ϕ_{SP} in the same manner we use in proving the main theorems above. In other words, the social planner uses the optimal SNAP formulas above to achieve their own non-welfarist goals in the same way as above, conditional on ϕ_{SP}.

Specifically, we assume a non-welfarist social planner with the following "utility" function:

$$U_{SP} = \alpha_{SP,f_1} * \log(f_1) + \alpha_{SP,f_2} * \log(f_2) + \alpha_{SP,n_1} * \log(n_1) + \alpha_{SP,n_2} * \log(n_2) + \alpha_{SP,b} * \log(c_1^b).$$

In this case, $\phi_{SP} = \frac{\alpha_{SP,f_1}+\alpha_{SP,f_2}}{\alpha_{SP,f_1}+\alpha_{SP,f_2}+\alpha_{SP,n_1}+\alpha_{SP,n_2}+\alpha_{SP,c_1^b}}$ is the optimal food consumption share for the non-welfarist planner, and the planner will choose SNAP and cash so that the consumer chooses this food consumption share. The $\alpha_{SP,(\cdot)}$ parameters do not have to align at all with the actual parameters in the consumer's utility function.

Using this alternative model, we show that the optimal SNAP share is increasing in the "wedge" between the food consumption the individual prefers and what the social planner prefers. That is, as the social planner's preferred food consumption increases, the optimal SNAP share increases (holding constant the individual's preferred food consumption).[54] This result is summarized in the

[54]Formally, this corresponds to changing any combination of the $\alpha_{SP,(\cdot)}$ parameters in the planner's utility function

following lemma:

Lemma 4. *The optimal SNAP share is increasing in (ϕ_{SP} - ϕ) (holding ϕ constant) for all $\phi < \phi_{SP} < 1$.*

Proof: We prove this by showing that the optimal SNAP share ($b^*/\bar{y}$) is increasing in ϕ_{SP} starting from any $\phi_{SP} > \phi$. There are two cases to consider:

Case 1: $0 \leq \kappa \leq \kappa^*$. In this case, the optimal SNAP share is exactly equal to ϕ_{SP}, and so the result is immediate: as ϕ_{SP} goes up, the optimal SNAP share increases one-for-one.

Case 2: $\kappa^* < \kappa$. In this case the optimal SNAP benefits are inframarginal, and the optimal SNAP share is give by equation (7) reproduced below:

$$
\begin{aligned}
\frac{b^*}{\bar{y}} &= \frac{\alpha_g(1+\beta)+(1-\alpha_g)(1-\beta\gamma)}{2\kappa\bar{y}^2(1-\phi_0)}\left[\frac{1-\phi_0}{1-\phi_{SP}} - \frac{\phi_0}{\phi_{SP}}\right] + \frac{\phi_{SP}-\phi_0}{1-\phi_0} \\
&= K\left[\frac{1-\phi_0}{1-\phi_{SP}} - \frac{\phi_0}{\phi_{SP}}\right] + \frac{\phi_{SP}-\phi_0}{1-\phi_0}
\end{aligned}
$$

We implicitly differentiate the expression above to solve for $d(b^*/\bar{y})/d\phi_{SP}$:

$$
\begin{aligned}
d(b^*/\bar{y}) &= K\left[\frac{1-\phi_0}{(1-\phi_{SP})^2}d\phi_{SP} + \frac{\phi_0}{(\phi_{SP})^2}d\phi_{SP}\right] + \frac{d\phi_{SP}}{1-\phi_0} \\
\frac{d(b^*/\bar{y})}{d\phi_{SP}} &= K\left[\frac{1-\phi_0}{(1-\phi_{SP})^2} + \frac{\phi_0}{(\phi_{SP})^2}\right] + \frac{1}{1-\phi_0} \\
&> 0
\end{aligned}
$$

The last line follows because $0 < \phi_0 < \phi_{SP} < 1$ and $K > 0$, which completes the proof. ■

D.4 Dynamic Model to Compare Within-Month Effects to Effects of Permanent Policy Changes

In this section, we develop a simple dynamic model to understand the relationship between the short-run, within-month response to anticipated income transfers and the (counterfactual) uncompensated behavioral response (i.e., the behavioral response to a permanent policy change). We use the model to derive formal conditions under which violations of fungibility in within-month responses implies violations of fungibility for the "lifetime" (i.e., uncompensated) responses.

Model setup

There are four periods $t = 1...4$. The consumer receives cash transfers y_t in periods $t = 1$ and $t = 3$ and SNAP benefits b_1 and b_3 in $t = 1$ and $t = 3$ and also receives wage income w_t in every period. The consumer can freely borrow and save at an exogenous interest rate $r = 0$ between periods.

As in the main model, we allow for self-control problems ($\beta < 1$) as well as mental accounting ($\kappa = 0$). Specifically, we use a β-δ utility function assuming $\delta = 1$ so that the individual at the

but holding constant all of the individual's preference parameters so that ϕ stays constant while ϕ_{SP} varies.

start of period 1 maximizes the following:

$$\begin{aligned} U &= U_1 + \beta * (U_2 + U_3 + U_4) \\ &\quad -\kappa * \left(\phi_0 Y + (b_1 + b_3 * (1+r)^{-2}) - p_f F\right)^2 \end{aligned}$$

where κ governs the strength of mental accounting as in the main model, Y is the presented discounted value of wage income and cash transfers ($Y = (y_1 + w_1) + w_2 * (1+r)^{-1} + (y_3 + w_3) * (1+r)^{-2} + w_4 * (1+r)^{-4}$), F is the presented discounted value of food spending ($F = f_1 + f_2 * (1+r)^{-1} + f_3 * (1+r)^{-2} + f_4 * (1+r)^{-3}$), and $U_1, ..., U_4$ are the per-period utility functions. The per-period utility functions are defined as follows:

$$\begin{aligned} U_1 &= \alpha_g \alpha_f \log(f_1) + \alpha_g(1-\alpha_f)\log(n_1) + (1-\alpha_g)\log(c_1^b) \\ U_2 &= \alpha_g \alpha_f \log(f_2) + \alpha_g(1-\alpha_f)\log(n_2) + (1-\alpha_g)\log(c_2^b) - \gamma(1-\alpha_g)\log(c_1^b) \\ U_3 &= \alpha_g \alpha_f \log(f_3) + \alpha_g(1-\alpha_f)\log(n_3) + (1-\alpha_g)\log(c_3^b) - \gamma(1-\alpha_g)\log(c_2^b) \\ U_4 &= \alpha_g \alpha_f \log(f_4) + \alpha_g(1-\alpha_f)\log(n_4) - \gamma(1-\alpha_g)\log(c_3^b) \end{aligned}$$

where the α_g and α_f parameters are the same share parameters as in the main two-period model. In each period except in the last period the consumer can consume the temptation good, with a future negative health consequence in the following period.

Benchmark: Permanent Income Hypothesis

If $\kappa = 0$ and $\beta = 1$ and $r = 0$, then since the consumer can freely borrow and save between periods, then the individual will have constant consumption for all of the goods in every period because of full consumption smoothing for all possible values of y_t, b_t, and w_t. This means there would be no observed change (or "spike") in consumption in any of the goods following the transfer in $t = 3$ relative to $t = 2$.

Formal Propositions Comparing the "Intertemporal" and "Lifetime" MPCs

Notation: We let ϕ_t denote the planned food share of income for each period $t, ..., 4$. Conditional on ϕ_t, consumption is pinned down by the Euler equation. The table below shows the consumption plan in each period t as a function of ϕ_t. Actual consumption decisions are higlighted in gray in the table below. The shares are out of a share of total unspent income at the time the plan is made, which is given by the path (M, $s_1(\phi_1)M$, $s_1(\phi_1)s_2(\phi_2)M$, $s_1(\phi_1)s_2(\phi_2)s_3(\phi_3)M$). Given the Cobb-Douglas functional form, all of these shares can be solved in closed form. The $s_t(\phi_t)$ functions determine the optimal savings/borrowing decisions each period, and these can also be solved in closed form.[55]

[55] For example, since the optimal choice of each good in the first period can be read off of the table, then $s_1(\phi_1)$ is given by the following expression:

$$s_1(\phi_1) = \frac{(1+r)[M - (p_f f_1 + n_1 + p_b c_1^b)]}{M}$$

where M is the lifetime present discounted value of all income (wages, cash, and SNAP benefits). Similarly, $s_2(\phi_2)$ is given by the following:

$$s_2(\phi_2) = \frac{(1+r)[s_1 M - (p_f f_2 + n_2 + p_b c_2^b)]}{s_1 M}$$

Planned Consumption Shares in each Period

	$t = 1$ plan	$t = 2$ plan	$t = 3$ plan	$t = 4$ plan
f_1	$\frac{\phi_1}{1+3\beta}$	-	-	-
f_2	$\frac{\beta\phi_1}{1+3\beta}$	$\frac{\phi_2}{1+2\beta}$	-	-
f_3	$\frac{\beta\phi_1}{1+3\beta}$	$\frac{\beta\phi_2}{1+2\beta}$	$\frac{\phi_3}{1+\beta}$	-
f_4	$\frac{\beta\phi_1}{1+3\beta}$	$\frac{\beta\phi_2}{1+2\beta}$	$\frac{\beta\phi_3}{1+\beta}$	ϕ_4
n_1	$\frac{(1-\phi_1)\alpha_g(1-\alpha_f)}{(1-\alpha_g)(1-3\beta\gamma+2\beta)+\alpha_g(1-\alpha_f)(1+3\beta)}$	-	-	-
n_2	$\frac{\beta(1-\phi_1)\alpha_g(1-\alpha_f)}{(1-\alpha_g)(1-3\beta\gamma+2\beta)+\alpha_g(1-\alpha_f)(1+3\beta)}$	$\frac{(1-\phi_2)\alpha_g(1-\alpha_f)}{(1-\alpha_g)(1-2\beta\gamma+\beta)+\alpha_g(1-\alpha_f)(1+2\beta)}$	-	-
n_3	$\frac{\beta(1-\phi_1)\alpha_g(1-\alpha_f)}{(1-\alpha_g)(1-3\beta\gamma+2\beta)+\alpha_g(1-\alpha_f)(1+3\beta)}$	$\frac{\beta(1-\phi_2)\alpha_g(1-\alpha_f)}{(1-\alpha_g)(1-2\beta\gamma+\beta)+\alpha_g(1-\alpha_f)(1+2\beta)}$	$\frac{(1-\phi_3)\alpha_g(1-\alpha_f)}{(1-\alpha_g)(1-\beta\gamma)+\alpha_g(1-\alpha_f)(1+\beta)}$	-
n_4	$\frac{\beta(1-\phi_1)\alpha_g(1-\alpha_f)}{(1-\alpha_g)(1-3\beta\gamma+2\beta)+\alpha_g(1-\alpha_f)(1+3\beta)}$	$\frac{\beta(1-\phi_2)\alpha_g(1-\alpha_f)}{(1-\alpha_g)(1-2\beta\gamma+\beta)+\alpha_g(1-\alpha_f)(1+2\beta)}$	$\frac{\beta(1-\phi_3)\alpha_g(1-\alpha_f)}{(1-\alpha_g)(1-\beta\gamma)+\alpha_g(1-\alpha_f)(1+\beta)}$	$1-\phi_4$
c_1^b	$\frac{(1-\phi_1)(1-\alpha_g)(1-\beta\gamma)}{(1-\alpha_g)(1-3\beta\gamma+2\beta)+\alpha_g(1-\alpha_f)(1+3\beta)}$	-	-	-
c_2^b	$\frac{\beta(1-\phi_1)(1-\alpha_g)(1-\gamma)}{(1-\alpha_g)(1-3\beta\gamma+2\beta)+\alpha_g(1-\alpha_f)(1+3\beta)}$	$\frac{(1-\phi_2)(1-\alpha_g)(1-\beta\gamma)}{(1-\alpha_g)(1-2\beta\gamma+\beta)+\alpha_g(1-\alpha_f)(1+2\beta)}$	-	-
c_3^b	$\frac{\beta(1-\phi_1)(1-\alpha_g)(1-\gamma)}{(1-\alpha_g)(1-3\beta\gamma+2\beta)+\alpha_g(1-\alpha_f)(1+3\beta)}$	$\frac{\beta(1-\phi_2)(1-\alpha_g)(1-\gamma)}{(1-\alpha_g)(1-2\beta\gamma+\beta)+\alpha_g(1-\alpha_f)(1+2\beta)}$	$\frac{(1-\phi_3)(1-\alpha_g)(1-\beta\gamma)}{(1-\alpha_g)(1-\beta\gamma)+\alpha_g(1-\alpha_f)(1+\beta)}$	-

We next define the following differences between the "intertemporal" and "lifetime" MPC:

$$\begin{aligned} MPCf^{SNAP}_{lifetime} - MPCf^{SNAP}_{intertemporal} &= \frac{dp_f((1+r)f_2 + f_3)}{db} - \frac{dp_f(f_3 - f_2)}{db} \\ MPCf^{cash}_{lifetime} - MPCf^{cash}_{intertemporal} &= \frac{dp_f((1+r)f_2 + f_3)}{dy} - \frac{dp_f(f_3 - f_2)}{dy} \end{aligned}$$

where the derivatives db and dy refer to marginal increases in either SNAP or the cash transfer (i.e., the notiation db means that SNAP benefits increase from b_t to $b_t + db$ each period the benefits are distributed). In order to make quantities comparable, we define the "lifetime" MPCs as the sum of consumption over periods 2 and 3, and discount from the perspective of $t = 3$.[56]

Intertemporal responses to anticipated transfers weakly understate the uncompensated responses. To see the intuition, start with the case in which the consumer is fully rational (i.e., $\beta = 1$ and $\kappa = 0$). In this case, there is no "spike" in consumption in response to anticipated transfers since the consumer behaves according to the permanent income hypothesis. As a result, the intertemporal response is zero and the uncompensated response will be positive because a permanent policy change will increase consumption in all periods. At the other extreme, if $\beta << 1$ and borrowing is sufficiently expensive, then the consumer will be (endogenously) "hand to mouth" as a result of their present bias. In this case, the intertemporal and uncompensated responses are identical. In between these extremes, the intertemporal responses are smaller in magnitude than the uncompensated responses, with present bias working to bring the two magnitudes closer together.[57] Intuitively, a permanent change in policy increases consumption in both periods, while

[56]We could have alternatively defined the "lifetime" MPC as the effect of a permanent policy change on total lifetime consumption (appropriately discounted to $t = 3$ to be comparable), but the proof approach is much simpler using our definition instead, and we have done many numerical simulations which have led us to conjecture that all of the results still go through using total lifetime consumption instead.

[57]In fact, we have found in simulations of our simple dynamic model that the magnitude of the "spike" in temptation good consumption can be informative about the degree of present bias. In particular, we could in theory

the "intertemporal" response differences out the effect of the policy change on second-period consumption.

We can state this result formally as follows:

Proposition 2. *The intertemporal responses to SNAP or cash understate the associated "lifetime" or uncompensated responses to permanent policy changes:*

$$
\begin{aligned}
MPCf^{SNAP}_{lifetime} - MPCf^{SNAP}_{intertemporal} &> 0 \\
MPCf^{cash}_{lifetime} - MPCf^{cash}_{intertemporal} &> 0
\end{aligned}
$$

Proof: Begin with the definition of the difference in the $MPCf^{SNAP}$ quantities:

$$
\begin{aligned}
MPCf^{SNAP}_{lifetime} - MPCf^{SNAP}_{intertemporal} &= \frac{dp_f((1+r)f_2+f_3)}{db} - \frac{dp_f(f_3-f_2)}{db} \\
&= \frac{d}{db}p_f(2+r)f_2 \\
&= \frac{d}{db}\left[\frac{(2+r)\phi_2 M s_1}{1+2\beta}\right] \\
&> 0
\end{aligned}
$$

Because we have ruled out corner solutions, the envelope theorem can be used to show that $\frac{d}{db}\left[\frac{(2+r)\phi_2 M s_1}{1+2\beta}\right] > 0$. The endogenous choices are ϕ_2 and s_1, and M increases mechanically from the exogenous increase in b. Since all the terms are positive and $dM/db > 0$, the entire expression is positive. Substituting dy for db in the expressions above gives the analogous result for $MPCf^{cash}_{lifetime} - MPCf^{cash}_{intertemporal}$. ■

Using the differences above the ϕ_t definitions, we can now state and prove the main result for the dynamic model. The main proposition is that non-fungibility based on the difference in intertemporal MPCs between SNAP and cash implies non-fungibility in response to permanent change in policy.

Proposition 3. *Non-fungibility in terms of intertemporal MPCs implies non-fungibility in lifetime MPCs.* $MPCf^{SNAP}_{intertemporal} - MPCf^{cash}_{intertemporal} > 0$ *implies* $MPCf^{SNAP}_{lifetime} - MPCf^{cash}_{lifetime} > 0$, *with both differences increasing in* κ*. Similarly,* $MPCb^{cash}_{intertemporal} - MPCb^{SNAP}_{intertemporal} > 0$ *implies* $MPCb^{cash}_{lifetime} - MPCb^{SNAP}_{lifetime} > 0$, *with both differences increasing in* κ*.*

Proof: All $\phi_t, s_t, M, \beta, \frac{ds_t}{\phi_t}$, are greater than 0. If $\kappa > 0$, then $(\frac{d\phi_t}{db} - \frac{d\phi_t}{dy})$ is also greater than 0.[58]

calibrate β with precise knowledge of the individual's income process and borrowing constraints using the estimated spike in consumption in response to anticipated transfers.

[58] To prove this use implicit differentiation and solve for $(\frac{d\phi_t}{db} - \frac{d\phi_t}{dy})$ for each value of t. Each expression will be of the form $A\kappa/(B + C\kappa)$ where $A, B, C > 0$, and so the difference is zero if $\kappa = 0$ and greater than 0 if $\kappa > 0$.

We then can solve for the following expression for $MPCf^{SNAP}_{intertemporal} - MPCf^{cash}_{intertemporal}$:

$$\begin{aligned} MPCf^{SNAP}_{intertemporal} - MPCf^{cash}_{intertemporal} &= \left(\frac{d\phi_1}{db} - \frac{d\phi_1}{dy}\right)\left(\frac{ds_1}{d\phi_1}M\left[\frac{\phi_3 s_2}{1+\beta} - \frac{\phi_2}{1+2\beta}\right]\right) \\ &+ \left(\frac{d\phi_2}{db} - \frac{d\phi_2}{dy}\right)\left(s_1 M\left[\frac{\phi_3}{1+\beta}\frac{ds_2}{d\phi_2} - \frac{1}{1+2\beta}\right]\right) \\ &+ \left(\frac{d\phi_3}{db} - \frac{d\phi_3}{dy}\right)\left(\frac{s_1 s_2 M}{1+\beta}\right) \end{aligned}$$

The first part of the proposition assumes that the above expression is greater than 0. Next, the overall "lifetime" difference in MPCfs (from the $t = 3$ perspective, which is the point at which the intertemporal MPCfs can be evaluated) is given by the following:

$$\begin{aligned} MPCf^{SNAP}_{lifetime} &- MPCf^{cash}_{lifetime} \\ &= \left(\frac{d\phi_1}{db} - \frac{d\phi_1}{dy}\right)\left[\frac{(1+r)^2 M}{1+3\beta} + \frac{ds_1}{d\phi_1}\left(\frac{\phi_2(1+r)M}{1+2\beta} + \frac{\phi_3 s_2 M}{1+\beta} + \frac{\phi_4 s_3 s_2 M}{1+r}\right)\right] \\ &+ \left(\frac{d\phi_2}{db} - \frac{d\phi_2}{dy}\right)\left[\frac{(1+r)s_1 M}{(1+2\beta)} + \frac{ds_2}{d\phi_2}\left(\frac{\phi_3 s_1 M}{1+\beta} + \frac{\phi_4 s_3 s_1 M}{1+r}\right)\right] \\ &+ \left(\frac{d\phi_3}{db} - \frac{d\phi_3}{dy}\right)\left[\frac{s_1 s_2 M}{1+\beta} + \frac{ds_3}{d\phi_3}\frac{\phi_4 s_2 s_1 M}{1+r}\right] \\ &+ \left(\frac{d\phi_4}{db} - \frac{d\phi_4}{dy}\right)\left[\frac{s_3 s_2 s_1 M}{1+r}\right]. \end{aligned}$$

We then take the difference between the two differences (i.e., subtract the intertemporal difference from the lifetime difference in $MPCf$s):

$$\begin{aligned} (MPCf^{SNAP}_{lifetime} &- MPCf^{cash}_{lifetime}) \\ &- (MPCf^{SNAP}_{intertemporal} - MPCf^{cash}_{intertemporal}) \\ &= \left(\frac{d\phi_1}{db} - \frac{d\phi_1}{dy}\right)\left[\frac{(1+r)^2 M}{1+3\beta} + \frac{ds_1}{d\phi_1}\left(\frac{\phi_2(2+r)M}{1+2\beta} + \frac{\phi_4 s_3 s_2 M}{1+r}\right)\right] \\ &+ \left(\frac{d\phi_2}{db} - \frac{d\phi_2}{dy}\right)\left[\frac{(2+r)s_1 M}{(1+2\beta)} + \frac{\phi_4 s_3 s_1 M}{1+r}\right)\right] \\ &+ \left(\frac{d\phi_3}{db} - \frac{d\phi_3}{dy}\right)\left[\frac{ds_3}{d\phi_3}\frac{\phi_4 s_2 s_1 M}{1+r}\right] + \left(\frac{d\phi_4}{db} - \frac{d\phi_4}{dy}\right)\left[\frac{s_3 s_2 s_1 M}{1+r}\right] \\ &> 0 \end{aligned}$$

Therefore, since the difference is strictly greater than 0, then $MPCf^{SNAP}_{intertemporal} - MPCf^{cash}_{intertemporal} > 0$ implies $MPCf^{SNAP}_{lifetime} - MPCf^{cash}_{lifetime} > 0$.

We can follow the same steps for the temptation good. Similarly, begin with the necessary condition $MPCb^{SNAP} - MPCb^{cash} < 0$. This expression is given by:

$$
\begin{aligned}
& MPCb^{SNAP}_{intertemporal} - MPCb^{cash}_{intertemporal} \\
&= -\Big(\frac{d\phi_1}{db} - \frac{d\phi_1}{dy}\Big)\Big(\frac{ds_1}{d\phi_1} M (1-\alpha_g)(1-\beta\gamma) \\
&\Big[\frac{(1-\phi_2)}{\alpha_g(1-\alpha_f)(1+2\beta)+(1-\alpha_g)(1-2\beta\gamma+\beta)} - \frac{(1-\phi_3)\, s_2(\phi_2)}{\alpha_g(1-\alpha_f)(1+\beta)+(1-\alpha_g)(1-\beta\gamma)}\Big]\Big) \\
&- \Big(\frac{d\phi_2}{db} - \frac{d\phi_2}{dy}\Big)\Big(s_1(\phi_1)\, M (1-\alpha_g)(1-\beta\gamma) \\
&\Big[\frac{1}{\alpha_g(1-\alpha_f)(1+2\beta)+(1-\alpha_g)(1-2\beta\gamma+\beta)} - \frac{(1-\phi_3)}{\alpha_g(1-\alpha_f)(1+\beta)+(1-\alpha_g)(1-\beta\gamma)}\frac{ds_2}{d\phi_2}\Big]\Big) \\
&- \Big(\frac{d\phi_3}{db} - \frac{d\phi_3}{dy}\Big)\Big(s_1(\phi_1)\, M (1-\alpha_g)(1-\beta\gamma) \\
&\cdot\Big[\frac{s_2(\phi_2)}{\alpha_g(1-\alpha_f)(1+\beta)+(1-\alpha_g)(1-\beta\gamma)}\Big]\Big).
\end{aligned}
$$

As before, we next derive the overall lifetime difference in MPCbs (from the $t = 3$ perspective, which is the point at which the intertemporal MPCfs can be evaluated):

$$
\begin{aligned}
MPCb^{SNAP}_{lifetime} &- MPCb^{cash}_{lifetime} \\
&= -\Big(\frac{d\phi_1}{db} - \frac{d\phi_1}{dy}\Big)\Big[\frac{(1-\alpha_g)(1-\beta\gamma)(1+r)^2 M}{\alpha_g(1-\alpha_f)(1+3\beta)+(1-\alpha_g)(1-3\beta\gamma+2\beta)} \\
&\quad +\frac{ds_1}{d\phi_1}\Big(\frac{(1-\phi_2)(1-\alpha_g)(1-\beta\gamma)(1+r)M}{\alpha_g(1-\alpha_f)(1+2\beta)+(1-\alpha_g)(1-2\beta\gamma+\beta)} \\
&\qquad +\frac{(1-\phi_3)(1-\alpha_g)(1-\beta\gamma)s_2(\phi_2)M}{\alpha_g(1-\alpha_f)(1+\beta)+(1-\alpha_g)(1-\beta\gamma)}\Big)\Big] \\
&- \Big(\frac{d\phi_2}{db} - \frac{d\phi_2}{dy}\Big)\Big[\frac{(1-\alpha_g)(1-\beta\gamma)s_1(\phi_1)(1+r)M}{\alpha_g(1-\alpha_f)(1+2\beta)+(1-\alpha_g)(1-2\beta\gamma+\beta)} \\
&\quad +\frac{ds_2}{d\phi_2}\Big(\frac{(1-\phi_3)(1-\alpha_g)(1-\beta\gamma)s_1(\phi_1)M}{\alpha_g(1-\alpha_f)(1+\beta)+(1-\alpha_g)(1-\beta\gamma)}\Big)\Big] \\
&- \Big(\frac{d\phi_3}{db} - \frac{d\phi_3}{dy}\Big)\Big[\frac{(1-\alpha_g)(1-\beta\gamma)s_1(\phi_1)s_2(\phi_2)M}{\alpha_g(1-\alpha_f)(1+\beta)+(1-\alpha_g)(1-\beta\gamma)}\Big].
\end{aligned}
$$

The lifetime difference in $MPCb$s is smaller than the intertemporal difference and is given by:

$$\begin{aligned}
MPCb^{SNAP}_{lifetime} &- MPCb^{cash}_{lifetime} - (MPCb^{SNAP}_{intertemporal} - MPCb^{cash}_{intertemporal}) \\
&= -\left(\frac{d\phi_1}{db} - \frac{d\phi_1}{dy}\right)\left[\frac{(1-\alpha_g)(1-\beta\gamma)(1+r)^2 M}{\alpha_g(1-\alpha_f)(1+3\beta)+(1-\alpha_g)(1-3\beta\gamma+2\beta)}\right. \\
&\quad \left.+\frac{ds_1}{d\phi_1}\frac{(1-\phi_2)(1-\alpha_g)(1-\beta\gamma)(2+r)M}{\alpha_g(1-\alpha_f)(1+2\beta)+(1-\alpha_g)(1-2\beta\gamma+\beta)}\right] \\
&- \left(\frac{d\phi_2}{db} - \frac{d\phi_2}{dy}\right)\left[\frac{(1-\alpha_g)(1-\beta\gamma)s_1(\phi_1)(1+r)M}{\alpha_g(1-\alpha_f)(1+2\beta)+(1-\alpha_g)(1-2\beta\gamma+\beta)}\right] \\
&< 0.
\end{aligned}$$

Therefore, since the difference is strictly less than 0, then $MPCb^{SNAP}_{intertemporal} - MPCb^{cash}_{intertemporal} < 0$ implies $MPCb^{SNAP}_{lifetime} - MPCb^{cash}_{lifetime} < 0$. This completes the proof. ■

Note that the model allows the agent to save and borrow at an exogenous interest rate r, which allows us to use the first-order approach throughout the proof. We have also simulated the model with binding liquidity constraints (such as the inability to borrow beyond an exogenous amount).

The result also has important necessary conditions, which are satisfied in our empirical analysis (namely, that there is non-fungibility in the expected direction for both food and temptation good), and this implies non-fungibility in response to permanent policy change. We want to emphasize that this does not mean that non-fungibility in response to permanent policy change implies "intertemporal" non-fungibility. This is easy to see by consider a situation where the intertemporal responses are all exactly zero because of perfect consumption smoothing. Then the necessary conditions for the proposition above are not satisfied, but it could still be the case that $\kappa > 0$ but we would not be able to test for it using intertemporal responses. In other words, having something like β-δ preferences which generate "spikes" in consumption in response to anticipated benefits can help test for non-fungibility using intertemporal responses. Related to this discussion, the next result gives a condition for the intertemporal response to be positive.

Proposition 4. *If* $\kappa > 0$*, then* $MPCf^{SNAP}_{intertemporal} - MPCf^{cash}_{intertemporal} > 0$ *whenever* $\phi_3 \frac{ds_2}{d\phi_2} > \frac{1+\beta}{1+2\beta}$

Proof: The difference between the intertemporal $MPCf$s is given by:

$$\begin{aligned}
MPCf^{SNAP}_{intertemporal} - MPCf^{cash}_{intertemporal} &= \left(\frac{d\phi_1}{db} - \frac{d\phi_1}{dy}\right)\left(\frac{ds_1}{d\phi_1} M\left[\frac{\phi_3 s_2}{1+\beta} - \frac{\phi_2}{1+2\beta}\right]\right) \\
&+ \left(\frac{d\phi_2}{db} - \frac{d\phi_2}{dy}\right)\left(s_1 M\left[\frac{\phi_3}{1+\beta}\frac{ds_2}{d\phi_2} - \frac{1}{1+2\beta}\right]\right) \\
&+ \left(\frac{d\phi_3}{db} - \frac{d\phi_3}{dy}\right)\left(\frac{s_1 s_2 M}{1+\beta}\right).
\end{aligned}$$

The third line is always weakly positive, and the condition in the proposition states that the second line is positive. Further, the condition in the proposition implies that the first line is also positive.

To see this, note that

$$\frac{s_2}{\phi_2} = \frac{2\beta(1+r)}{1+2\beta} + \frac{1-\phi_2}{\phi_2}\frac{(1+r)[2\beta\alpha_g(1-\alpha_f)+\beta(1-\alpha_g)(1-\gamma)]}{(1+2\beta)\alpha_g(1-\alpha_f)+(1-\alpha_g)(1-2\beta\gamma+\beta)}$$

while

$$\frac{ds_2}{d\phi_2} = \frac{2\beta(1+r)}{1+2\beta} - \frac{(1+r)[2\beta\alpha_g(1-\alpha_f)+\beta(1-\alpha_g)(1-\gamma)]}{(1+2\beta)\alpha_g(1-\alpha_f)+(1-\alpha_g)(1-2\beta\gamma+\beta)}.$$

Since $\phi_2 \in (0,1)$, $\frac{s_2}{\phi_2} > \frac{ds_2}{d\phi_2}$ and so $\phi_3\frac{ds_2}{d\phi_2} > \frac{1+\beta}{1+2\beta}$ implies $\frac{\phi_3 s_2}{1+\beta} > \frac{\phi_2}{1+\beta}$ (which is equivalent to $f_3 > f_2$. So a food consumption spike sufficiently large implies that $MPCf^{SNAP}_{intertemporal} - MPCf^{cash}_{intertemporal} > 0$. ■

This result shows that as long as food spending share after SNAP benefits are distributed is sufficiently larger than food spending share in the period before SPAN benefits are distributed, then we expect to see non-fungibility in intertemporal MPCs when $\kappa > 0$. This is useful because the "food stamp nutrition cycle" would generally predict spikes in food consumption immediately after SNAP benefits are distributed.

The final result is that the difference between the degree of non-fungibility in the intertemporal MPCs and the lifetime MPCs is increase in κ.

Proposition 5. *The difference between non-fungibility in lifetime $MPCs$ and non-fungibility in intertemporal $MPCs$ is positive and increasing in κ*

Proof: Combining some of the results above, we have that the wedge in lifetime $MPCf$s exceeds the wedge in intertemporal $MPCf$s by:

$$\begin{aligned} & (MPCf^{SNAP}_{lifetime} - MPCf^{cash}_{lifetime}) - (MPCf^{SNAP}_{intertemporal} - MPCf^{cash}_{intertemporal}) \\ = \; & (MPCf^{SNAP}_{lifetime} - MPCf^{SNAP}_{intertemporal}) - (MPCf^{cash}_{lifetime} - MPCf^{cash}_{intertemporal}) \\ = \; & \left(\frac{d\phi_2}{db} - \frac{d\phi_2}{dy}\right)\left[\frac{(2+r)s_1 M}{1+2\beta}\right] \end{aligned}$$

Since $(\frac{d\phi_2}{db} - \frac{d\phi_2}{dy})$ is increasing in κ, the extent to which the difference in intertemporal MPCs under-states the difference in lifetime MPCs is increasing in κ.

Similarly, for the temptation good:

$$\begin{aligned} & (MPCb^{SNAP}_{lifetime} - MPCb^{cash}_{lifetime}) - (MPCb^{SNAP}_{intertemporal} - MPCb^{cash}_{intertemporal}) \\ = \; & (MPCb^{SNAP}_{lifetime} - MPCb^{SNAP}_{intertemporal}) - (MPCb^{cash}_{lifetime} - MPCb^{cash}_{intertemporal}) \\ = \; & -\left(\frac{d\phi_2}{db} - \frac{d\phi_2}{dy}\right)\left[\frac{(2+r)(1-\alpha_g)(1-\beta\gamma)s_1 M}{\alpha_g(1-\alpha_f)(1+2\beta)+(1-\alpha_g)(1-2\beta\gamma+\beta)}\right] \end{aligned}$$

.

Since $(\frac{d\phi_2}{db} - \frac{d\phi_2}{dy})$ is increasing in κ, the extent to which the difference in intertemporal MPCs under-states in magnitude (i.e. is less negative) the difference in lifetime MPCs is increasing in κ. ■

D.5 Alternative Policy Instruments

D.5.1 Representative Agent

Optimal Pigouvian Tax. The optimal Pigouvian tax on the temptation good is given by the following:

$$\tau_b = \frac{(1-\beta)(1+\gamma)}{(1+\beta)(1-\gamma)}$$

If we have tax/subsidy instruments for any two of the goods (plus a lump-sum tax/transfer so we can compare welfare), then the social planner can always implement their optimal allocation across $\bar{f}, \bar{n}, c_1^b$. We only need two taxes because only relative prices matter.[59]

Consider the case in which the government can tax/subsidize both food and bads. Let $q_f = (1+\tau_f)p_f$ and q_b be the post-tax prices for food and the bad, respectively, that are faced by the consumer when the consumer chooses the consumption bundle. The planner wants change prices to induce (using first-order conditions):

$$\frac{\frac{\partial U_{\kappa=0,\beta=1}}{\partial \bar{f}}}{\frac{\partial U_{\kappa=0,\beta=1}}{\partial \bar{n}}} = p_f, \quad \frac{\frac{\partial U_{\kappa=0,\beta=1}}{\partial c_1^b}}{\frac{\partial U_{\kappa=0,\beta=1}}{\partial \bar{n}}} = p_b$$

subject to the choice constraint

$$\frac{\frac{\partial U}{\partial \bar{f}}}{\frac{\partial U}{\partial \bar{n}}} = q_f, \quad \frac{\frac{\partial U}{\partial c_1^b}}{\frac{\partial U}{\partial \bar{n}}} = q_b.$$

The optimal Pigouvian tax on food is then given by:

$$\begin{aligned}
\tau_f &= \frac{q_f}{p_f} - 1 = \frac{\frac{\partial U}{\partial \bar{f}}}{\frac{\partial U}{\partial \bar{n}}} / \frac{\frac{\partial U_{\kappa=0,\beta=1}}{\partial \bar{f}}}{\frac{\partial U_{\kappa=0,\beta=1}}{\partial \bar{n}}} - 1 \\
&= \frac{\frac{(1+\beta)\alpha_g\alpha_f}{\bar{f}}}{\frac{(1+\beta)\alpha_g\alpha_f}{\bar{n}}} / \frac{\frac{2\alpha_g\alpha_f}{\bar{f}}}{\frac{2\alpha_g\alpha_f}{\bar{n}}} - 1 = 0
\end{aligned}$$

and the optimal Pigouvian tax on the bad is then given by:

$$\begin{aligned}
\tau_b &= \frac{q_b}{p_b} - 1 = \frac{\frac{\partial U}{\partial c_1^b}}{\frac{\partial U}{\partial \bar{n}}} / \frac{\frac{\partial U_{\kappa=0,\beta=1}}{\partial c_1^b}}{\frac{\partial U_{\kappa=0,\beta=1}}{\partial \bar{n}}} - 1 \\
&= \frac{\frac{(1-\alpha_g)(1-\beta\gamma)}{c_1^b}}{\frac{(1+\beta)\alpha_g\alpha_f}{\bar{n}}} / \frac{\frac{(1-\alpha_g)(1-\gamma)}{c_1^b}}{\frac{2\alpha_g\alpha_f}{\bar{n}}} - 1 \\
&= \frac{2(1-\beta\gamma)}{(1+\beta)(1-\gamma)} - 1 = \frac{(1-\beta)(1+\gamma)}{(1+\beta)(1-\gamma)} > 0.
\end{aligned}$$

The optimal tax on food is zero and the optimal tax on the bad is positive. This is intuitive: the "internality" the social planner is concerned with is the over-consumption of the bad. Govern-

[59]In theory, the social planner could do *even better* if they could price separately in each period since they also differ in weights for period 1 versus period 2 consumption. We abstract from that here.

ment revenue from such a tax is $\tau_b c_1^b$, the size of the tax times the consumption of the after-tax consumption of the temptation good.

Theorem 3. *Suppose the planner can either choose cash and SNAP or cash and a tax on the temptation good. In this case the optimal Pigouvian tax and the cash transfer strictly dominates the optimal SNAP share of the cash transfer. At the same fiscal cost, the planner strictly prefers the optimal Pigouvian tax to SNAP.*

Proof:

From above, we know that the planner's utility can be written in terms of the income transfer $\bar{y}$, and the only effect of cash (y) versus SNAP (b) on planner's utility is through the effect on ϕ. At the optimal b (for all κ and β), the planner will choose b so that $\phi = \phi_{SP}$. So we can then plug in ϕ_{SP} and get the optimized planner utility as follows:

$$\begin{aligned} U^{SP} &= 2\alpha_g\alpha_f\left(\log\frac{\phi_{SP}\bar{y}}{2p_f}\right) + 2\alpha_g(1-\alpha_f)\left(\log\frac{(1-\phi_{SP})(1-\phi_0-\theta_0)\bar{y}}{2(1-\phi_0)}\right) \\ &\quad +(1-\alpha_g)(1-\gamma)\log\left(\frac{(1-\phi_{SP})\theta_0\bar{y}}{(1-\phi_0)p_b}\right) \end{aligned}$$

We can then compare this utility to the optimal Pigouvian tax, which increases p_b to $p_b*(1+\tau_b) = p_b*\left(1+\frac{(1-\beta)(1+\gamma)}{(1+\beta)(1-\gamma)}\right)$. Since the planner choosing the optimal Pigouvian tax choose $b=0$ then that means that the individual chooses ϕ_0 and θ_0, so that the planner utility given the consumer's choices is given by the following:

$$\begin{aligned} U^{SP}_{(\tau_b)} &= 2\alpha_g\alpha_f\left(\log\frac{\phi_0\bar{y}_{(\tau_b)}}{2p_f}\right) + 2\alpha_g(1-\alpha_f)\left(\log\frac{(1-\phi_0-\theta_0)\bar{y}_{(\tau_b)}}{2}\right) \\ &\quad +(1-\alpha_g)(1-\gamma)\log\left(\frac{\theta_0\bar{y}_{(\tau_b)}}{p_b(1+\tau_b)}\right) \end{aligned}$$

Note that the total income transfer is $\bar{y}_{(\tau_b)} = \bar{y}/(1-\frac{\tau_b\theta_0}{1+\tau_b})$ in order to keep the total fiscal cost at $\bar{y}$ (by redistributing the tax revenue to individual as additional income).

To prove that the planner utility is higher when choosing Pigouvian tax we need to prove that $U^{SP}_{(\tau_b)} > U^{SP}$. To do this, we calculate the difference $D := U^{\mathrm{SP}}_{(\tau_b)} - U^{\mathrm{SP}}$ and prove that it is positive. We begin with the following definitions:

$$\begin{aligned} D_0 &:= \alpha_g(1+\beta) + (1-\alpha_g)(1-\beta\gamma), \\ D_{\mathrm{SP}} &:= 2\alpha_g + (1-\alpha_g)(1-\gamma). \end{aligned}$$

Using these definitions we have the following:

$$\phi_0 := \frac{(1+\beta)\alpha_g\alpha_f}{D_0}, \qquad \theta_0 := \frac{(1-\alpha_g)(1-\beta\gamma)}{D_0},$$

$$\phi^{\mathrm{SP}} := \frac{2\alpha_g\alpha_f}{D_{\mathrm{SP}}}, \qquad \tau_b := \frac{(1-\beta)(1+\gamma)}{(1+\beta)(1-\gamma)}.$$

Note that each of these terms lie in $(0,1)$. Direct substitution gives the following result:

$$\frac{\phi_0}{\phi^{\mathrm{SP}}} \;=\; 1 - \frac{\tau_b\theta_0}{1+\tau_b}. \tag{8}$$

The result above is useful for simplifying the expression for D.[60] After inserting the above definitions and collecting logarithms we obtain the following expression for D:

$$\begin{aligned} D = {} & 2\alpha_g\alpha_f \, \log[(1-k)Y] \\ & + 2\alpha_g(1-\alpha_f)\, \log(R_2 Y) + (1-\alpha_g)(1-\gamma)\, \log\Big(R_2\,\frac{Y}{1+\tau_b}\Big), \end{aligned}$$

with

$$Y := \frac{1}{1-k}, \quad k := \frac{\tau_b\theta_0}{1+\tau_b}, \quad R_2 := \frac{1+k\lambda}{1-k}, \quad \lambda := \frac{\phi^{\mathrm{SP}}}{1-\phi^{\mathrm{SP}}} > 0.$$

The first log equals zero because of (8). Set

$$c_1 := 2\alpha_g(1-\alpha_f) > 0, \qquad c_2 := (1-\alpha_g)(1-\gamma) > 0.$$

Hence

$$D = (c_1+c_2)\,\log R_2 \;-\; c_2\,\log(1+\tau_b). \tag{9}$$

Bounding the logarithms: Lower bound on $\log R_2$. Using $\log(1+z) \geq z/(1+z)$ for $z > -1$ and $-\log(1-z) \geq z$ for $z \in (0,1)$,

$$\log R_2 = \log(1+\lambda k) - \log(1-k) \;\geq\; \frac{\lambda k}{1+\lambda k} + k > k.$$

Upper bound on $\log(1+\tau_b)$. Since $0 < \tau_b < 1$, we have $\log(1+\tau_b) \leq \tau_b$.

Putting the bounds together, and inserting these bounds in (9):

$$D \;>\; (c_1+c_2)k - c_2\tau_b = c_2\Big(\frac{c_1}{c_2}+1\Big)k - c_2\tau_b.$$

[60] To see this result, re-write the left-hand side and cancel the common factor $\alpha_g\alpha_f$, which leads to

$$\frac{\phi_0}{\phi^{SP}} = \frac{(1+\beta)D_{SP}}{2D_0}$$

Then we can re-write the term on the right through algebra and substitution:

$$1 - \frac{\tau_b\theta_0}{1+\tau_b} = 1 - \frac{(1-\alpha_g)(1-\beta)(1+\gamma)}{2D_0} = \frac{2D_0 - (1-\alpha_g)(1-\beta)(1+\gamma)}{2D_0}$$

Lastly, we need show that the two numerators coincide. The left-hand side numerator is given by:

$$(1+\beta)D_{SP} = (1+\beta)[2\alpha_g + (1-\alpha_g)(1-\gamma)]$$

And the right-hand side numerator is given by:

$$\begin{aligned} 2D_0 - (1-\alpha_g)(1-\beta)(1+\gamma) &= 2[\alpha_g(1+\beta) + (1-\alpha_g)(1-\beta\gamma)] - (1-\alpha_g)(1-\beta)(1+\gamma) \\ &= (1+\beta)[2\alpha_g + (1-\alpha_g)(1-\gamma)] \end{aligned}$$

Because $k = \tau_b\theta_0/(1+\tau_b) \geq \tau_b\theta_0/2$, we get

$$D \; > \; c_2\tau_b\Big[\Big(\frac{c_1}{c_2}+1\Big)\frac{\theta_0}{2}-1\Big].$$

Now $\theta_0 > 1-\alpha_g$ and $\dfrac{c_1}{c_2}+1 \geq 1+\dfrac{2\alpha_g}{1-\alpha_g} > 2$, so the bracket is strictly positive. Hence $D > 0$. This shows that the planner utility is higher with Pigouvian tax compared to the optimal "cash and SNAP" combination. ■

Theorem 3 therefore establishes the intuitive benchmark that the optimal Pigouvian tax of the "internality" strictly dominates SNAP from the planner's perspective, but we show in the reminder of this subsection that this benchmark does not always hold when there is population heterogeneity. With heterogeneity, there can be conditions under which the planner strictly prefers SNAP to using an optimal Pigouvian tax.

Optimal Linear Food Subsidy. The optimal (linear) food subsidy is given by the following:

$$\tau_f = \frac{-(1-\alpha_g)(1-\beta)(1+\gamma)}{2(1+\beta)\alpha_g(1-\alpha_f)+2(1-\alpha_g)(1-\beta\gamma)}$$

Now, suppose the planner can only change food prices but cannot tax/subsidize non-foods or bads separately. In this case, they can only affect the tradeoff of food versus other goods (but cannot directly remedy overconsumption of the bad). In the full tax-instruments case, we saw that in the first-best, the social planner wants to tax the bad. Because we are not able to affect the relevant tradeoff, food subsidies will not be able to totally correct the behavioral internality, but can skew consumption towards food and away from the non-food and the bad.

We want to calculate the food subsidy that is optimal for the social planner holding fixed the prices of the non-food versus the bad. To hold fixed the non-food versus bad trade-off faced by the consumer, we can write c_1^b in terms of $\bar{n}$:

$$p_b = \frac{\frac{\partial U}{\partial c_1^b}}{\frac{\partial U}{\partial \bar{n}}} = \frac{\frac{(1-\alpha_g)(1-\beta\gamma)}{c_1^b}}{\frac{\alpha_g(1-\alpha_g)(1+\beta)}{\bar{n}}} \implies c_1^b = \frac{\bar{n}}{p_b}\frac{(1-\alpha_g)(1-\beta\gamma)}{\alpha_g(1-\alpha_f)(1+\beta)}$$

This makes the social planner's utility function

$$\begin{aligned} U_{\kappa=0,\beta=1}(\phi) &= 2\alpha_g\alpha_f\log\Big(\frac{\bar{f}}{2}\Big)+2\alpha_g(1-\alpha_f)\log\Big(\frac{\bar{n}}{2}\Big) \\ &+ (1-\alpha_g)(1-\gamma)\log\Big(\frac{\bar{n}}{p_b}\frac{(1-\alpha_g)(1-\beta\gamma)}{\alpha_g(1-\alpha_f)(1+\beta)}\Big) \end{aligned}$$

Setting the social planner's ratio of marginal utilities equal to the pre-tax price ratio:

$$\begin{aligned} p_f &= \frac{\partial U_{\kappa=0,\beta=1}}{\partial \bar{f}}\Big/\frac{\partial U_{\kappa=0,\beta=1}}{\partial \bar{n}} \\ &= \Big(\frac{2\alpha_g\alpha_f}{\bar{f}}\Big)\Big/\Big(\frac{2\alpha_g(1-\alpha_f)+(1-\alpha_g)(1-\gamma)}{\bar{n}}\Big) \end{aligned}$$

Analogously setting the consumer's ratio of marginal utilities equal to the post-tax price ratio gives:

$$q_f = \frac{\partial U}{\partial \bar{f}} / \frac{\partial U}{\partial \bar{n}} = \left(\frac{(1+\beta)\alpha_g\alpha_f}{\bar{f}}\right) / \left(\frac{(1+\beta)\alpha_g(1-\alpha_f)+(1-\alpha_g)(1-\beta\gamma)}{\bar{n}}\right)$$

Setting the tax to correct the wedge between the marginal utility of consumption for the consumer versus the planner gives:

$$\begin{aligned} \tau_f &= \frac{q_f}{p_f} - 1 = \frac{2(1+\beta)\alpha_g(1-\alpha_f)+(1+\beta)(1-\alpha_g)(1-\gamma)}{2(1+\beta)\alpha_g(1-\alpha_f)+2(1-\alpha_g)(1-\beta\gamma)} - 1 \\ &= \frac{-(1-\alpha_g)(1-\beta)(1+\gamma)}{2(1+\beta)\alpha_g(1-\alpha_f)+2(1-\alpha_g)(1-\beta\gamma)} \end{aligned}$$

When only the price of food can be manipulated, the optimal policy is a subsidy of size τ_f on each unit of food consumed. The government's revenue is $\tau_f f < 0$. If this subsidy can be financed lump-sum out of the cash transfer that the government would have otherwise distributed, then this achieves the same effect on consumption at the same fiscal cost, as summarized by the following result:

Theorem 4. *Suppose the planner can either choose cash and SNAP or cash and a linear food subsidy (where the subsidy only applies to the cash transfer recipients). In this case the optimal SNAP share and the optimal linear food subsidy lead to the same consumption choices at the same fiscal cost.*

Proof:

In order to keep the same fiscal cost, we have to finance the food subsidy out of the transfer $\bar{y}$ (similar to the way that the optimal Pigouvian tax on the temptation good was rebated back to the consumer).

When choosing SNAP and cash, we know from above that planner's utility can be written in terms of the income transfer $\bar{y}$, and the only effect of cash (y) versus SNAP (b) on planner's utility is through the effect on ϕ. At the optimal b (for all κ and β), the planner will choose b so that $\phi = \phi_{SP}$. So we can then plug in ϕ_{SP} and get the optimized planner utility as follows:

$$\begin{aligned} U^{SP} &= 2\alpha_g\alpha_f\left(\log\frac{\phi_{SP}\bar{y}}{2p_f}\right) + 2\alpha_g(1-\alpha_f)\left(\log\frac{(1-\phi_{SP})(1-\phi_0-\theta_0)\bar{y}}{2(1-\phi_0)}\right) \\ &\quad +(1-\alpha_g)(1-\gamma)\log\left(\frac{(1-\phi_{SP})\theta_0\bar{y}}{(1-\phi_0)p_b}\right) \end{aligned}$$

We can then compare this utility to the utility under the optimal food subsidy. The food subsidy decreases p_f to $p_f * (1+\tau_f) = p_f * \left(1 - \frac{(1-\alpha_g)(1-\beta)(1+\gamma)}{2(1+\beta)\alpha_g(1-\alpha_f)+2(1-\alpha_g)(1-\beta\gamma)}\right)$. Since the planner choosing the optimal food subsidy chooses $b = 0$ then that means that the individual chooses ϕ_0 and θ_0, so that the planner utility given the consumer's choices is given by the following:

$$
\begin{aligned}
U^{SP}_{(\tau_f)} &= 2\alpha_g\alpha_f\left(\log\frac{\phi_0\bar{y}_{(\tau_f)}}{2p_f(1+\tau_f)}\right)+2\alpha_g(1-\alpha_f)\left(\log\frac{(1-\phi_0-\theta_0)\bar{y}_{(\tau_f)}}{2}\right)\\
&\quad+(1-\alpha_g)(1-\gamma)\log\left(\frac{\theta_0\bar{y}_{(\tau_f)}}{p_b}\right)
\end{aligned}
$$

Note that the total income transfer is $\bar{y}_{(\tau_f)} = \bar{y}/(1-\frac{\tau_f\phi_0}{1+\tau_f})$ in order to keep the total fiscal cost at $\bar{y}$. Since $\tau_f < 0$ this means that the income transfer is smaller than the total transfer under "cash and SNAP" to keep total fiscal cost constant.

To prove that the planner utility is the same in both of these scenarios we need to prove that $U^{SP}_{(\tau_f)} = U^{SP}$. This can be done by showing equality term-by-term. Start with the third term:

$$
\begin{aligned}
(1-\alpha_g)(1-\gamma)\log\left(\frac{(1-\phi_{SP})\theta_0\bar{y}}{(1-\phi_0)p_b}\right) &= (1-\alpha_g)(1-\gamma)\log\left(\frac{\theta_0\bar{y}_{(\tau_f)}}{p_b}\right)\\
\frac{(1-\phi_{SP})\theta_0\bar{y}}{(1-\phi_0)p_b} &= \frac{\theta_0\bar{y}_{(\tau_f)}}{p_b}\\
\frac{1-\phi_0}{1-\phi_{SP}} &= 1-\frac{\tau_f\phi_0}{1+\tau_f}
\end{aligned}
$$

Re-arranging the last line gives the following:

$$
\tau_f = -\frac{\phi_{SP}-\phi_0}{\phi_{SP}(1-\phi_0)} = \frac{-(1-\alpha_g)(1-\beta)(1+\gamma)}{2(1+\beta)\alpha_g(1-\alpha_f)+2(1-\alpha_g)(1-\beta\gamma)}
$$

which proves equality since this matches the optimal τ_f derived above. Comparing the second term leads to the same expressions as the third term, so the second term is also equal. Lastly, comparing the first term gives the following:

$$
\begin{aligned}
2\alpha_g\alpha_f\left(\log\frac{\phi_{SP}\bar{y}}{2p_f}\right) &= 2\alpha_g\alpha_f\left(\log\frac{\phi_0\bar{y}_{(\tau_f)}}{2p_f(1+\tau_f)}\right)\\
\frac{\phi_{SP}\bar{y}}{2p_f} &= \frac{\phi_0\bar{y}_{(\tau_f)}}{2p_f(1+\tau_f)}\\
\frac{\phi_{SP}}{\phi_0} &= \frac{1}{(1-\frac{\tau_f\phi_0}{1+\tau_f})(1+\tau_f)}\\
\tau_f &= -\frac{\phi_{SP}-\phi_0}{\phi_{SP}(1-\phi_0)}
\end{aligned}
$$

This matches the definition of τ_f above, which confirms that the first term is also equal, and since all three terms are equal then this proves that $U^{SP}_{(\tau_f)} = U^{SP}$. ■

Intuitively, since the optimal food subsidy "targets" the same food consumption as the optimal SNAP share of the transfer, they have the same effects on utility and have the same effects on the government budget.

D.5.2 Heterogeneous Agents

Here, we establish the claim in Section 5.3 that when we allow for heterogeneity across individuals in both β and κ, the planner may strictly prefer SNAP to the optimal uniform Pigouvian tax.

To show this, we model heterogeneity in a "2x2" setup where consumers have either $\beta = 1$ or $\beta = \bar{\beta}$ and have either $\kappa = 0$ or $\kappa = \bar{\kappa}$. All of the consumers have otherwise identical preference parameters (i.e., identical α_g, α_f, and γ). There is a unit mass of consumers, with population shares given by the following:

$$s_{\bar{\beta},\bar{\kappa}} + s_{\bar{\beta},0} + s_{1,\bar{\kappa}} + s_{1,0} = 1$$

where $s_{\bar{\beta},\bar{\kappa}}$ is the share of the population with $\beta = \bar{\beta}$ and $\kappa = \bar{\kappa}$, and the other population shares are defined analogously. With this setup, we have the following result for the optimal Pigouvian tax:

Proposition 6. *The optimal Pigouvian tax with population heterogeneity is given by:*

$$\begin{aligned} \tau_b^{heterogeneity} &= \tau_b(\bar{\beta}) * \bar{s} + \tau_b(1) * (1 - \bar{s}_b) \\ &= \tau_b(\bar{\beta}) * \bar{s} \end{aligned}$$

where $\bar{s}_b = \frac{(s_{\bar{\beta},\bar{\kappa}} + s_{\bar{\beta},0})/\theta_0(\bar{\beta})}{(s_{\bar{\beta},\bar{\kappa}} + s_{\bar{\beta},0})/\theta_0(\bar{\beta}) + (s_{1,\bar{\kappa}} + s_{1,0})/\theta_0(1)}$, $\theta_0(\beta)$ *is the* θ_0 *value for the consumers with either* $\beta = \bar{\beta}$ *or* $\beta = 1$, *and* $\tau_b(\beta) = \frac{(1-\beta)(1+\gamma)}{(1+\beta)(1-\gamma)}$ *is the optimal tax for each type of consumers as a function of* β *if the* $\beta = \bar{\beta}$ *and* $\beta = 1$ *consumers could be taxed separately.*

Proof:

The planner chooses $\tau_b^{heterogeneity}$ (hereafter τ_b^{het}) to maximize the share-weighted average of consumer utility evaluated at $\kappa = 0$ and $\beta = 1$ for all consumers, subject to consumers making privately-optimal choices (given their actual κ and β parameter values and the planner's choice of τ_b^{het}).

This leads to the following first-order condition for the planner:

$$\frac{2\alpha_g \alpha_f}{(1-\alpha_g)(1-\gamma)} = \frac{\sum \frac{s_{\beta_i,\kappa_i}}{c_i^b p_b}}{\sum \frac{s_{\beta_i,\kappa_i}}{n_i}}$$

where i is used to indicate the "type" of the consumer (i.e., i indicates one of the four combinations of β and κ given above).

Given the planner's choice of the Pigouvian tax, τ_b^{het}, the first-order condition for each consumer type is given by the following:

$$\frac{(1-\alpha_g)(1-\beta_i\gamma)}{c_i^b p_b (1+\tau_b^{het})} = \frac{(1+\beta_i)\alpha_g\alpha_f}{n_i}$$

Combining the two first-order conditions, substituting out n_i, and canceling terms gives the following:

$$2\sum \frac{s_{\beta_i,\kappa_i}}{c_i^b p_b} \frac{(1-\beta_i\gamma)}{(1-\gamma)(1+\beta_i)} = (1+\tau_b^{het}) \sum \frac{s_{\beta_i,\kappa_i}}{c_i^b p_b}$$

In the expression above, we can replace c_i^b with θ_β which is the value of θ_0 for a consumer with β. Since the planner is not choosing SNAP benefits, there is no effect of $\kappa > 0$ on consumer decisions, and so we can combine consumers with different values of κ but with the same values of β as follows:

$$2\left(\frac{s_{\bar{\beta},\bar{\kappa}}+s_{\bar{\beta},0}}{\theta_0(\bar{\beta})}\frac{(1-\bar{\beta}\gamma)}{(1-\gamma)(1+\bar{\beta})}+\frac{s_{\bar{1},\bar{\kappa}}+s_{\bar{1},0}}{\theta_0(1)}\frac{(1-1*\gamma)}{(1-\gamma)(1+1)}\right)=(1+\tau_b^{het})\left(\frac{s_{\bar{\beta},\bar{\kappa}}+s_{\bar{\beta},0}}{\theta_{\bar{\beta}}}+\frac{s_{1,\bar{\kappa}}+s_{1,0}}{\theta_0(1)}\right)$$

This expression can be re-arranged to give the main result above, completing the proof. ■

This result has an intuitive form as a share-weighted average of the optimal tax on the subpopulation with $\beta=\bar{\beta}$ (which has population share $(s_{\bar{\beta},\bar{\kappa}}+s_{\bar{\beta},0})$) and the optimal tax on the subpopulation with $\beta=1$, which has an optimal tax of $\tau_b(\beta=1)=0$. Intuitively, with heterogeneity in preferences, the planner is unable to achieve the first best with a single uniform Pigouvian tax, as in Diamond (1973).

We have a similar expression for the optimal food subsidy under heterogeneity:

Proposition 7. *The optimal linear food subsidy with population heterogeneity is given by:*

$$\begin{aligned}\tau_f^{heterogeneity} &= \tau_f(\bar{\beta})*\bar{s_f}+\tau_f(1)*(1-\bar{s_f})\\ &= \tau_f(\bar{\beta})*\bar{s_f}\end{aligned}$$

where $\bar{s_f}=\frac{(s_{\bar{\beta},\bar{\kappa}}+s_{\bar{\beta},0})/\phi_0(\bar{\beta})}{(s_{\bar{\beta},\bar{\kappa}}+s_{\bar{\beta},0})/\phi_0(\bar{\beta})+(s_{1,\bar{\kappa}}+s_{1,0})/\phi_0(1)}$, $\phi_0(\beta)$ *is the value of* ϕ_0 *for consumers with either* $\beta=\bar{\beta}$ *and* $\beta=1$, *and* $\tau_f(\beta)$ *is the optimal food subsidy for each type of consumer as a function of* β *if* $\beta=\bar{\beta}$ *and* $\beta=1$ *consumers could be subsidized separately, with* $\tau_f(\beta=1)=0$.

Proof: The proof follows the exact same steps as the previous Proposition but using the first-order conditions for f and n instead of c_1^b and n to solve for the optimal τ_f instead of τ_b. ■

Comparing SNAP to Optimal Pigouvian Tax and Optimal Food Subsidy. An implication of the previous results is that the optimal Pigouvian tax will not achieve the "first best" in general with population heterogeneity, but there will be situations under which the optimal SNAP benefits will be closer to the first best than the optimal Pigouvian tax. This is summarized in the following result:

Theorem 5. *Suppose population heterogeneity is such that* $s_{\bar{\beta},\bar{\kappa}}+s_{1,0}=1$ *so that* $s_{\bar{\beta},0}=s_{1,\bar{\kappa}}=0$. *In this case, the optimal SNAP share is the same as the optimal SNAP share without population heterogeneity as long as* $\bar{\kappa}$ *is "sufficiently large" so that the optimal SNAP benefits are inframarginal for all consumers. In this case, there exist values of the other preference parameters such that the social planner strictly prefers SNAP to the optimal uniform Pigouvian tax.*

Proof:

Our proof is by construction, with a numerical example that shows that the social planner will prefer optimal SNAP to the optimal uniform Pigouvian tax. We choose the following parameters:

- $s_{\bar{\beta},\bar{\kappa}}=s_{1,0}=0.5$
- $s_{\bar{\beta},0}=s_{1,\bar{\kappa}}=0$

- $\bar{y} = 10$
- $\bar{\beta} = 0.5$, $\bar{\kappa} = 0.09$
- $\alpha_g = 0.1$, $\alpha_f = 0.75$
- $\gamma = 0.95$
- $p_b = p_f = 1$ (p_n normalized to 1)

With these parameters, the optimal Pigouvian tax for just the "behavioral" types (i.e., the $\beta = \bar{\beta}$ and $\kappa = \bar{\kappa}$ population), is given by $tau_b = \frac{(1-\bar{\beta})(1+\gamma)}{(1+\bar{\beta})(1-\gamma)} = \frac{(1-0.5)(1+0.95)}{(1+0.5)(1-0.95)} = 13$. This is a substantial Pigouvian tax given the low $\bar{\beta}$ (which leads to large departure between individual's and planner's preferences) and the large value of γ which means that over-consumption of the temptation good is very costly from planner's perspective.

The optimal uniform Pigouvian tax is $\tau_b^{het} = 2.52$ according to formula above, and so transferring $y_1 = 10$ (choosing $b_1 = 0$) and rebating back the taxes collected as additional income gives a social welfare (from the planner's perspective) of $U^S P = 0.075$. This is based ona utilitarian social welfare function that takes a weighted average using the population weights.

If planner instead chooses mix of SNAP and cash, the planner finds optimal $b_1^* = 6.01$ and $y_1^* = 3.99$. SNAP benefits are inframarginal for both types of individuals because $\phi = 0.611$ for the $s_{\bar{\beta},\bar{\kappa}}$ population and $\phi = 0.612$ for the $s_{1,0}$ population. This means that there is no negative welfare effect for the $s_{1,0}$ population from substituting cash for SNAP, and the optimal SNAP for this heterogeneous population is the same as the optimal SNAP if $s_{\bar{\beta},\bar{\kappa}} = 1$, so that the whole pouplation was "behavioral".

The social welfare from planner's perspective with optimal SNAP is $U^{SP} = 0.161$, which is larger than the aggregate welfare under the optimal uniform Pigouvian tax, completing the numerical proof. ■

D.6 Welfare Calibration Details

Representative agent

First, we calibrate γ using the assumption that individuals with $\beta = 0.7$ consume 7.5 times more temptation goods than individuals with $\beta = 1$. This assumption comes from Panel A of Appendix Table OA.6, which shows that individuals with prior behavioral issues (our proxy for lower β) have roughly 7.5x more drug-and-alcohol-related ED visits than individuals without such issues (8.81 vs 1.17 per day per 10,000) in the on-SSI sample.

Because γ and the preference parameters α_g, α_f are chosen in tandem, we choose α_g, α_f enforcing that average temptation good consumption is 3%, per the pooled 2008, 2010, and 2012 Consumer Expenditure Surveys (Bureau of Labor Statistics 2008, 2010, 2012).

To do so, we solve the system:

$$\theta_0(\beta = 0.7) = \frac{(1-\alpha_g)(1-\beta\gamma)}{\alpha_g(1+\beta) + (1-\alpha_g)(1-\beta\gamma)}$$

$$\theta_0(\beta = 1) = \frac{\theta_0(\beta = 0.7)}{7.5} = \frac{(1-\alpha_g)(1-\beta\gamma)}{\alpha_g(1+\beta) + (1-\alpha_g)(1-\beta\gamma)}$$

$$\frac{\theta_0(\beta=1)+\theta_0(\beta=0.7)}{2} = \frac{\frac{\theta_0(\beta=0.7)}{7.5}+\theta_0(\beta=0.7)}{2} = .03$$

obtaining $\gamma = 0.950$, $\alpha_g = 0.779$, $\theta_0(\beta = 0.7) = 0.053$, and $\theta_0(\beta = 1) = 0.007$.

To obtain α_f, we assume $\phi_0 = .20$ (again, per the Consumer Expenditure surveys). We then solve for α_f using the following equation:

$$\phi_0 = 0.20 = \frac{(1+\beta)\alpha_g\alpha_f}{\alpha_g(1+\beta)+(1-\alpha_g)(1-\beta\gamma)}$$

obtaining $\alpha_f = 0.211$ given $\beta = 0.7$, and α_g, γ are as calculated in the previous step.

Finally, we calibrate κ using the above parameter values, such that the $MPCf^{SNAP}$ falls between 0.5 and 0.6, as calculated by Hastings and Shapiro (2018).

To numerically estimate the $MPCf^{SNAP}$, we fix κ, solve for food budget shares separately given $y_1 = 4.999, b_1 = 5.001$ and $y_1 = b_1 = 5$, then approximate the $MPCf^{SNAP}$ as

$$\frac{\phi^*(y_1 = 4.999, b_1 = 5.001) * (4.999 + 5.001) + \phi^*(y_1 = 5, b_1 = 5) * (5 + 5)}{5.001 - 5}$$

Iterating through $\kappa = (.001, .999)$, we find that $0.042 \leq \kappa \leq 0.079$ corresponds to $0.5 < MPCf^{SNAP} < 0.6$.

Finally, we solve the representative agent model for ϕ^*, given previously calibrated parameter values, and assuming $y_1 + b_1 = \bar{y} = 10$. Searching over $y_1 = [0, 10]$ and $b_1 = [0, 10 - y_1]$, for each budget set we identify the ϕ, θ which maximize total consumer utility:

$$\begin{aligned} U = \quad & \alpha_g\alpha_f\left[\log\left(\frac{\phi(y_1+b_1)}{p_f(1+\beta)}\right)+\beta\log\left(\frac{\beta\phi(y_1+b_1)}{p_f(1+\beta)}\right)\right]+ \\ & \alpha_g(1-\alpha_f)\left[\log\left(\frac{(1-\phi-\theta)(y_1+b_1)}{1+\beta}\right)+\beta\log\left(\frac{\beta(1-\phi-\theta)(y_1+b_1)}{1+\beta}\right)\right] \\ & +(1-\alpha_g)(1-\beta\gamma)\log\left(\frac{\theta(y_1+b_1)}{p_b}\right)-\kappa(\phi_0 y_1+b_1-p_f\phi(y_1+b_1))^2 \end{aligned}$$

normalizing $p_f = p_b = 1$.

Next, we evaluate U^{SP} at each tuple (b_1, y_1, ϕ, θ), selecting the tuple which maximizes planner utility. U^{SP} is given by:

$$\begin{aligned} U^{SP} = \quad & 2\alpha_g\alpha_f\log\left(\frac{\phi(y_1+b_1)}{2p_f}\right)+ \\ & 2\alpha_g(1-\alpha_f)\log\left(\frac{(1-\phi-\theta)(y_1+b_1)}{2}\right)+ \\ & +(1-\alpha_g)(1-\gamma)\log\left(\frac{\theta(y_1+b_1)}{p_b}\right) \end{aligned}$$

Then, the SNAP share of food expenditures can be calculated as

$$\frac{b_1(\phi = \phi^*)}{\phi^* \bar{y}}$$

Representative agent with CES preferences

We explored the sensitivity of our calibration results to allow for a richer model of consumer demand where, instead of our baseline Cobb-Douglas utility function, we calibrate a nested CES demand system. Specifically, the utility function is Cobb-Doublas in the temptation good and a CES aggregate of food and non-food, so that food and non-food are in the "inner nest" with an elasticity of substitution parameter $\sigma = \frac{1}{1-\epsilon}$.

First, we choose parameter values based on the Cobb-Douglas representative agent calibration: $\beta = 0.7, \gamma = 0.950, \alpha_g = .779, \alpha_f = .221, \phi_0 = .20, 0.042 \leq \kappa \leq 0.079$. We also fix a value of ϵ, the CES parameter defined by $\sigma = \frac{1}{1-\epsilon}$ where σ is the elasticity of substitution between food and non-food.

Searching over $y_1 = [0, 10]$ and $b_1 = [0, 10 - y_1]$, for each budget set we identify the ϕ, θ which maximize total consumer utility:

$$\begin{aligned} U &= \log\left(\left(\alpha_f\left(\frac{\phi(y_1+b_1)}{p_f(1+\beta)}\right)^{\epsilon} + (1-\alpha_f)\left(\frac{(1-\phi-\theta)(y_1+b_1)}{1+\beta}\right)^{\epsilon}\right)^{\frac{\alpha_g}{\epsilon}} \cdot \left(\frac{\theta(y_1+b_1)}{p_b}\right)^{(1-\alpha_g)}\right) \\ &+ \beta\log\left(\left(\alpha_f\left(\frac{\beta\phi(y_1+b_1)}{p_f(1+\beta)}\right)^{\epsilon} + (1-\alpha_f)\left(\frac{\beta(1-\phi-\theta)(y_1+b_1)}{1+\beta}\right)^{\epsilon}\right)^{\frac{\alpha_g}{\epsilon}} \cdot \left(\frac{\theta(y_1+b_1)}{p_b}\right)^{-\gamma(1-\alpha_g)}\right) \\ &+ -\kappa\left[(\phi_0 y_1 + b_1) - p_f\,\phi(y_1+b_1)\right]^2 \end{aligned}$$

and we again normalize $p_f = p_b = 1$.

Next, we evaluate U^{SP} at each tuple (b_1, y_1, ϕ, θ), selecting the tuple which maximizes planner utility. U^{SP} here is given by:

$$\begin{aligned} U &= \log\left(\left(\alpha_f\left(\frac{\phi(y_1+b_1)}{2p_f}\right)^{\epsilon} + (1-\alpha_f)\left(\frac{(1-\phi-\theta)(y_1+b_1)}{2}\right)^{\epsilon}\right)^{\frac{\alpha_g}{\epsilon}} \cdot \left(\frac{\theta(y_1+b_1)}{p_b}\right)^{(1-\alpha_g)}\right) \\ &+ \log\left(\left(\alpha_f\left(\frac{\phi(y_1+b_1)}{2p_f}\right)^{\epsilon} + (1-\alpha_f)\left(\frac{(1-\phi-\theta)(y_1+b_1)}{2}\right)^{\epsilon}\right)^{\frac{\alpha_g}{\epsilon}} \cdot \left(\frac{\theta(y_1+b_1)}{p_b}\right)^{-\gamma(1-\alpha_g)}\right) \end{aligned}$$

And the optimal SNAP share is again given by:

$$\frac{b_1(\phi = \phi^*)}{\phi^* \bar{y}}$$

Appendix Figure OA.22 shows that the optimal SNAP share is decreasing in ϵ until eventually ϵ is sufficiently large that the optimal SNAP share is driven down to zero. Intuitively, low values of ϵ imply that increased food spending due to SNAP primarily reduces temptation good spending, which enables the planner to choose a higher optimal SNAP share. At higher values of ϵ, food and non-food become stronger demand substitutes, which means that increased food spending due to SNAP will primarily substitute for non-food spending rather than spending on the temptation good. To rationalize the current SNAP share of food spending with CES demand, we would need a value of ϵ of approximately -0.425, which corresponds to an elasticity of substitution between food and non-food of 0.70.

Heterogeneous agents

We now assume that 50% of individuals have $\beta = 1$ and 50% have $\beta = 0.4$ (such that the population average remains 0.7).

We are interested in how the optimal SNAP share changes as we vary the correlation ρ between β and κ. For simplicity, we also assume that individuals can only have $\kappa = .042$ or $\kappa = 0$. This leaves us with four types: $\beta = 0.4$, $\kappa = 0.042$; $\beta = 0.4$, $\kappa = 0$; $\beta = 1$, $\kappa = 0.042$; and $\beta = 1$, $\kappa = 0$.

In order to vary the correlation between β and κ, we can change the share of individuals with $\beta = 1$ or $\beta = .4$ who have a given value of κ, while keeping shares with each value of β constant at 0.5.

For given γ, α_g and α_f (determined by the assumed temptation food budget share ratio), we first solve for ϕ_0 for each β. Recall:

$$\theta_0 = \frac{(1-\alpha_g)(1-\beta\gamma)}{\alpha_g(1+\beta) + (1-\alpha_g)(1-\beta\gamma)}$$

Next, searching over $y_1 = [0, 10]$ and $b_1 = [0, 10 - y_1]$, we solve the consumer's optimization problem given the budget set separately for each β, assuming $\kappa = 0.042$, because $\kappa = 0$ types receive a weight of 0 in the welfare function when SNAP is inframarginal. We obtain the optimal food budget share ϕ for each agent type, and solve for the optimal temptation good budget share θ for each agent using the relationship

$$\theta = \frac{(1-\phi)(1-\alpha_g)(1-\beta\gamma)}{(1+\beta)\alpha_g(1-\alpha_f) + (1-\alpha_g)(1-\beta\gamma)}$$

Social planner utility U^{SP} is the share-weighted sum of U^{SP} for each consumer type with non-zero κ:

$$\begin{aligned}
U^{SP} \quad = \quad & s_{\beta=0.4,\kappa=0.042} * \left(2\alpha_g \alpha_f \log\left(\frac{\phi(\beta = 0.4) * (y_1 + b_1)}{2p_f} \right) \right. \\
+ \quad & 2\alpha_g(1-\alpha_f) \log\left(\frac{(1 - \phi(\beta = 0.4) - \theta(\beta = 0.4)) * (y_1 + b_1)}{2} \right) \\
+ \quad & \left. (1-\alpha_g)(1-\gamma) \log\left(\frac{\theta(\beta = 0.4) * (y_1 + b_1)}{p_b} \right) \right) \\
+ \quad & s_{\beta=1,\kappa=0.042} * \left(2\alpha_g \alpha_f \log\left(\frac{\phi(\beta = 1) * (y_1 + b_1)}{2p_f} \right) \right. \\
+ \quad & 2\alpha_g(1-\alpha_f) \log\left(\frac{(1 - \phi(\beta = 1) - \theta(\beta = 1)) * (y_1 + b_1)}{2} \right) \\
+ \quad & \left. (1-\alpha_g)(1-\gamma) \log\left(\frac{\theta(\beta = 1) * (y_1 + b_1)}{p_b} \right) \right)
\end{aligned}$$

where we normalize $p_f = p_b = 1$.

We evaluate U^{SP} at each tuple $(y_1, b_1, \phi(\beta = 0.4), \theta(\beta = 0.4), \phi(\beta = 1), \theta(\beta = 1))$, and select the tuple which maximizes planner utility.

The optimal SNAP share of food expenditures for given type shares $s_{\beta=0.4,\kappa=0.042}$, $s_{\beta=0.4,\kappa=0}$, $s_{\beta=1,\kappa=0.042}$ and $s_{\beta=1,\kappa=0}$ (that is, for a given correlation between β and κ) is given by:

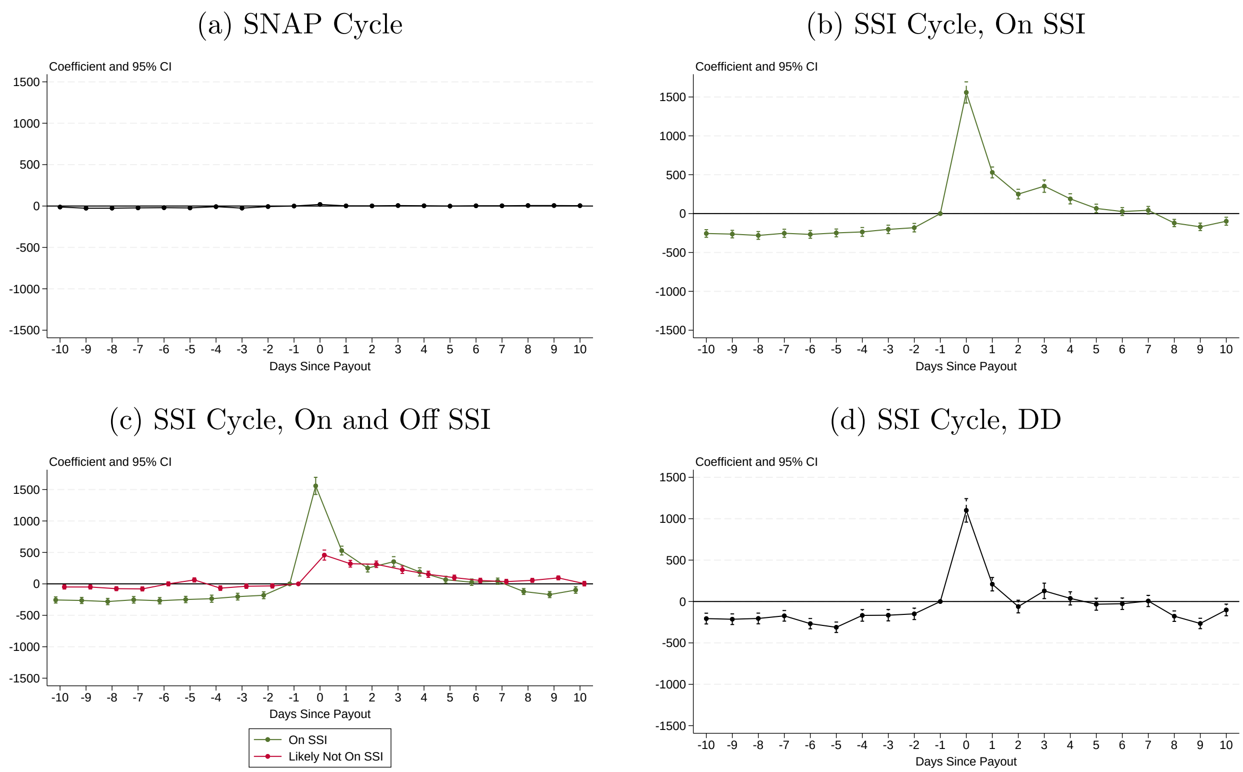
$$\frac{b_1}{\frac{s_{\beta=0.4,\kappa=0.042}}{0.5}\phi^*(\beta = 0.4)\bar{y} + \frac{s_{\beta=1,\kappa=0.042}}{0.5}\phi^*(\beta = 1)\bar{y}}$$

Appendix Figure OA.23 shows that, as expected, the optimal SNAP share is decreasing in ρ. If $\rho = 0$ (so that β and κ are completely uncorrelated in the population), then we calculate an optimal SNAP share of 0.142, which is slightly larger than the representative agent scenario.[61] Appendix Figure OA.23 also shows that, regardless of the value of ρ we assume, given our assumptions about the other parameters, the optimal SNAP share of food spending is almost always below the actual SNAP share of food spending.

[61] The $\rho = 0$ case corresponds to equal shares of all $s_{\beta,\kappa}$ types, and in this case there is a trade-off between increasing SNAP share for the $(\bar{\beta},\bar{\kappa})$ behavioral type and not imposing a welfare cost on the $\beta = 1$ type that engages in mental accounting (i.e., the $(\beta = 1,\kappa = \bar{\kappa})$ type. The planner resolves this trade-off by choosing an optimal SNAP share that is somewhat larger than 50 percent of the optimal SNAP share if the planner only optimized for the $(\bar{\beta},\bar{\kappa})$ type. This is because the planner does more to correct the mistake of the $(\bar{\beta},\bar{\kappa})$ type. Intuitively, starting from no SNAP, the planner recognizes that there is no first-order welfare cost of increasing SNAP for the $(\beta = 1,\kappa = \bar{\kappa})$ type, but there is a first-order welfare benefit of swapping cash for SNAP for the $(\bar{\beta},\bar{\kappa})$ type.

E Appendix Figures

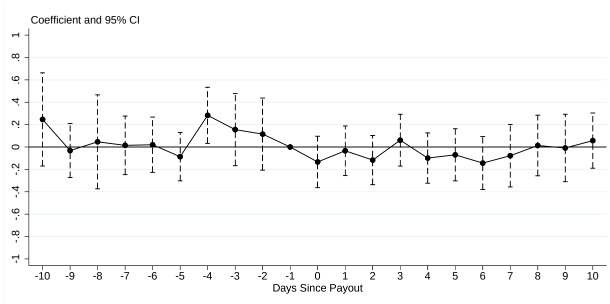
Figure OA.1: Effects of SNAP and SSI on Refills, Full Samples



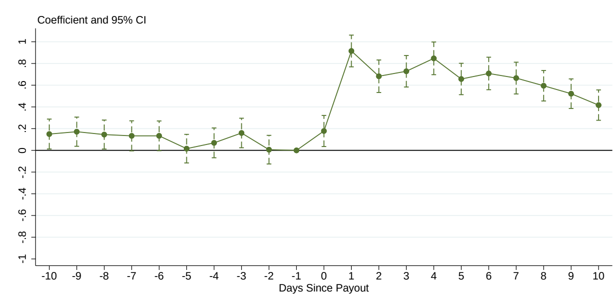
Notes: This figure shows estimates of (a) β_r from equation (2), (b) $\alpha_l + \beta_l$ from equation (1), (c) $\alpha_l + \beta_l$ from equation (1) (in green) overlaid with α_l from equation (1) (in red), and (d) β_l from equation (1). The outcome variable is refills per day per 10,000. In (a), N person-months on SNAP (and on SSI) = 4,568,532. In (b)-(d), N person-months on SSI (and on SNAP) = 4,568,532, and N person-months likely not on SSI (but on SNAP) = 2,441,425. Standard errors are clustered at the date (day-month-year) level.

Figure OA.2: Effects of SNAP and SSI on Drug and Alcohol ED Visits, Overlap Sample

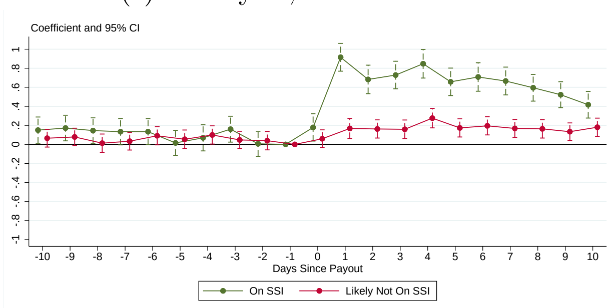
(a) SNAP Cycle



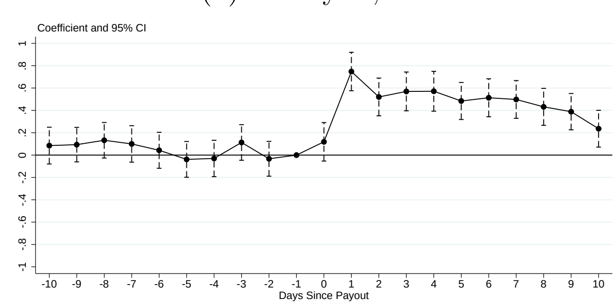
(b) SSI Cycle, On SSI



(c) SSI Cycle, On and Off SSI

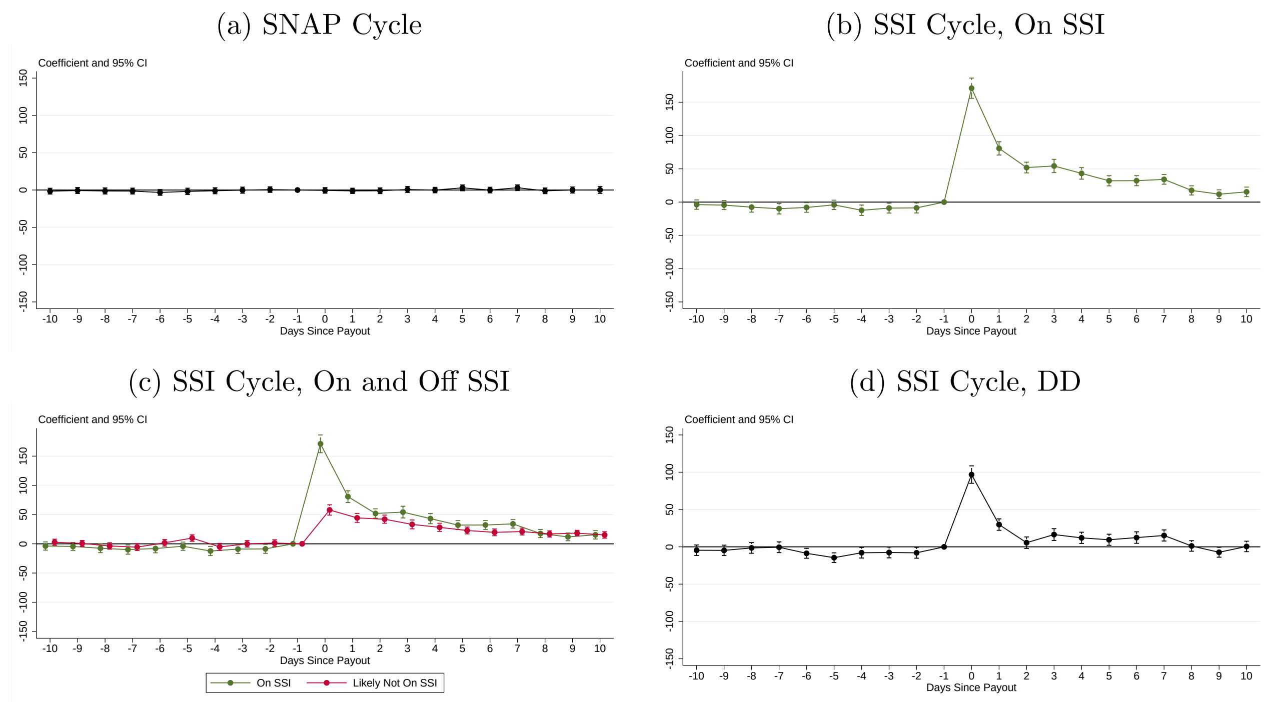


(d) SSI Cycle, DD



Notes: This figure shows estimates of (a) β_r from equation (2), (b) $\alpha_l + \beta_l$ from equation (1), (c) $\alpha_l + \beta_l$ from equation (1) (in green) overlaid with α_l from equation (1) (in red), and (d) β_l from equation (1). The outcome variable is ED visits for drug-and-alcohol-related conditions per day per 10,000. In (a), N person-months on SNAP (and on SSI) = 9,794,149. In (b)-(d), N person-months on SSI (and on SNAP) = 9,794,149, and N person-months likely not on SSI (but on SNAP) = 12,815,630. Standard errors are clustered at the date (day-month-year) level.

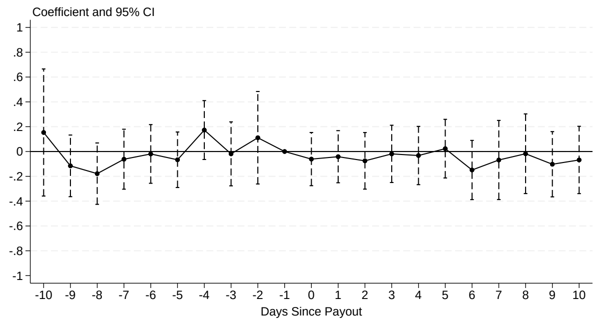
Figure OA.3: Effects of SNAP and SSI on First Fills, Overlap Samples



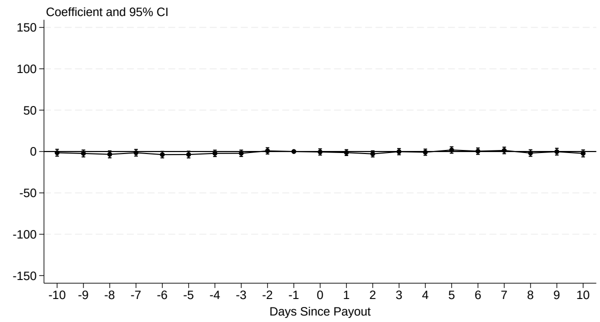
Notes: This figure shows estimates of (a) β_r from equation (2), (b) $\alpha_l + \beta_l$ from equation (1), (c) $\alpha_l + \beta_l$ from equation (1) (in green) overlaid with α_l from equation (1) (in red), and (d) β_l from equation (1). The outcome variable is first fills per day per 10,000. In (a), N person-months on SNAP (and on SSI) = 4,568,532. In (b)-(d), N person-months on SSI (and on SNAP) = 4,568,532, and N person-months likely not on SSI (but on SNAP) = 2,441,425. Standard errors are clustered at the date (day-month-year) level.

Figure OA.4: Effects of SNAP on Drug and Alcohol ED Visits and First Fills, Early Payouts Only

(a) Drug and Alcohol ED Visits



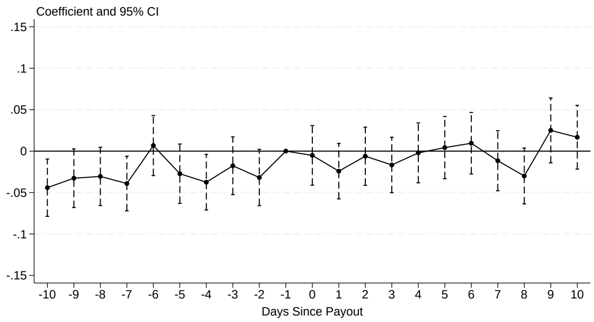
(b) First Fills



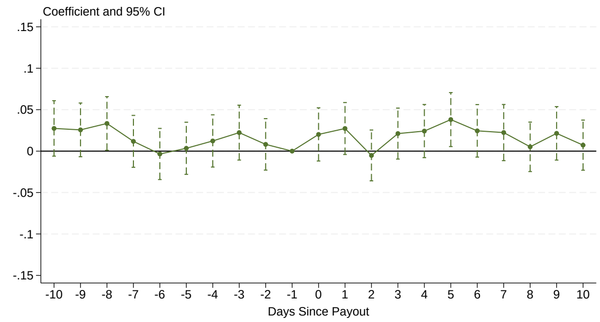
Notes: This figure shows estimates of β_r from equation (2), estimated using only person-months corresponding to individuals who are paid from the 1st to the 10th and who were assigned a SNAP case number before September 2012. Subfigure (a) uses the union of this restriction and the overlap ED sample, while subfigure (b) uses the union of this restriction and the overlap drug fills sample. The outcome variables are (a) ED visits for drug-and-alcohol-related conditions per day per 10,000 and (b) first fills per day per 10,000. In (a), N person-months on SNAP and SSI = 7,806,477. In (b), N person-months on SNAP and SSI = 3,950,760. Standard errors are clustered at the date (day-month-year) level.

Figure OA.5: Effects of SNAP and SSI on ED Visits for Neoplasms, Full Sample

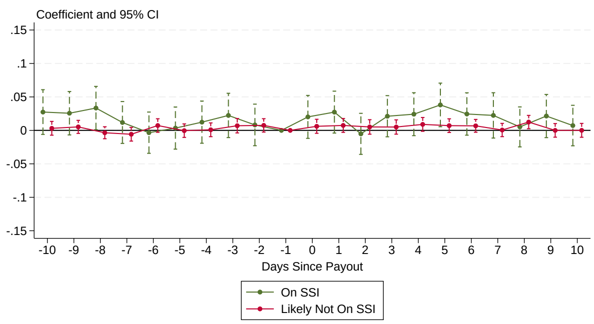
(a) SNAP Cycle



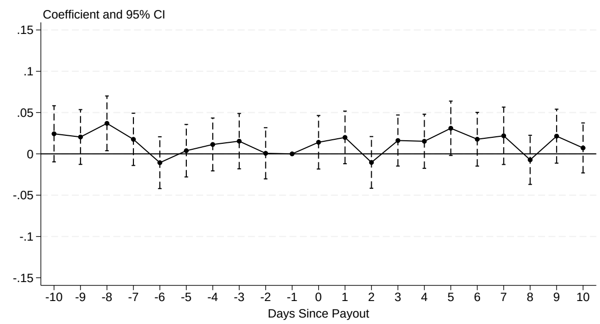
(b) SSI Cycle, On SSI



(c) SSI Cycle, On and Off SSI



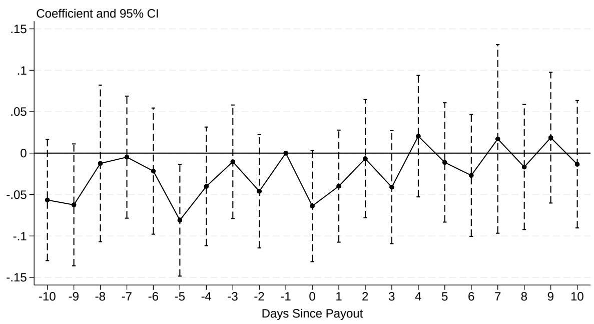
(d) SSI Cycle, DD



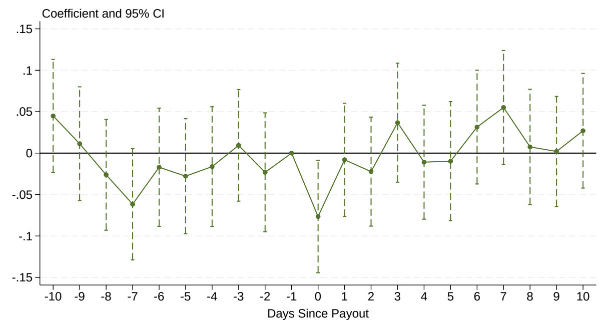
Notes: This figure shows estimates of (a) β_r from equation (2), (b) $\alpha_l + \beta_l$ from equation (1), (c) $\alpha_l + \beta_l$ from equation (1) (in green) overlaid with α_l from equation (1) (in red), and (d) β_l from equation (1). The outcome variable is ED visits for neoplasms (cancerous and benign tumors) per day per 10,000. In (a), N person-months on SNAP = 29,016,217. In (b)-(d), N person-months on SSI = 19,236,048, and N person-months likely not on SSI = 109,240,417. Standard errors are clustered at the date (day-month-year) level.

Figure OA.6: Effects of SNAP and SSI on ED Visits for Infectious Diseases, Full Sample

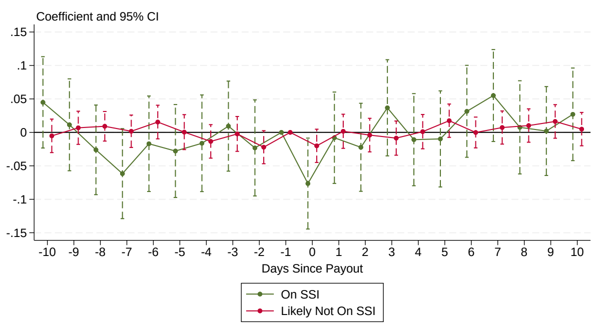
(a) SNAP Cycle



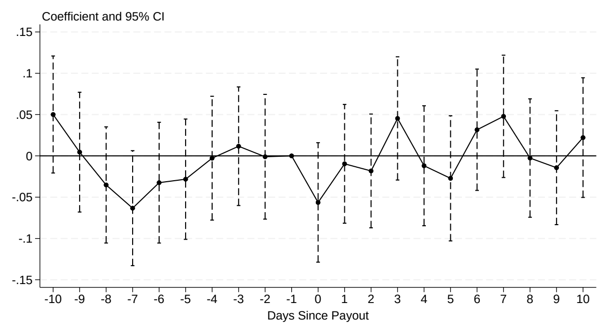
(b) SSI Cycle, On SSI



(c) SSI Cycle, On and Off SSI



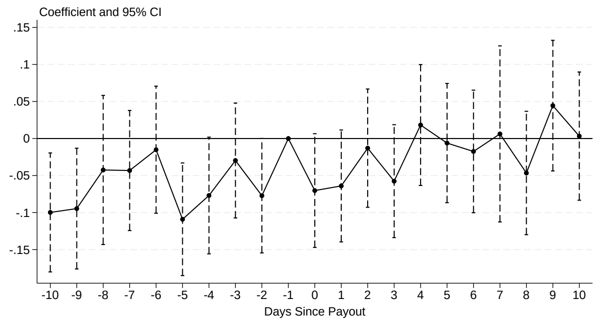
(d) SSI Cycle, DD



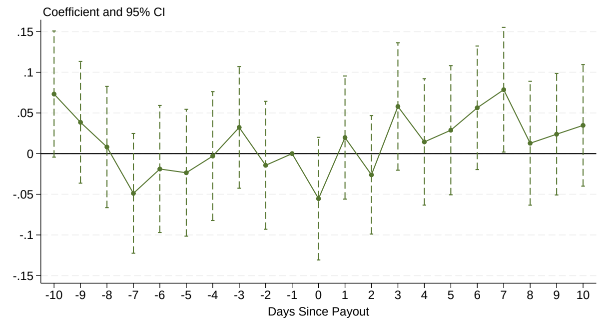
Notes: This figure shows estimates of (a) β_r from equation (2), (b) $\alpha_l + \beta_l$ from equation (1), (c) $\alpha_l + \beta_l$ from equation (1) (in green) overlaid with α_l from equation (1) (in red), and (d) β_l from equation (1). The outcome variable is ED visits for infectious/parasitic diseases per day per 10,000. In (a), N person-months on SNAP = 29,016,217. In (b)-(d), N person-months on SSI = 19,236,048, and N person-months likely not on SSI = 109,240,417. Standard errors are clustered at the date (day-month-year) level.

Figure OA.7: Effects of SNAP and SSI on ED Visits for Either Neoplasms or Infectious Diseases, Full Sample

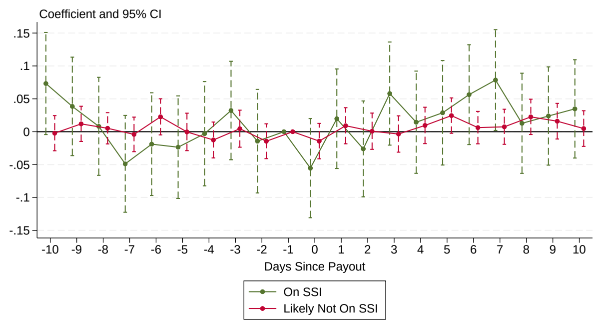
(a) SNAP Cycle



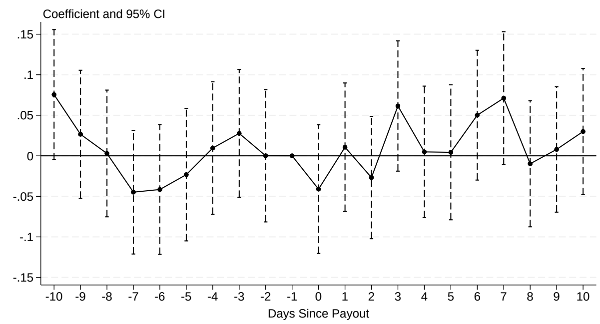
(b) SSI Cycle, On SSI



(c) SSI Cycle, On and Off SSI

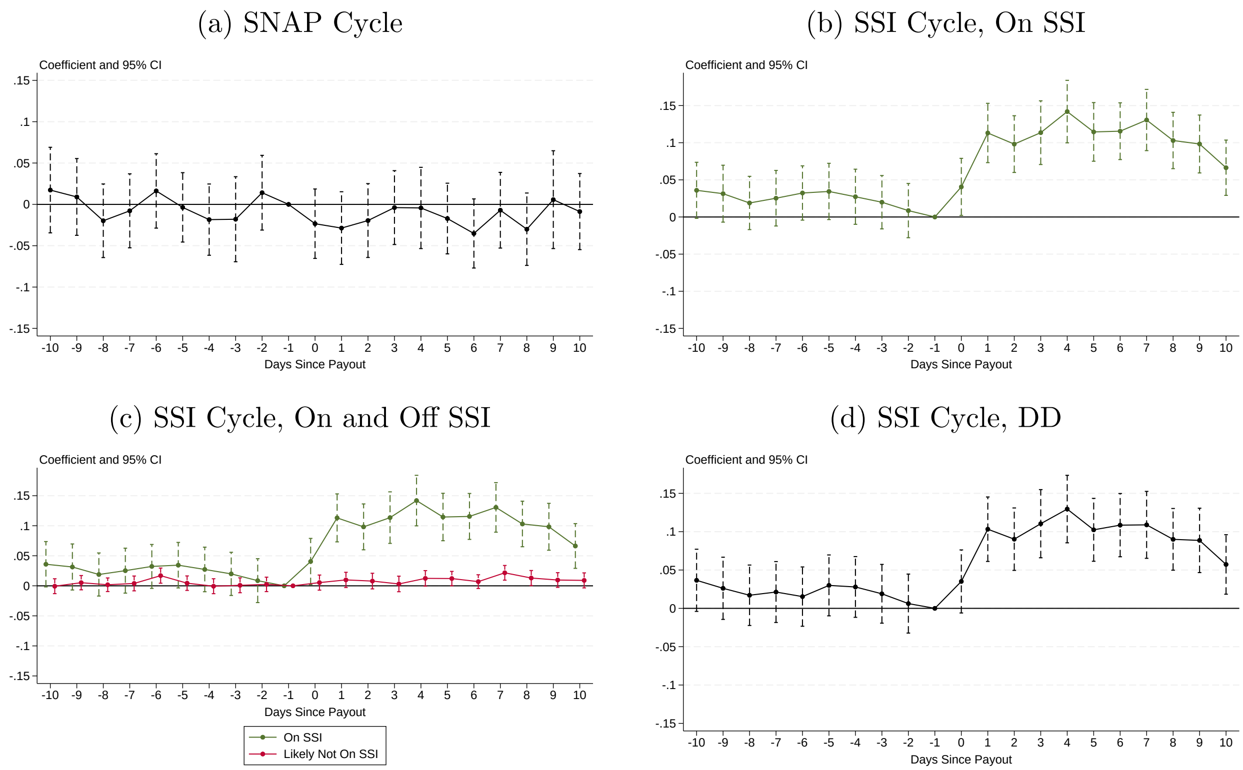


(d) SSI Cycle, DD



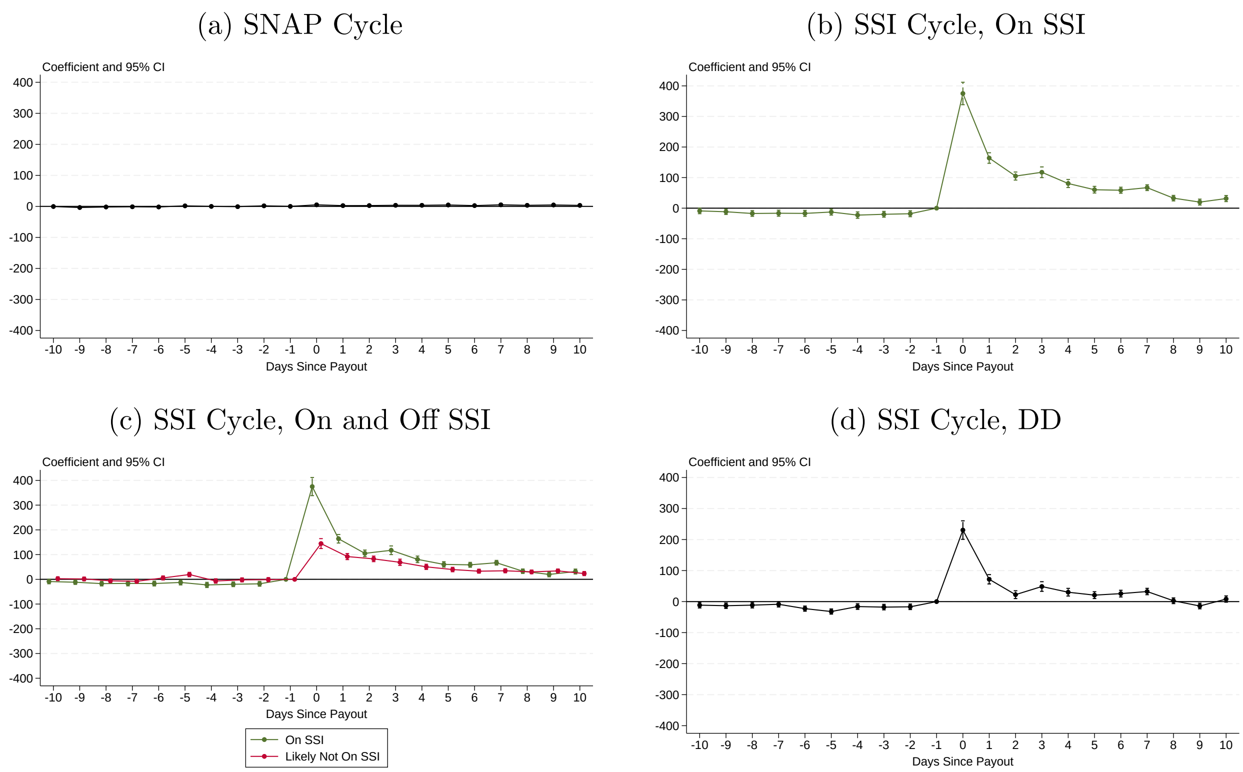
Notes: This figure shows estimates of (a) β_r from equation (2), (b) $\alpha_l + \beta_l$ from equation (1), (c) $\alpha_l + \beta_l$ from equation (1) (in green) overlaid with α_l from equation (1) (in red), and (d) β_l from equation (1). The outcome variable is ED visits for either neoplasms or infectious/parasitic diseases per day per 10,000. In (a), N person-months on SNAP = 29,016,217. In (b)-(d), N person-months on SSI = 19,236,048, and N person-months likely not on SSI = 109,240,417. Standard errors are clustered at the date (day-month-year) level.

Figure OA.8: Effects of SNAP and SSI on Drug and Alcohol ED Visits With An ICU Stay, Full Sample



Notes: This figure shows estimates of (a) β_r from equation (2), (b) $\alpha_l + \beta_l$ from equation (1), (c) $\alpha_l + \beta_l$ from equation (1) (in green) overlaid with α_l from equation (1) (in red), and (d) β_l from equation (1). The outcome variable is drug-and-alcohol-related ED visits which involve an ICU stay per day per 10,000. In (a), N person-months on SNAP = 29,016,217. In (b)-(d), N person-months on SSI = 19,236,048, and N person-months likely not on SSI = 109,240,417. Standard errors are clustered at the date (day-month-year) level.

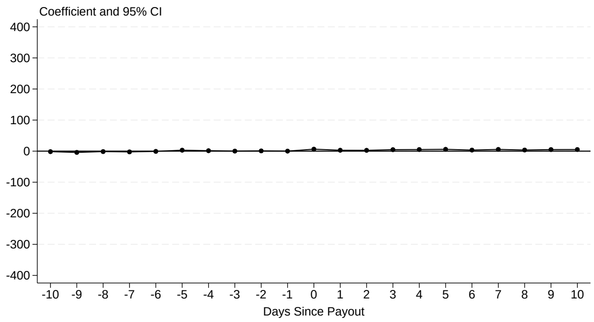
Figure OA.9: Effects of SNAP and SSI on Non-Maintenance Fills, Full Samples



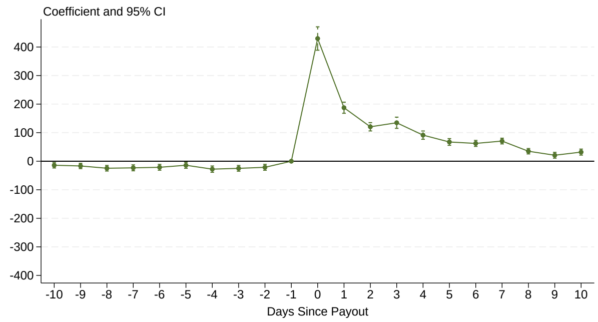
Notes: This figure shows estimates of (a) β_r from equation (2), (b) $\alpha_l + \beta_l$ from equation (1), (c) $\alpha_l + \beta_l$ from equation (1) (in green) overlaid with α_l from equation (1) (in red), and (d) β_l from equation (1). The outcome variable is non-maintenance fills per day per 10,000. In (a), N person-months on SNAP = 7,877,590. In (b)-(d), N person-months on SSI = 9,288,812, and N person-months likely not on SSI = 7,377,659. Standard errors are clustered at the date (day-month-year) level.

Figure OA.10: Effects of SNAP and SSI on Non-Maintenance Fills, Overlap Samples

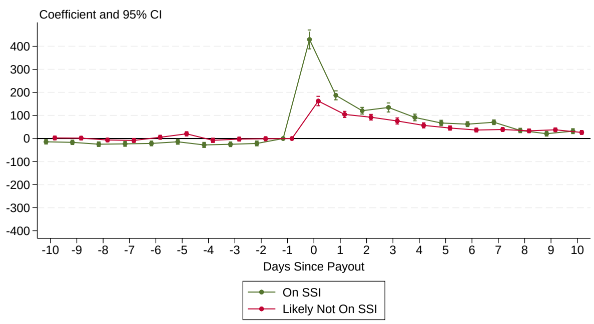
(a) SNAP Cycle



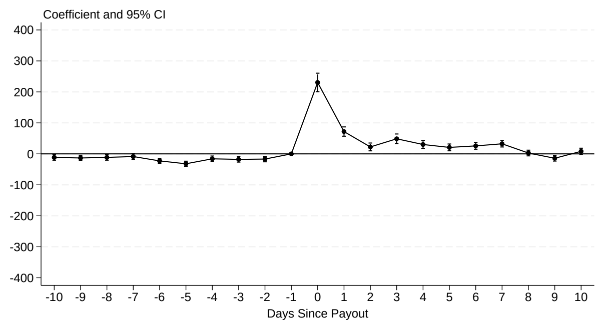
(b) SSI Cycle, On SSI



(c) SSI Cycle, On and Off SSI

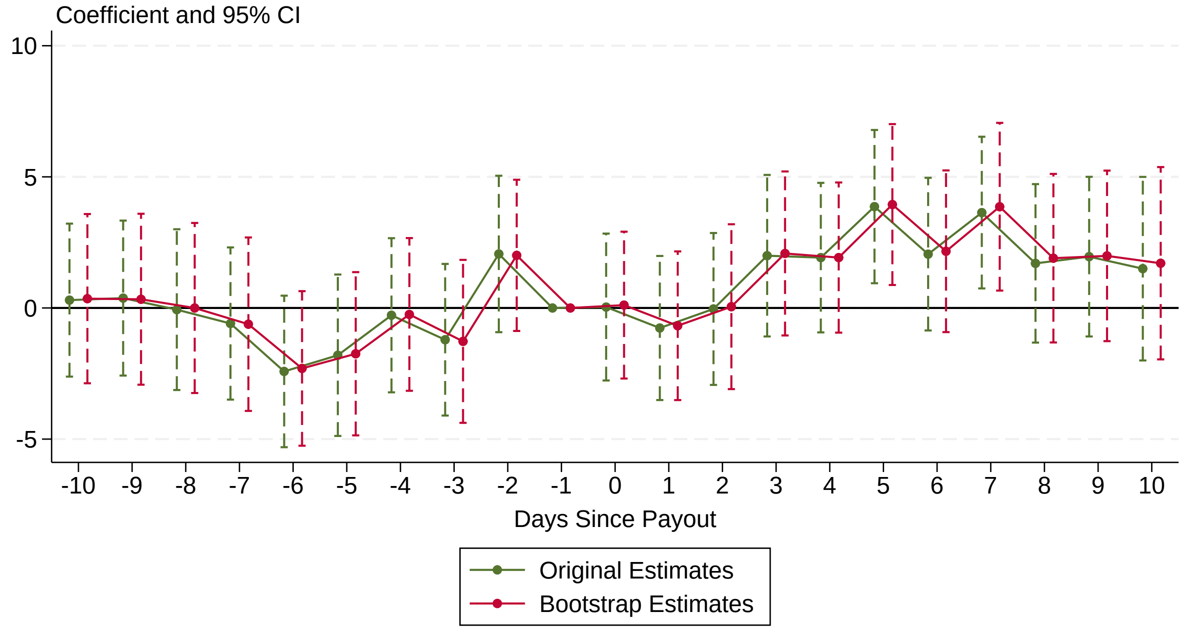


(d) SSI Cycle, DD



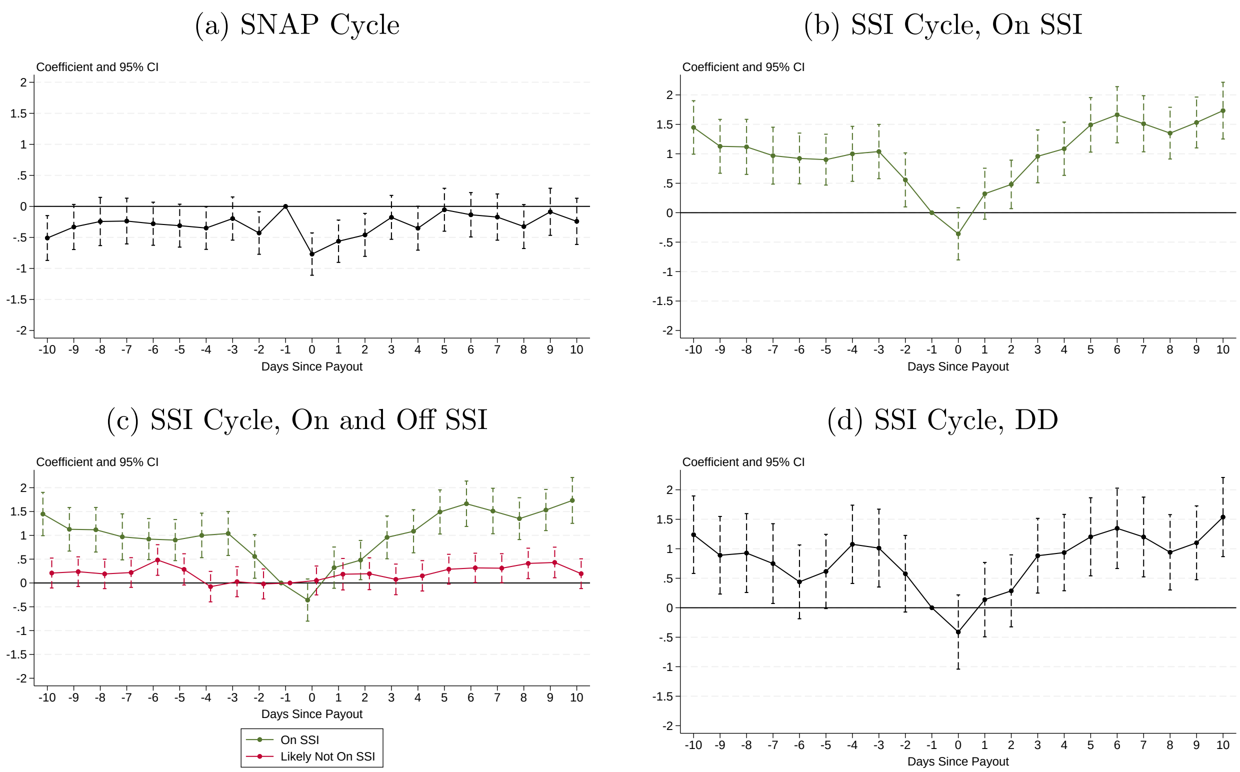
Notes: This figure shows estimates of (a) β_r from equation (2), (b) $\alpha_l + \beta_l$ from equation (1), (c) $\alpha_l + \beta_l$ from equation (1) (in green) overlaid with α_l from equation (1) (in red), and (d) β_l from equation (1). The outcome variable is non-maintenance fills per day per 10,000. In (a), N person-months on SNAP (and on SSI) = 4,568,532. In (b)-(d), N person-months on SSI (and on SNAP) = 4,568,532, and N person-months likely not on SSI (but on SNAP) = 2,441,425. Standard errors are clustered at the date (day-month-year) level.

Figure OA.11: Effects of SNAP on First Fills, Original vs. Bootstrap Estimates



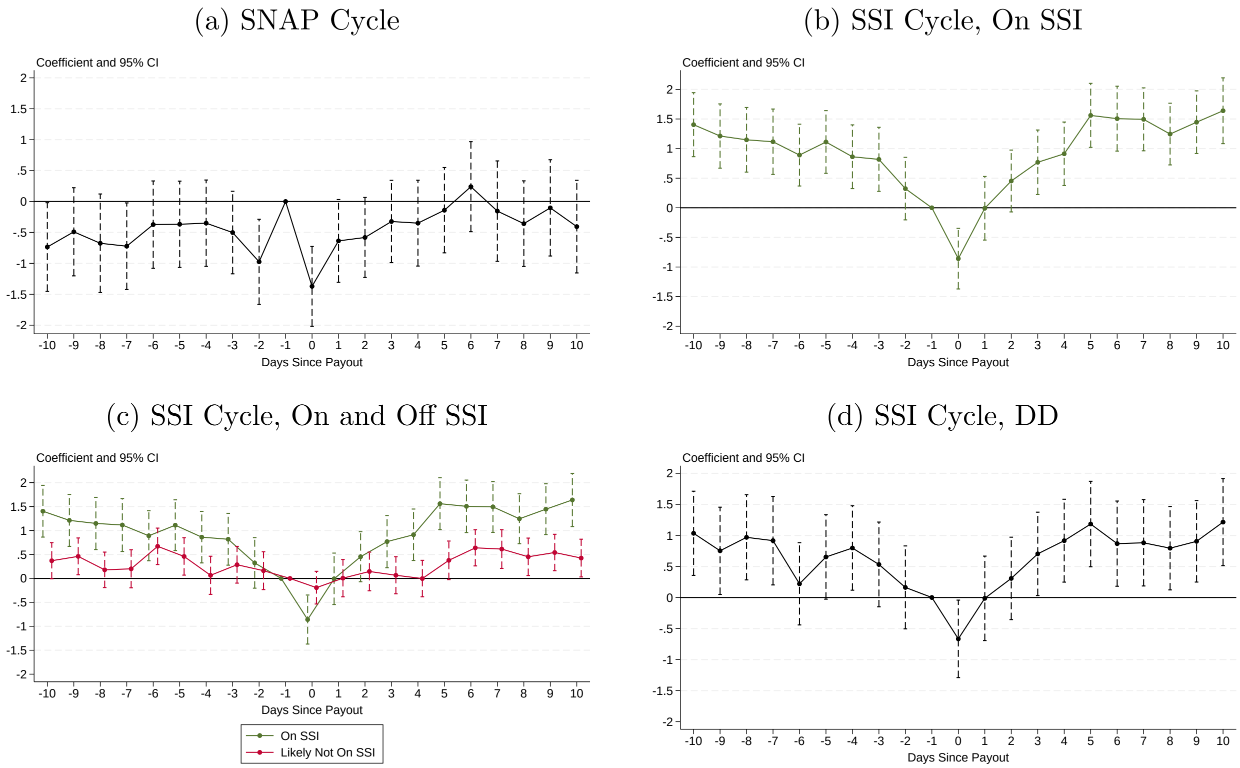
Notes: This figure shows estimates of β_r from equation (2). β_r is estimated using the SNAP drug fills sample collapsed to the date-case number-assignment time level (in green) as well as using a bootstrapping procedure with 250 repetitions which simulates standard errors clustered at the individual level (in red). Original estimates use clustered standard errors at the date (day-month-year) level, while bootstrap estimates use simulated clustered standard errors at the individual level.

Figure OA.12: Effects of SNAP and SSI on Nutrition-Sensitive ED Visits, Full Sample



Notes: This figure shows estimates of (a) β_r from equation (2), (b) $\alpha_l + \beta_l$ from equation (1), (c) $\alpha_l + \beta_l$ from equation (1) (in green) overlaid with α_l from equation (1) (in red), and (d) β_l from equation (1). The outcome variable is ED visits for nutrition-sensitive conditions per day per 10,000. In (a), N person-months on SNAP = 29,016,217. In (b)-(d), N person-months on SSI = 19,236,048, and N person-months likely not on SSI = 109,240,417. Standard errors are clustered at the date (day-month-year) level.

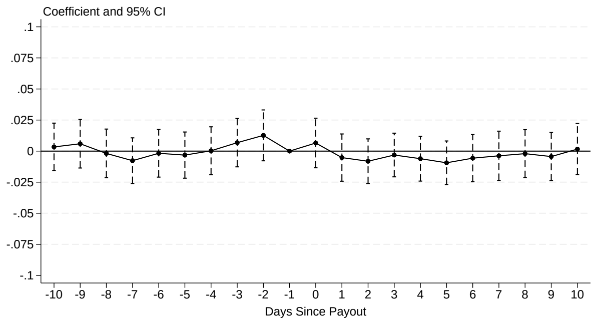
Figure OA.13: Effects of SNAP and SSI on Nutrition-Sensitive ED Visits, Overlap Sample



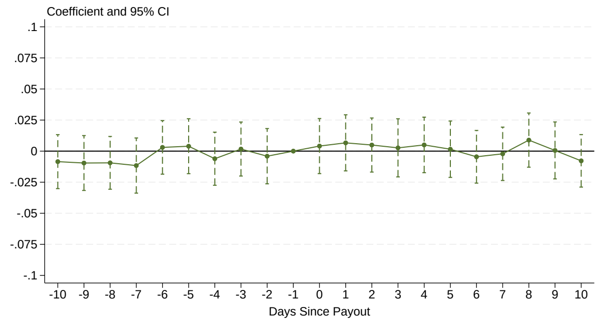
Notes: This figure shows estimates of (a) β_r from equation (2), (b) $\alpha_l + \beta_l$ from equation (1), (c) $\alpha_l + \beta_l$ from equation (1) (in green) overlaid with α_l from equation (1) (in red), and (d) β_l from equation (1). The outcome variable is ED visits for nutrition-sensitive conditions per day per 10,000. In (a), N person-months on SNAP (and on SSI) = 9,794,149. In (b)-(d), N person-months on SSI (and on SNAP) = 9,794,149, and N person-months likely not on SSI (but on SNAP) = 12,815,630. Standard errors are clustered at the date (day-month-year) level.

Figure OA.14: Effects of SNAP and SSI on ED Visits for Hypoglycemia, Full Sample

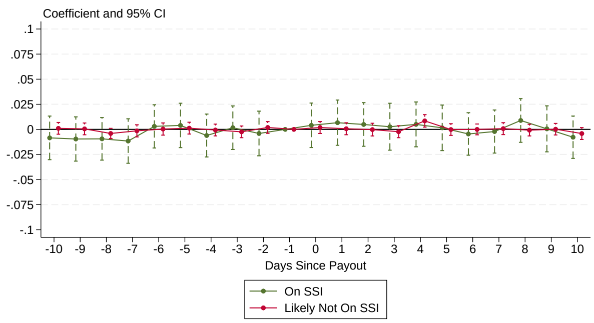
(a) SNAP Cycle



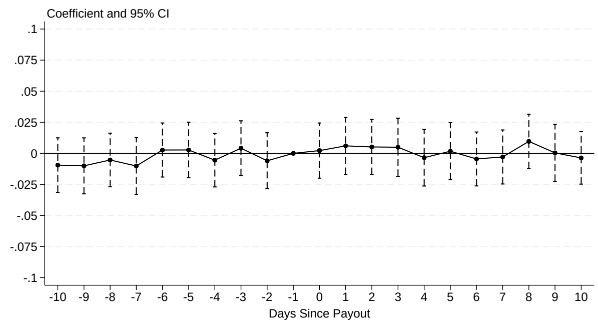
(b) SSI Cycle, On SSI



(c) SSI Cycle, On and Off SSI

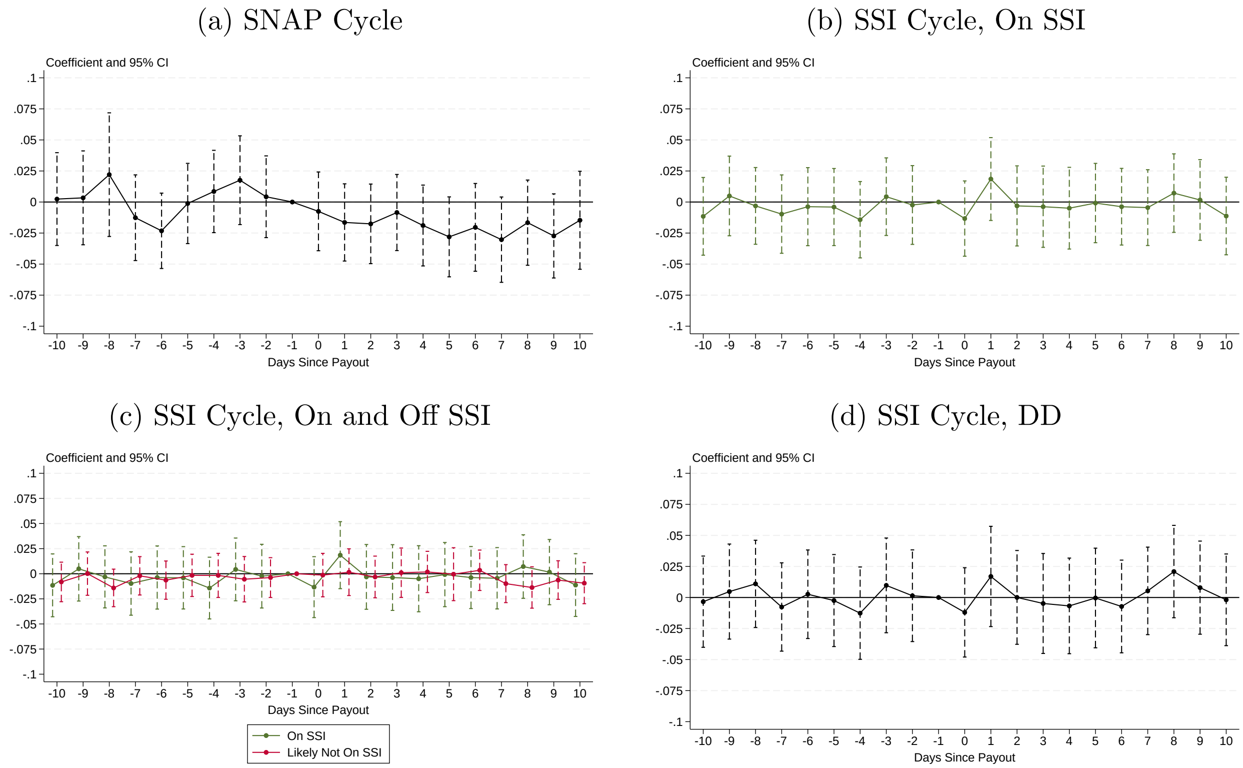


(d) SSI Cycle, DD



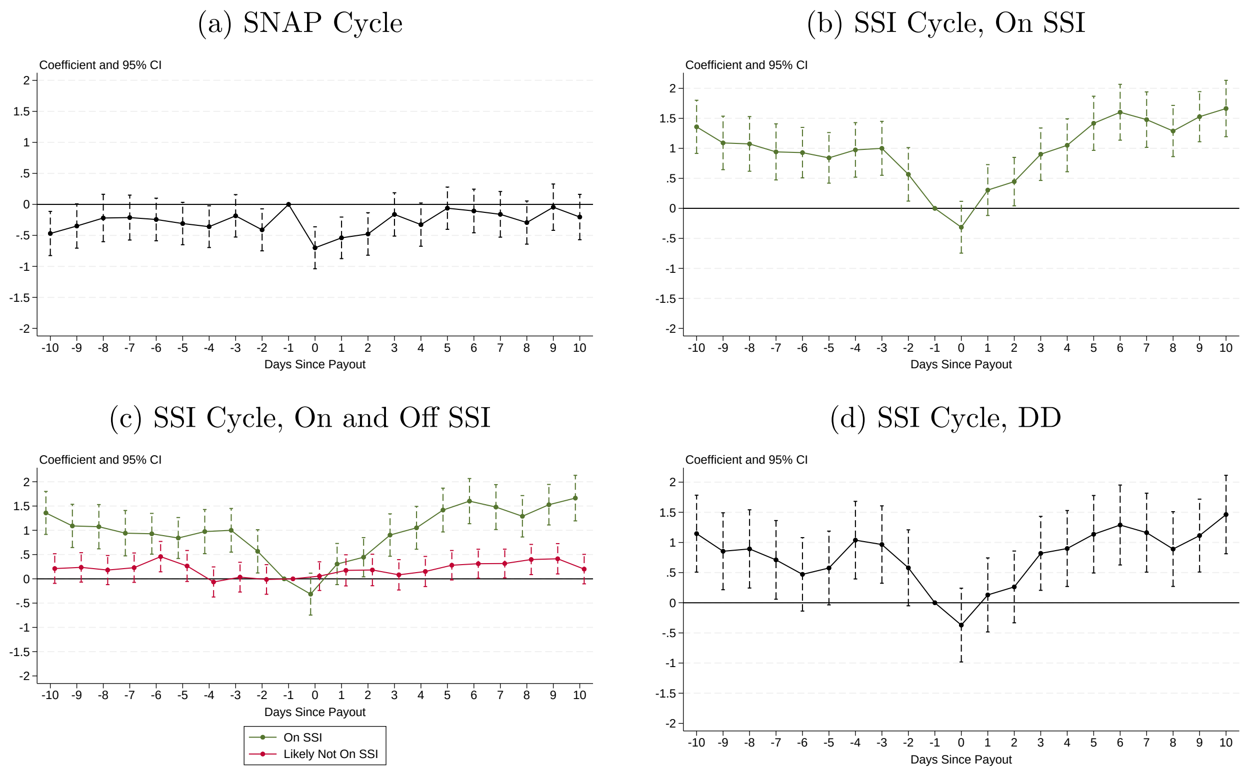
Notes: This figure shows estimates of (a) β_r from equation (2), (b) $\alpha_l + \beta_l$ from equation (1), (c) $\alpha_l + \beta_l$ from equation (1) (in green) overlaid with α_l from equation (1) (in red), and (d) β_l from equation (1). The outcome variable is ED visits for hypertension per day per 10,000. In (a), N person-months on SNAP = 29,016,217. In (b)-(d), N person-months on SSI = 19,236,048, and N person-months likely not on SSI = 109,240,417. Standard errors are clustered at the date (day-month-year) level.

Figure OA.15: Effects of SNAP and SSI on ED Visits for Hypoglycemia, Overlap Sample



Notes: This figure shows estimates of (a) β_r from equation (2), (b) $\alpha_l + \beta_l$ from equation (1), (c) $\alpha_l + \beta_l$ from equation (1) (in green) overlaid with α_l from equation (1) (in red), and (d) β_l from equation (1). The outcome variable is ED visits for hypertension per day per 10,000. In (a), N person-months on SNAP (and on SSI) = 9,794,149. In (b)-(d), N person-months on SSI (and on SNAP) = 9,794,149, and N person-months likely not on SSI (but on SNAP) = 12,815,630. Standard errors are clustered at the date (day-month-year) level.

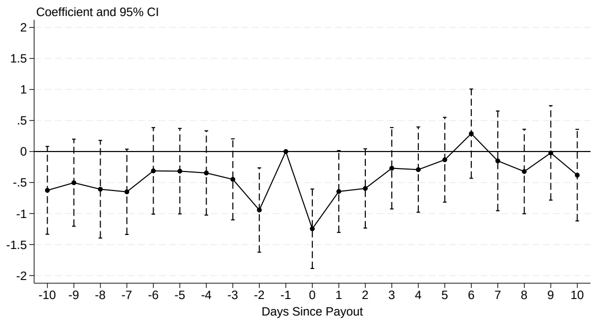
Figure OA.16: Effects of SNAP and SSI on ED Visits for Diabetes-Related Complications, Full Sample



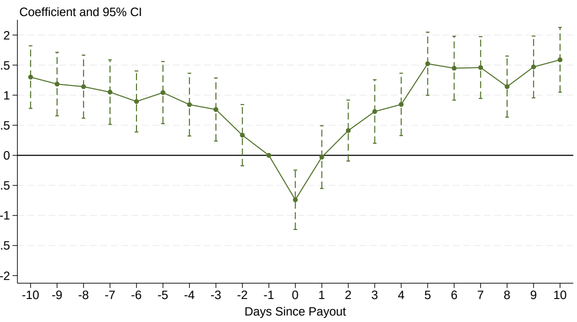
Notes: This figure shows estimates of (a) β_r from equation (2), (b) $\alpha_l + \beta_l$ from equation (1), (c) $\alpha_l + \beta_l$ from equation (1) (in green) overlaid with α_l from equation (1) (in red), and (d) β_l from equation (1). The outcome variable is ED visits for diabetes-related complications per day per 10,000. In (a), N person-months on SNAP = 29,016,217. In (b)-(d), N person-months on SSI = 19,236,048, and N person-months likely not on SSI = 109,240,417. Standard errors are clustered at the date (day-month-year) level.

Figure OA.17: Effects of SNAP and SSI on ED Visits for Diabetes-Related Complications, Overlap Sample

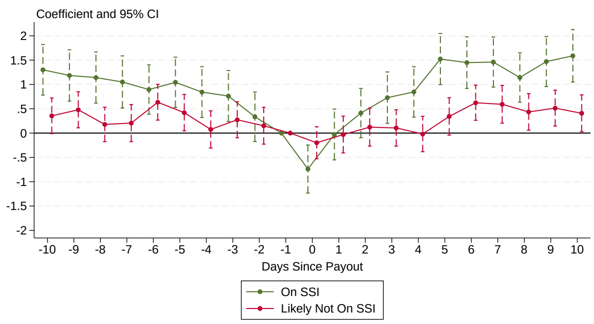
(a) SNAP Cycle



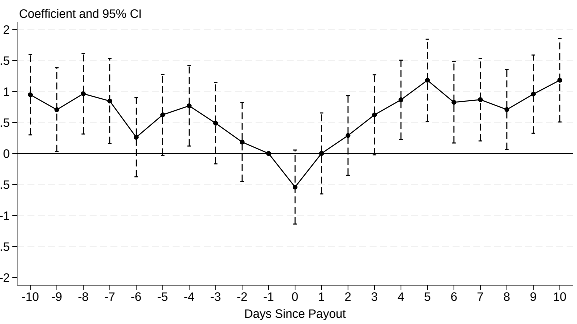
(b) SSI Cycle, On SSI



(c) SSI Cycle, On and Off SSI



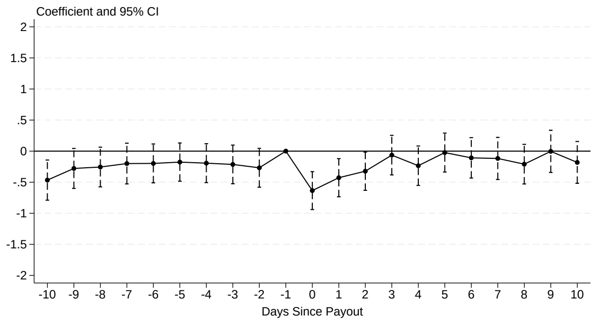
(d) SSI Cycle, DD



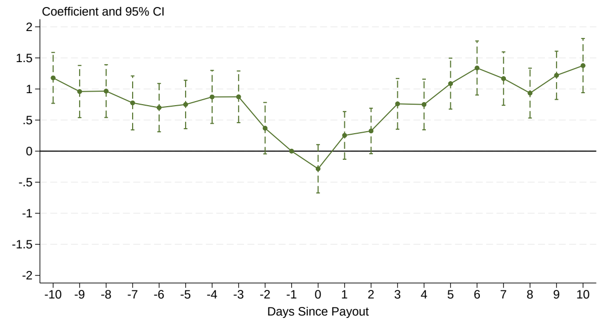
Notes: This figure shows estimates of (a) β_r from equation (2), (b) $\alpha_l + \beta_l$ from equation (1), (c) $\alpha_l + \beta_l$ from equation (1) (in green) overlaid with α_l from equation (1) (in red), and (d) β_l from equation (1). The outcome variable is ED visits for diabetes-related complications per day per 10,000. In (a), N person-months on SNAP (and on SSI) = 9,794,149. In (b)-(d), N person-months on SSI (and on SNAP) = 9,794,149, and N person-months likely not on SSI (but on SNAP) = 12,815,630. Standard errors are clustered at the date (day-month-year) level.

Figure OA.18: Effects of SNAP and SSI on ED Visits for Hypertension, Full Sample

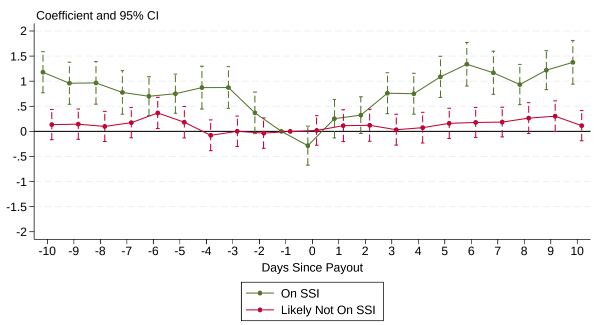
(a) SNAP Cycle



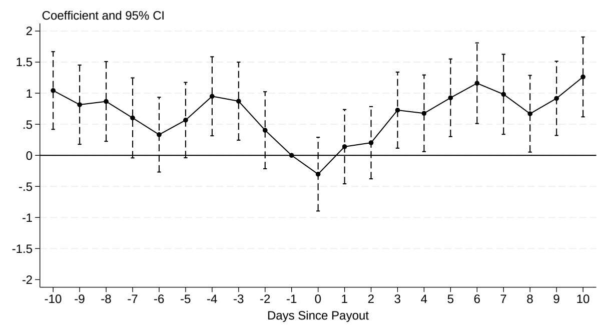
(b) SSI Cycle, On SSI



(c) SSI Cycle, On and Off SSI

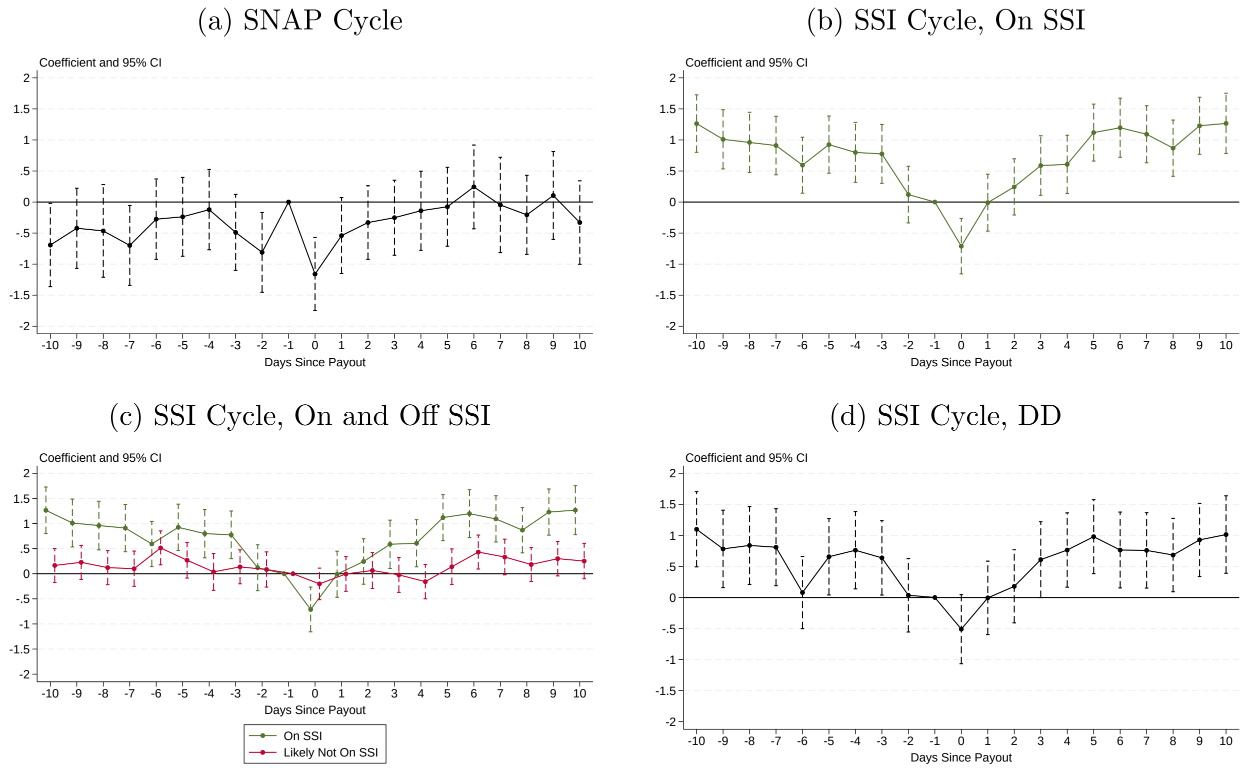


(d) SSI Cycle, DD



Notes: This figure shows estimates of (a) β_r from equation (2), (b) $\alpha_l + \beta_l$ from equation (1), (c) $\alpha_l + \beta_l$ from equation (1) (in green) overlaid with α_l from equation (1) (in red), and (d) β_l from equation (1). The outcome variable is ED visits for hypertension per day per 10,000. In (a), N person-months on SNAP = 29,016,217. In (b)-(d), N person-months on SSI = 19,236,048, and N person-months likely not on SSI = 109,240,417. Standard errors are clustered at the date (day-month-year) level.

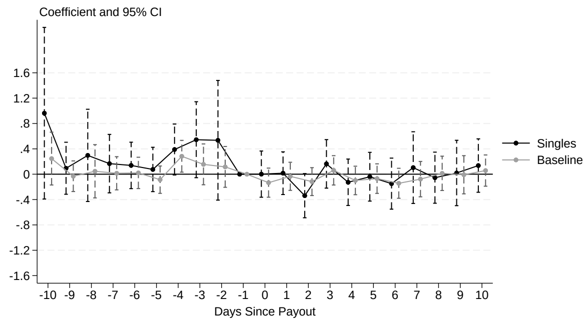
Figure OA.19: Effects of SNAP and SSI on ED Visits for Hypertension, Overlap Sample



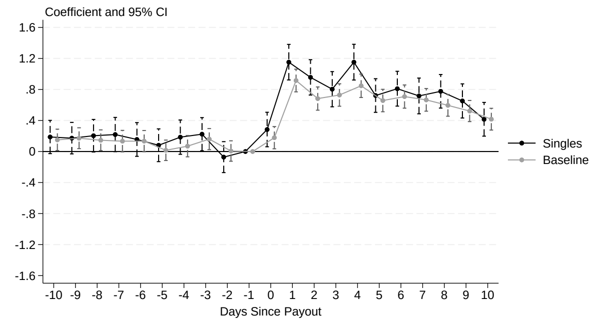
Notes: This figure shows estimates of (a) β_r from equation (2), (b) $\alpha_l + \beta_l$ from equation (1), (c) $\alpha_l + \beta_l$ from equation (1) (in green) overlaid with α_l from equation (1) (in red), and (d) β_l from equation (1). The outcome variable is ED visits for hypertension per day per 10,000. In (a), N person-months on SNAP (and on SSI) = 9,794,149. In (b)-(d), N person-months on SSI (and on SNAP) = 9,794,149, and N person-months likely not on SSI (but on SNAP) = 12,815,630. Standard errors are clustered at the date (day-month-year) level.

Figure OA.20: Effects of SNAP and SSI on Drug and Alcohol ER Visits for Singles, Overlap Sample

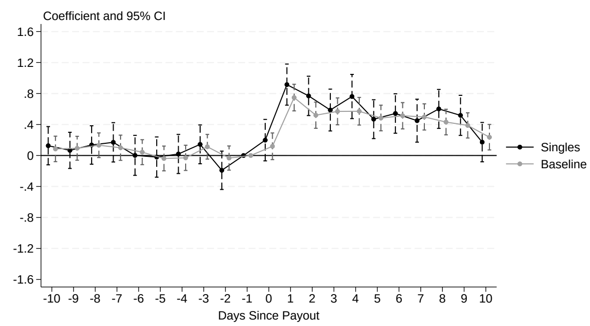
(a) SNAP Cycle



(b) SSI Cycle, On SSI



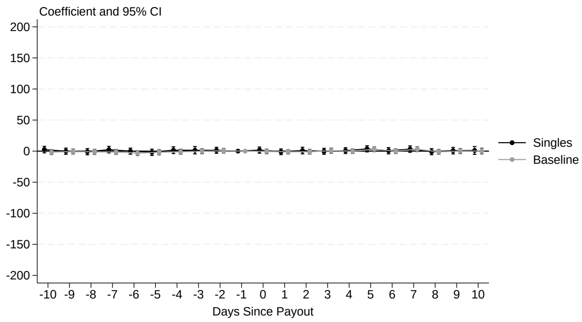
(c) SSI Cycle, DD



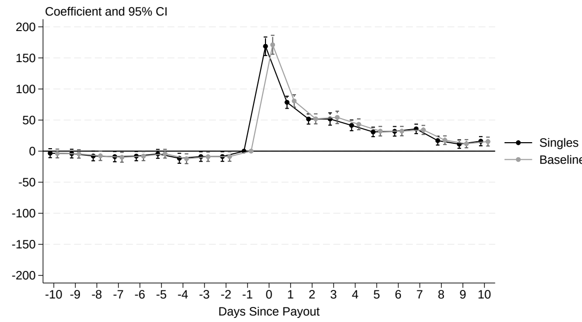
Notes: This figure shows estimates of (a) β_r from equation (2), (b) $\alpha_l + \beta_l$ from equation (1), and (c) β_l from equation (1), using baseline overlap samples (in grey) and overlap samples restricted to singles, as identified in the DSS data (in black). The outcome variable is drug-and-alcohol-related ER visits per day per 10,000. In (a) N single person-months on SNAP and SSI = 4,952,166; N person-months on SSI and SNAP in the baseline overlap sample = 9,794,149. In (b) N single person-months on SSI and SNAP = 4,952,166; N person-months on SSI and SNAP in the baseline overlap sample = 9,794,149. In (c), N single person-months on SSI and SNAP = 4,952,166, and N single person-months likely not on SSI but on SNAP = 6,819,566; N person-months on SSI and SNAP in the baseline overlap sample = 9,794,149, and N person-months likely not on SSI but on SNAP = 12,815,630. Standard errors are clustered at the date (day-month-year) level.

Figure OA.21: Effects of SNAP and SSI on First Fills for Singles, Overlap Sample

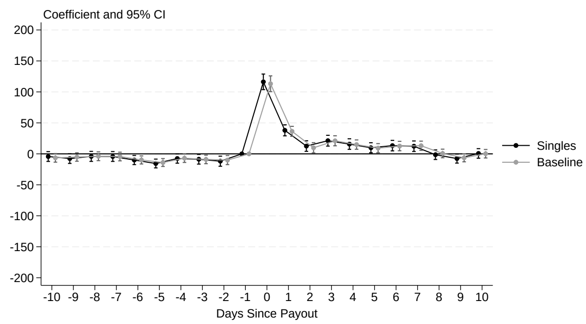
(a) SNAP Cycle



(b) SSI Cycle, On SSI

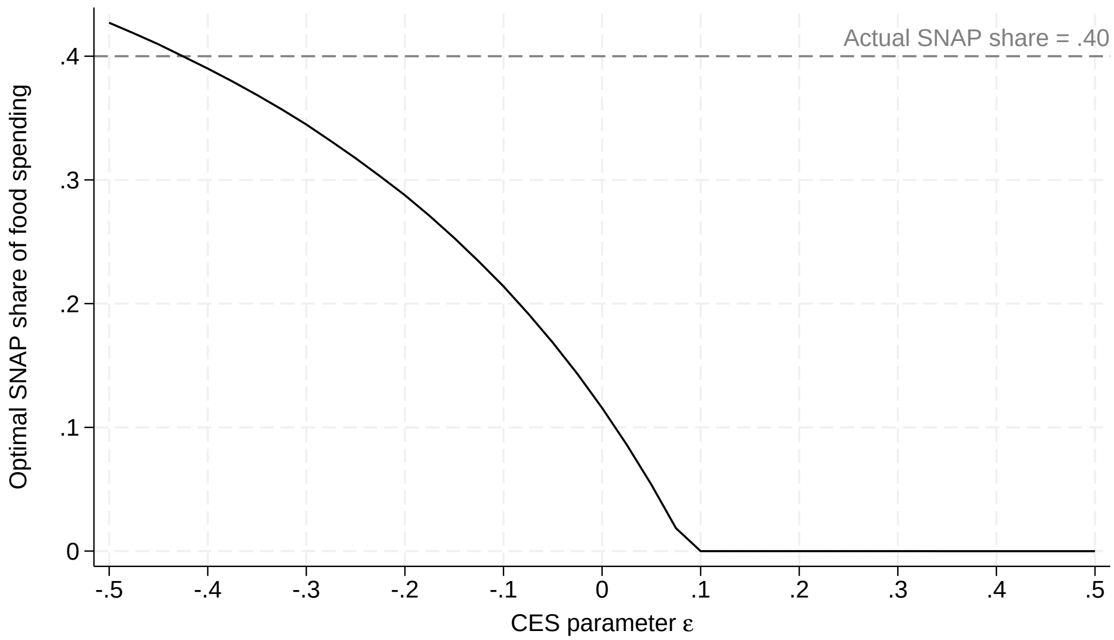


(c) SSI Cycle, DD



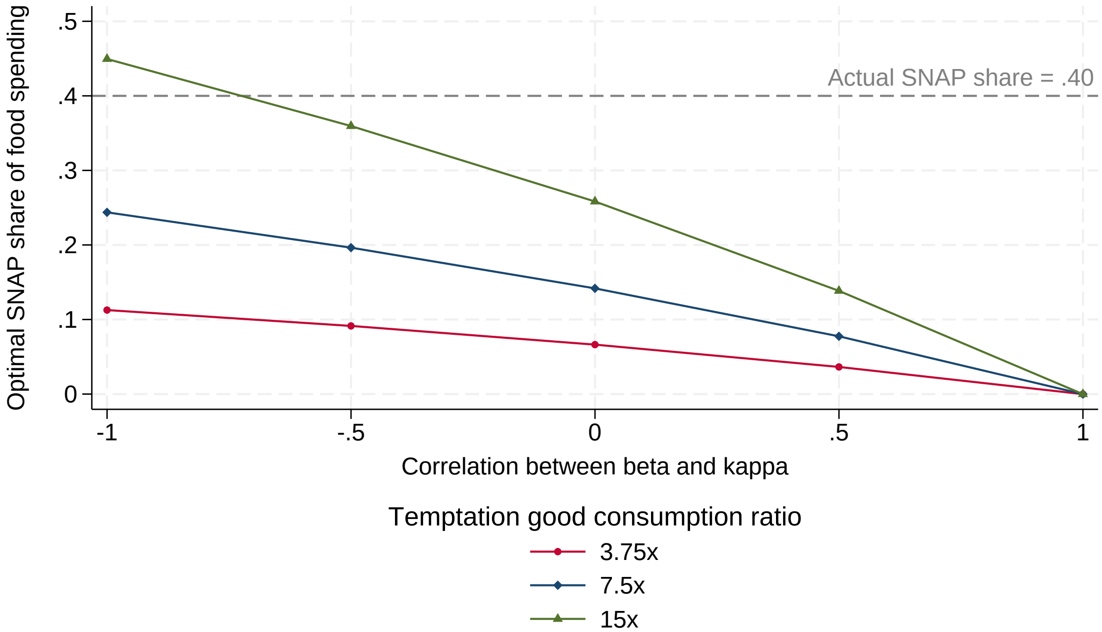
Notes: This figure shows estimates of (a) β_r from equation (2), (b) $\alpha_l + \beta_l$ from equation (1), and (c) β_l from equation (1), using baseline overlap samples (in grey) and overlap samples restricted to singles, as identified in the DSS data (in black). The outcome variable is first fills per day per 10,000. In (a) N single person-months on SNAP and SSI = 2,226,949; N person-months on SSI and SNAP in the baseline overlap sample = 4,568,532. In (b) N single person-months on SSI and SNAP = 2,226,949; N person-months on SSI and SNAP in the baseline overlap sample = 4,568,532. In (c), N single person-months on SSI and SNAP = 2,226,949, and N single person-months likely not on SSI but on SNAP = 1,302,557; N person-months on SSI and SNAP in the baseline overlap sample = 4,568,532, and N person-months likely not on SSI but on SNAP = 2,441,425. Standard errors are clustered at the date (day-month-year) level.

Figure OA.22: Relationship Between ϵ and Optimal SNAP Share



Notes: This figure shows how the optimal SNAP share of food spending evolves as we vary the CES parameter ϵ. Elasticity of substitution σ between food and non-food is $\frac{1}{1-\epsilon}$; hence, e.g. $\epsilon = 0$ translates to an elasticity of substitution of 1. Grey line indicates the actual SNAP share of food expenditures per Hastings and Shapiro (2018). All parameter values are pulled from the Cobb-Douglas representative agent calibration; $\kappa = .042$.

Figure OA.23: Relationship Between Correlation of β and κ and Optimal SNAP Share



Notes: This figure shows how the optimal SNAP share of food spending evolves as we vary the correlation between β and κ, separately assuming a 3.75-fold (red), 7.5-fold (blue), and 15-fold (green) higher rate of spending on temptation goods for individuals with $\beta = 1$ compared to those with $\beta = 0.7$. Under a 3.75-fold higher rate, $\gamma = .882$; under a 7.5-fold higher rate it is .950; and under a 15-fold higher rate it is .978. Grey line indicates the actual SNAP share of food expenditures per Hastings and Shapiro (2018). $\kappa = .042$.

F Appendix Tables

Table OA.1: SNAP Payout Day Schedule

Last Digit of Case Number	Day of the Month (before 9/1/2012)	Day of the Month (before 9/1/2012)
1	1	11
2	2	2
3	3	13
4	4	4
5	5	15
6	6	6
7	7	17
8	8	8
9	9	19
0	10	10

Notes: This table shows conversion between last digit of a SNAP recipient's case number and SNAP payout day. In 9/2012, SNAP recipients beginning a new SNAP spell whose case number ended with an odd digit were assigned different payout days than previously, as noted by the difference in columns 2 and 3.

Table OA.2: Balance Table Before 9/1/2012

	Digit 0	Digit 1	Digit 2	Digit 3	Digit 4	Digit 5	Digit 6	Digit 7	Digit 8	Digit 9	F-statistic	P-value
Panel A: Demographics												
Mean Age	54.257	53.976	54.117	54.279	54.096	54.234	54.244	53.974	54.338	54.172	3.130	0.001
Share Female	0.640	0.640	0.643	0.643	0.643	0.643	0.640	0.644	0.640	0.636	0.955	0.476
Share White	0.386	0.387	0.387	0.385	0.383	0.385	0.385	0.387	0.384	0.386	0.218	0.992
Share Black	0.457	0.453	0.455	0.458	0.460	0.458	0.459	0.457	0.457	0.459	0.612	0.788
Share Other	0.153	0.157	0.155	0.155	0.153	0.154	0.153	0.153	0.155	0.152	0.616	0.785
Share Missing	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.324	0.967
Panel B: ED Visits Per Month (Per 10,000)												
Drug/alcohol-related	66.904	64.733	59.933	62.221	62.343	66.661	60.042	62.210	60.822	61.967	1.635	0.099
Any cause	1,055.767	1,047.729	1,055.995	1,053.399	1,047.932	1,079.785	1,039.001	1,055.340	1,044.017	1,047.230	1.158	0.317
Omnibus test of equality											1.115	0.247
N individuals	34,258	34,429	34,647	34,696	34,862	34,610	34,435	34,556	34,384	34,281		

Notes: This table presents the mean value of the row variables across all individuals with a given last digit of their case number (listed in the column headers), restricting to SNAP spells corresponding to case numbers assigned before September 2012. The last two columns report the F-statistic and corresponding p-value from a regression of the row variable on indicator variables for the last digit of the case number with heteroskedasticity-robust standard errors. The bottom row reports an omnibus test of equality that jointly tests significance of the coefficients on all of the indicator variables across all of the row variables, clustering standard errors on the individual. N individuals = 345,158.

Table OA.3: Balance Table After 9/1/2012

	Digit 0	Digit 1	Digit 2	Digit 3	Digit 4	Digit 5	Digit 6	Digit 7	Digit 8	Digit 9	F-statistic	P-value
Panel A: Demographics												
Mean Age	60.196	60.267	60.216	60.340	60.200	60.153	60.304	60.232	60.416	60.254	0.918	0.508
Share Female	0.637	0.646	0.645	0.644	0.646	0.647	0.644	0.639	0.646	0.636	1.216	0.280
Share White	0.343	0.341	0.345	0.341	0.342	0.342	0.343	0.340	0.341	0.333	0.857	0.563
Share Black	0.424	0.415	0.416	0.416	0.418	0.421	0.418	0.417	0.421	0.428	1.232	0.270
Share Other	0.224	0.234	0.230	0.233	0.230	0.228	0.228	0.234	0.229	0.230	0.898	0.526
Share Missing	0.009	0.010	0.009	0.010	0.010	0.009	0.010	0.010	0.010	0.010	0.391	0.940
Panel B: ED Visits Per Month (Per 10,000)												
Drug/alcohol-related	74.096	70.158	63.163	72.946	66.654	75.743	71.832	73.057	74.191	66.252	1.432	0.168
Any cause	1,202.641	1,190.180	1,133.707	1,177.640	1,205.647	1,193.035	1,206.282	1,200.179	1,214.383	1,161.306	2.453	0.009
Omnibus test of equality											1.149	0.196
N individuals	17,308	17,414	17,539	17,530	17,350	17,240	17,450	17,562	17,233	17,223		

Notes: This table presents the mean value of the row variables across all individuals with a given last digit of their case number (listed in the column headers), restricting to SNAP spells corresponding to case numbers assigned during or after September 2012. The last two columns report the F-statistic and corresponding p-value from a regression of the row variable on indicator variables for the last digit of the case number with heteroskedasticity-robust standard errors. The bottom row reports an omnibus test of equality that jointly tests significance of the coefficients on all of the indicator variables across all of the row variables, clustering standard errors on the individual. N individuals = 173,849.

Table OA.4: Sample Size Restrictions

	On SNAP	On SSI	Likely Not On SSI
Original Samples	36,735,361	20,228,283	184,736,301
SNAP Restrictions			
SNAP Benefit Amount > 0	36,560,144		
Unique Benefit Amount and Benefit Type	35,020,822		
One Case Number per Spell	34,730,779		
SSI Restrictions			
Control Households Never on SSI			133,954,392
Restrictions on All Samples			
Spells 12+ Months Long	30,505,480	19,791,440	133,954,392
No Observations from Year After Death	30,294,187	19,758,055	110,157,888
Person-Months not on TANF	29,016,217	19,236,048	109,240,417
ED Analysis Samples	29,016,217	19,236,048	109,240,417
Drug Fills Restrictions			
ED Analysis Sample	29,016,217	19,236,048	109,240,417
Person-Months on Medicaid	19,333,909	19,236,048	27,162,770
Not Dual After 2006	10,408,775	11,500,661	15,830,614
Can Observe Drug Fill Dates	8,494,422	9,801,524	8,379,201
≥6 Months into Medicaid Spell	7,877,590	9,288,812	7,377,659
Drug Fills Samples	7,877,590	9,288,812	7,377,659

Notes: This table tracks the change in number of person-months in the SNAP, on-SSI, and likely-not-on-SSI samples, as we sequentially restrict the samples. A "spell" is defined as a set of consecutive months on or off SSI, or on SNAP. Within the drug fills restrictions, the restriction "Not Dual After 2006" entails dropping the following: (1) any person-years after 2006 in which a person is age 65+ and on Medicaid and (2) all person-years after 2006 if a person is ever a dual from 2006-2019 when they are age 64 or below. The restriction "Can Observe Drug Fill Dates" refers to the fact that we do not directly observe drug fill dates in the Medicaid pharmacy files; we use an algorithm which matches Medicaid pharmacy data to the all-payer hospital and ED records, allowing us to back out the dates of fills, and in the process drop individuals who do not match across the files. We impose that person-months be preceded by 6 months on Medicaid in order to confirm that a "first fill" is indeed the first of its kind in 6 months.

Table OA.5: Summary Statistics, Drug Fills Samples

	SNAP Sample	SSI Sample		Overlap Sample	
	(1)	(2)	(3)	(4)	(5)
	On SNAP	On SSI	Likely Not On SSI	On SNAP & On SSI	On SNAP & Likely Not On SSI
Panel A: Demographics					
Mean Age	53.6	56.5	53.6	57.2	48.7
Share 65+	0.18	0.23	0.27	0.22	0.13
Share 40-64	0.69	0.69	0.50	0.73	0.62
Share less than 40	0.13	0.08	0.23	0.05	0.25
Share Female	0.70	0.64	0.73	0.66	0.76
Share White	0.38	0.34	0.51	0.33	0.45
Share Black	0.48	0.47	0.43	0.48	0.49
Share Other	0.14	0.19	0.06	0.19	0.06
Share Missing	0.00	0.00	0.00	0.00	0.00
Panel B: Fills Per Day (Per 10,000)					
First Fills	143	141	112	150	126
Refills	751	923	474	926	477
Maintenance Fills	521	643	355	645	344
Non-Maintenance Fills	211	221	154	233	169
All Drug Fills	894	1,064	586	1,077	603
Panel C: Share Receiving Benefits					
Person-months on SNAP	1.00	0.52	0.37	1.00	1.00
Person-months on SSI	0.58	1.00	0.00	1.00	0.00
People ever on SNAP	1.00	0.72	0.58	1.00	1.00
People ever on SSI	0.53	1.00	0.00	1.00	0.00
N Person-months	7,877,590	9,288,812	7,377,659	4,568,532	2,441,425
N unique individuals	164,235	121,383	137,603	80,388	65,941

Notes: This table presents descriptive statistics for the SNAP sample (column (1)), the SSI sample (columns (2) and (3)), and the overlap sample (columns (4)-(5)), derived from the Medicaid data. Mean age is calculated as the average age across person-months in each sample defined by the column headers. Drug fills per day per 10,000 are calculated by averaging the number of drug fills in a given category to the day level, multiplying by 10,000, then averaging across all days. "Other" nests all non-Black, non-white, and non-missing racial categories. As of 2014, filling out the race field was no longer required on the South Carolina Medicaid application form.

Table OA.6: Heterogeneity in SSI effects on ED Visits for Drug and Alcohol Use

	Has prior behavioral issues	Does not have prior behavioral issues	Difference
Panel A: Sample on SSI			
Share of sample	0.129	0.871	-
Drug and alcohol ED visits per day (per 10,000)	8.81	1.17	7.64
Estimated impact of SSI cycle	2.923	0.364	2.559
	(0.254)	(0.037)	(0.258)
Panel B: Sample Likely Not on SSI			
Share of sample	0.033	0.967	-
Drug and alcohol ED visits per day (per 10,000)	3.60	0.47	3.13
Estimated impact of SSI cycle	0.409	0.064	0.345
	(0.132)	(0.012)	(0.131)
Panel C: Difference-in-Differences			
Estimated impact of SSI cycle	2.515	0.300	2.214
	(0.297)	(0.039)	(0.298)

Notes: Table shows the difference in the impact of SSI between individuals with and without prior behavioral health issues, separately for the on-SSI (Panel A) and likely-not-on-SSI (Panel B) sample, as well as considering difference-in-differences (Panel C) estimates (between on-SSI and and likely-not-on SSI). The first row of panels A and B shows the share of the restricted (to years 5+ that an individual is in the sample) on-SSI and likely-not-on-SSI sample respectively with and without prior behavioral issues. The second row of Panels A and B shows the mean number of drug-and-alcohol-related ED visits per day per 10,000 individuals in that sample. The third row of Panels A and B shows the average first week (relative days 0 through 6) effect of the SSI cycle from equation (1) on individuals with and without prior behavioral issues, as well as the difference in effects between these groups. Panel C shows the difference-in-differences estimate for the average first week effect of the SSI cycle from equation (1), again separately for individuals with and without prior behavioral health issues, as well as the difference in these estimates. Standard errors are clustered at the date (day-month-year) level.

Table OA.7: Fungibility tests on ED visits for drug and alcohol use, by prior behavioral health issues

	(1) SNAP Estimate	(2) SSI Estimate, On SSI	(3) SSI Estimate, DD	(4) P-value of difference ($\frac{1}{4}$ * On SSI - SNAP)	(5) P-value of difference ($\frac{1}{4}$ * SSI DD - SNAP)
Has prior behavioral issues	0.331	2.923	2.515	0.296	0.439
	(0.376)	(0.254)	(0.296)		
Does not have prior behavioral issues	-0.015	0.364	0.300	0.027	0.062
	(0.047)	(0.037)	(0.039)		
Combined sample	0.011	0.694	0.620	0.006	0.016
	(0.058)	(0.046)	(0.051)		

Notes: This table shows point estimates and standard errors for the average effects of the SSI and SNAP cycles over the first week (relative days 0 through 6) on drug-and-alcohol-related ED visits, separately for individuals with and without prior behavioral issues, as well as combined. Column (1) shows the average first week SNAP effect from equation (2). Column (2) shows the average first week on-SSI effect from equation (1). Column (3) shows the average first week SSI DD effect from equation (1). Columns (4) and (5) show p-values of differences in one-fourth of the SSI estimate and the SNAP estimate. Standard errors are in parentheses. All estimates shown are from estimation of the two regression equations (2) and (1) stacked in block diagonal form to allow for correlation between the error terms of the two equations; standard errors are clustered at the date (day-month-year) level.

Table OA.8: Fungibility Tests on Major Causes of ED Visits, Full Samples

	(1) SNAP Estimate	(2) SSI Estimate, On SSI	(3) SSI Estimate, DD	(4) P-value of difference ($\frac{1}{4}$ * On SSI - SNAP)	(5) P-value of difference ($\frac{1}{4}$ * SSI DD - SNAP)	Share of all ER visits
Ill-Defined	-0.046	0.219	0.171	0.237	0.298	0.21
	(0.083)	(0.083)	(0.085)			
Injury/Poisoning	0.100	0.617	0.590	0.424	0.484	0.17
	(0.066)	(0.062)	(0.065)			
Respiratory	-0.087	0.302	0.216	0.007	0.020	0.11
	(0.058)	(0.060)	(0.067)			
Musculoskeletal	-0.147	0.040	0.022	0.011	0.014	0.10
	(0.060)	(0.053)	(0.058)			
Circulatory	-0.001	0.070	0.004	0.713	0.973	0.08
	(0.048)	(0.045)	(0.044)			
Digestive	-0.048	0.134	0.096	0.083	0.127	0.07
	(0.046)	(0.043)	(0.045)			
Genitourinary	-0.070	0.030	0.028	0.065	0.067	0.06
	(0.041)	(0.035)	(0.035)			
Metabolic	0.033	0.028	0.023	0.442	0.421	0.04
	(0.033)	(0.037)	(0.036)			
Mental	0.013	0.407	0.367	0.018	0.037	0.04
	(0.037)	(0.035)	(0.037)			
Nervous	-0.029	-0.021	-0.015	0.518	0.499	0.04
	(0.035)	(0.035)	(0.042)			
Infectious	-0.024	-0.009	-0.007	0.440	0.431	0.03
	(0.028)	(0.027)	(0.028)			
Skin	-0.004	0.040	0.026	0.687	0.764	0.03
	(0.034)	(0.026)	(0.028)			
Supplementary	-0.013	0.048	0.030	0.344	0.439	0.02
	(0.026)	(0.023)	(0.024)			
Neoplasms	-0.006	0.021	0.015	0.428	0.500	0.01
	(0.014)	(0.012)	(0.012)			
Residual	0.006	-0.001	0.000	0.703	0.711	0.01
	(0.015)	(0.016)	(0.016)			

Notes: This table shows point estimates and standard errors for the average effects of the SSI and SNAP cycles over the first week (relative days 0 through 6) on major causes of ED visits (conditions defined by the row labels), using full samples. Column (1) shows the average first week SNAP effect from equation (2). Column (2) shows the average first week on-SSI effect from equation (1). Column (3) shows the average first week SSI DD effect from equation (1). Columns (4) and (5) show p-values of differences in one-fourth of the SSI estimate and the SNAP estimate. Standard errors are in parentheses. All estimates shown are from estimation of the two regression equations (1) and (2) stacked in block diagonal form to allow for correlation between the error terms of the two equations; standard errors are clustered at the date (day-month-year). Rightmost column shows the share of all ED visits which correspond to each major cause of ED visits.

Table OA.9: Fungibility Tests on Major Causes of ED Visits, Overlap Samples

	(1) SNAP Estimate	(2) SSI Estimate, On SSI	(3) SSI Estimate, DD	(4) P-value of difference ($\frac{1}{4}$ * On SSI - SNAP)	(5) P-value of difference ($\frac{1}{4}$ * SSI DD - SNAP)	Share of all ER visits
Ill-Defined	-0.201	0.190	0.203	0.164	0.160	0.21
	(0.176)	(0.115)	(0.133)			
Injury/Poisoning	0.228	0.589	0.569	0.538	0.516	0.17
	(0.128)	(0.089)	(0.110)			
Respiratory	-0.180	0.307	0.210	0.036	0.058	0.11
	(0.120)	(0.076)	(0.089)			
Musculoskeletal	-0.263	0.087	0.067	0.029	0.034	0.10
	(0.130)	(0.077)	(0.090)			
Circulatory	0.052	0.099	-0.044	0.755	0.470	0.08
	(0.085)	(0.060)	(0.074)			
Digestive	-0.077	0.135	0.123	0.190	0.205	0.07
	(0.083)	(0.062)	(0.074)			
Genitourinary	-0.016	-0.001	0.002	0.825	0.821	0.06
	(0.071)	(0.052)	(0.065)			
Metabolic	0.050	0.025	0.070	0.510	0.626	0.04
	(0.065)	(0.050)	(0.057)			
Mental	-0.100	0.382	0.280	0.050	0.090	0.04
	(0.100)	(0.047)	(0.053)			
Nervous	-0.063	-0.075	-0.085	0.503	0.531	0.04
	(0.065)	(0.046)	(0.062)			
Infectious	-0.002	-0.035	-0.060	0.901	0.811	0.03
	(0.052)	(0.037)	(0.044)			
Skin	0.045	0.037	0.082	0.544	0.677	0.03
	(0.058)	(0.038)	(0.047)			
Supplementary	0.041	0.035	0.029	0.442	0.426	0.02
	(0.042)	(0.031)	(0.038)			
Neoplasms	-0.011	0.020	0.024	0.504	0.478	0.01
	(0.023)	(0.018)	(0.021)			
Residual	-0.006	0.003	0.020	0.816	0.701	0.01
	(0.026)	(0.023)	(0.031)			

Notes: This table shows point estimates and standard errors for the average effects of the SSI and SNAP cycles over the first week (relative days 0 through 6) on major causes of ED visits (conditions defined by the row labels), using overlap samples. Column (1) shows the average first week SNAP effect from equation (2). Column (2) shows the average first week on-SSI effect from equation (1). Column (3) shows the average first week SSI DD effect from equation (1). Columns (4) and (5) show p-values for differences in one-fourth of the SSI estimate and the SNAP estimate. Standard errors are in parentheses. All estimates shown are from estimation of the two regression equations (1) and (2) stacked in block diagonal form to allow for correlation between the error terms of the two equations; standard errors are clustered at the date (day-month-year). Rightmost column shows the share of all ED visits which correspond to each major cause of ED visits.

Table OA.10: Fungibility Tests on Placebo ED Visits and ED visits for Drug and Alcohol Use with an ICU stay

	(1) SNAP Estimate	(2) SSI Estimate, On SSI	(3) SSI Estimate, DD	(4) P-value of difference ($\frac{1}{4}$ * On SSI - SNAP)	(5) P-value of difference ($\frac{1}{4}$ * SSI DD - SNAP)	(6) Share of all ER Visits
Panel A: Full Samples						
Neoplasms	-0.006	0.021	0.015			
	(0.014)	(0.012)	(0.012)	0.428	0.500	0.01
	{0.20}	{0.25}	{0.25}			
Infectious diseases	-0.024	-0.009	-0.007			
	(0.028)	(0.027)	(0.028)	0.440	0.431	0.03
	{0.82}	{1.00}	{1.00}			
Neoplasms OR	-0.030	0.014	0.009			
Infectious diseases	(0.031)	(0.030)	(0.031)	0.295	0.312	0.03
	{1.02}	{1.25}	{1.25}			
DA ER visits	-0.019	0.105	0.097			
w/ ICU stay	(0.017)	(0.014)	(0.015)	0.010	0.015	0.01
	{0.31}	{0.40}	{0.40}			
Panel B: Overlap Samples						
Neoplasms	-0.011	0.020	0.024			
	(0.023)	(0.018)	(0.021)	0.504	0.478	0.01
	{0.25}	{0.25}	{0.25}			
Infectious diseases	-0.002	-0.035	-0.060			
	(0.052)	(0.037)	(0.044)	0.901	0.811	0.03
	{1.01}	{1.01}	{1.01}			
Neoplasms OR	-0.014	-0.015	-0.034			
Infectious diseases	(0.057)	(0.041)	(0.048)	0.864	0.932	0.03
	{1.26}	{1.26}	{1.26}			
DA ER visits	-0.054	0.096	0.079			
w/ ICU stay	(0.043)	(0.021)	(0.025)	0.072	0.090	0.01
	{0.41}	{0.41}	{0.41}			

Notes: This table shows point estimates and standard errors for the average effects of the SSI and SNAP cycles over the first week (relative days 0 through 6) on placebo outcomes indicated by row headers, using full and overlap samples. Column (1) shows the average first week SNAP effect from equation (2). Column (2) shows the average first week on-SSI effect from equation (1). Column (3) shows the average first week SSI DD effect from equation (1). Columns (4) and (5) show p-values for differences in one-fourth of the SSI estimate and the SNAP estimate. Standard errors are in parentheses. All estimates shown are from estimation of the two regression equations (2) and (1) stacked in block diagonal form to allow for correlation between the error terms of the two equations; standard errors are clustered at the date (day-month-year). Mean daily number of ED visits for each category of conditions per 10,000 people are in curly brackets below standard errors; SSI means are based on on-SSI sample. Rightmost column shows the share of all ED visits which correspond to each placebo outcome.

Table OA.11: Fungibility Tests on Nutrition-Sensitive ED Visits

	(1) SNAP Estimate	(2) SSI Estimate, On SSI	(3) SSI Estimate, DD	(4) P-value of difference ($\frac{1}{4}$ * On SSI - SNAP)	(5) P-value of difference ($\frac{1}{4}$ * SSI DD - SNAP)	Share of all ER visits
Panel A: Full Samples						
All nutrition-sensitive	-0.358	0.806	0.626	< 0.001	0.001	0.52
	(0.140)	(0.166)	(0.238)			
Hypertension	-0.260	0.604	0.504	0.002	0.005	0.39
	(0.125)	(0.148)	(0.227)			
Diabetes-related complications	-0.339	0.772	0.595	< 0.001	0.001	0.50
	(0.138)	(0.162)	(0.231)			
Hypoglycemia	-0.004	0.003	0.002	0.487	0.513	0.00
	(0.007)	(0.009)	(0.009)			
Panel B: Overlap Samples						
All nutrition-sensitive	-0.452	0.619	0.471	0.026	0.038	0.52
	(0.267)	(0.199)	(0.245)			
Hypertension	-0.323	0.433	0.397	0.084	0.094	0.39
	(0.246)	(0.170)	(0.218)			
Diabetes-related complications	-0.413	0.599	0.463	0.037	0.052	0.50
	(0.265)	(0.192)	(0.233)			
Hypoglycemia	-0.017	-0.002	-0.002	0.184	0.193	0.00
	(0.012)	(0.013)	(0.015)			

Notes: This table shows point estimates and standard errors for the average effects of the SSI and SNAP cycles over the first week (relative days 0 through 6) on nutrition-sensitive ED visits (first row in each panel) as well as the components of nutrition-sensitive ED visits (hypertension + diabetes-related complications + hypoglycemia), using full and overlap samples. Column (1) shows the average first week SNAP effect from equation (2). Column (2) shows the average first week on-SSI effect from equation (1). Column (3) shows the average first week SSI DD effect from equation (1). Columns (4) and (5) show p-values of differences in one-fourth of the SSI estimate and the SNAP estimate. Standard errors are in parentheses. All estimates shown are from estimation of the two regression equations (1) and (2) stacked in block diagonal form to allow for correlation between the error terms of the two equations; standard errors are clustered at the date (day-month-year). Rightmost column shows the share of all ED visits which fall into each subcategory of nutrition-sensitive ED visits, as well as the overall category; subcategory shares do not sum to the overall share because conditions are not mutually exclusive.

Table OA.12: Robustness Table, Drug and Alcohol ED Visits

		Full Samples					Overlap Samples				
		(1) SNAP Estimate	(2) SSI Estimate, On SSI	(3) SSI Estimate, DD	(4) P-value of difference ($\frac{1}{4}$*On SSI - SNAP)	(5) P-value of difference ($\frac{1}{4}$*SSI DD - SNAP)	(6) SNAP Estimate	(7) SSI Estimate, On SSI	(8) SSI Estimate, DD	(9) P-value of difference ($\frac{1}{4}$*On SSI - SNAP)	(10) P-value of difference ($\frac{1}{4}$*SSI DD - SNAP)
(1)	Baseline	-0.005	0.703	0.639	< 0.001	< 0.001	-0.076	0.674	0.504	0.008	0.030
		(0.043)	(0.035)	(0.042)			(0.092)	(0.053)	(0.061)		
(2)	SNAP controlling for SSI and SSI controlling for SNAP	-	-	-	-	-	-0.062	0.664	-	0.016	-
		-	-	-	-	-	(0.089)	(0.111)	-		-
(3)	Uniform covariate effects across SNAP assignment time	-0.010	-	-	< 0.001	< 0.001	-0.118	-	-	0.002	0.008
		(0.042)	-	-			(0.091)	-	-		
(4)	SSI in 2013 onwards	-	0.923	0.834	< 0.001	< 0.001	-0.044	0.825	0.643	0.104	0.185
		-	(0.070)	(0.073)			(0.151)	(0.107)	(0.115)		
(5)	Non-social security (people aged ¡ 62)	0.037	0.955	0.887	0.001	0.003	0.009	0.947	0.774	0.094	0.177
		(0.061)	(0.055)	(0.060)			(0.134)	(0.084)	(0.094)		
(6)	SNAP payouts on days 1-10 of month	-0.001	-	-	< 0.001	0.001	-0.051	-	-	0.035	0.082
		(0.049)	-	-			(0.091)	-	-		
(7)	Poisson version of specifications	-0.003	0.299	0.179	< 0.001	0.025	-0.027	0.270	0.122	0.004	0.085
		(0.020)	(0.016)	(0.022)			(0.032)	(0.024)	(0.039)		
	Proportional effect	{-0.003}	{0.297}	{0.270}	-	-	{-0.031}	{0.273}	{0.204}	-	-

Notes: This table shows point estimates and standard errors for the average effects on ED visits for drug and alcohol use over relative days (since benefit receipt) 0 through 6. Row 1 shows the baseline estimates for the full sample (columns 1 through 5) and overlap sample (columns 6 through 10); see notes to Table 3 for more details. Each subsequent row shows a one-off deviation from this baseline as indicated by the row label. Row 2 ("SNAP controlling for SSI and SSI controlling for SNAP") reports estimates from a specification where we add controls for SNAP payout day to the baseline SSI analysis and controls for SSI payout day to the SNAP analysis. Row 7 ("Poisson version of specifications") reports estimates from Poisson variants on equations (1) and (2); for ease of comparison to the baseline specification, we report in curly brackets below the Poisson estimate the implied proportional effect from the baseline linear specification. If SSI/SNAP results are not reported for a given check, tests of difference are conducted with reference to baseline estimates. Standard errors are clustered at the date (day-month-year) level.

Table OA.13: Robustness Table, First Fills

		Full Samples					Overlap Samples				
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		SNAP Estimate	SSI Estimate, On SSI	SSI Estimate, DD	P-value of difference ($\frac{1}{4}$*On SSI - SNAP)	P-value of difference ($\frac{1}{4}$*SSI DD - SNAP)	SNAP Estimate	SSI Estimate, On SSI	SSI Estimate, DD	P-value of difference ($\frac{1}{4}$*On SSI - SNAP)	P-value of difference ($\frac{1}{4}$*SSI DD - SNAP)
(1)	Baseline	9.066	400.931	182.597	< 0.001	< 0.001	0.807	465.319	217.148	< 0.001	< 0.001
		(7.985)	(21.342)	(21.305)			(10.537)	(23.041)	(21.355)		
(2)	SNAP controlling for SSI and SSI controlling for SNAP	-	-	-	-	-	-28.837	441.728	-	< 0.001	-
		-	-	-	-	-	(11.519)	(23.875)	-		-
(3)	Uniform covariate effects across SNAP assignment time	10.907	-	-	< 0.001	< 0.001	2.729	-	-	< 0.001	< 0.001
		(7.799)	-	-			(10.318)	-	-		
(4)	SSI in 2013 onwards	-	238.807	120.213	< 0.001	0.084	-2.137	258.410	128.365	0.001	0.076
		-	(38.077)	(36.038)			(16.887)	(40.470)	(35.013)		
(5)	Non-social security (people aged ¡ 62)	10.673	393.953	203.349	< 0.001	< 0.001	3.374	465.811	234.406	< 0.001	< 0.001
		(8.309)	(20.473)	(21.138)			(10.818)	(22.178)	(21.382)		
(6)	SNAP payouts on days 1-10 of month	3.194	-	-	< 0.001	< 0.001	-3.489	-	-	< 0.001	< 0.001
		(8.070)	-	-			(10.627)	-	-		
(7)	Poisson version of specifications	0.060	2.474	0.889	< 0.001	0.009	0.014	2.631	0.996	< 0.001	0.001
		(0.049)	(0.137)	(0.151)			(0.060)	(0.137)	(0.138)		
	Proportional effect	{0.063}	{2.851}	{1.298}	-	-	{0.005}	{3.097}	{1.445}	-	-
(8)	Non-maint- -enance fills	24.018	961.361	450.433	< 0.001	< 0.001	30.364	1,093.547	518.290	< 0.001	< 0.001
		(7.200)	(34.724)	(31.706)			(10.335)	(38.107)	(32.842)		

Notes: This table shows point estimates and standard errors for the sum of effects on first fills over relative days (since benefit receipt) 0 through 6. Row 1 shows the baseline estimates for the full sample (columns 1 through 5) and overlap sample (columns 6 through 10); see notes to Table 4 for more details. Each subsequent row shows a one-off deviation from this baseline as indicated by the row label. Row 2 ("SNAP controlling for SSI and SSI controlling for SNAP") reports estimates from a specification where we add controls for SNAP payout day to the baseline SSI analysis and controls for SSI payout day to the SNAP analysis. Row 7 ("Poisson version of specifications") reports estimates from Poisson variants on equations (1) and (2); for ease of comparison to the baseline specification, we report in curly brackets below the Poisson estimate the implied proportional effect from the baseline linear specification. If SSI/SNAP results are not reported for a given check, tests of difference are conducted with reference to baseline estimates. Standard errors are clustered at the date (day-month-year) level.

Table OA.14: Results from dropping covariates, drug-and-alcohol-related ED visits

	Full Samples					Overlap Samples				
	(1) SNAP Estimate	(2) SSI Estimate, On SSI	(3) SSI Estimate, DD	(4) P-value of difference ($\frac{1}{4}$*On SSI - SNAP)	(5) P-value of difference ($\frac{1}{4}$*SSI DD - SNAP)	(6) SNAP Estimate	(7) SSI Estimate, On SSI	(8) SSI Estimate, DD	(9) P-value of difference ($\frac{1}{4}$*On SSI - SNAP)	(10) P-value of difference ($\frac{1}{4}$*SSI DD - SNAP)
Baseline	-0.005	0.703	0.639	< 0.001	< 0.001	-0.076	0.674	0.504	0.008	0.030
	(0.043)	(0.035)	(0.042)			(0.092)	(0.053)	(0.061)		
Drop special days	-0.004	0.690	0.639	< 0.001	< 0.001	-0.077	0.656	0.504	0.009	0.029
	(0.043)	(0.035)	(0.042)			(0.092)	(0.052)	(0.061)		
Drop year	-0.005	0.692	0.639	< 0.001	< 0.001	-0.078	0.658	0.504	0.009	0.028
	(0.043)	(0.047)	(0.042)			(0.092)	(0.062)	(0.061)		
Drop month	-0.004	0.693	0.639	< 0.001	< 0.001	-0.077	0.659	0.504	0.009	0.029
	(0.043)	(0.048)	(0.042)			(0.092)	(0.063)	(0.061)		
Drop day of week	-0.005	0.702	0.639	< 0.001	< 0.001	-0.078	0.670	0.504	0.008	0.029
	(0.043)	(0.047)	(0.042)			(0.092)	(0.062)	(0.061)		
Drop day of month from SNAP	-0.031	-	-	< 0.001	< 0.001	-0.140	-	-	< 0.001	0.002
	(0.041)	-	-			(0.084)	-	-		

Notes: This table shows point estimates and standard errors for the average effects of the SSI and SNAP cycles as we sequentially (and cumulatively) drop covariates to our estimating equations, from relative days 0 through 6 on drug-and-alcohol-related ED visits. Covariates dropped are given by row headers, and each row builds on the last (that is, rows represent an *additional* covariate dropped). Row 1 shows the baseline estimates for the full sample (columns 1 through 5) and overlap sample (columns 6 through 10); see notes to Table 3 for more details. In final row ("drop day of month from SNAP"), SNAP estimates are compared to SSI estimates from previous row ("drop day of week"). Standard errors are clustered at the date (day-month-year) level.

Table OA.15: Results from dropping covariates, first fills

	Full Samples					Overlap Samples				
	(1) SNAP Estimate	(2) SSI Estimate, On SSI	(3) SSI Estimate, DD	(4) P-value of difference ($\frac{1}{4}$*On SSI - SNAP)	(5) P-value of difference ($\frac{1}{4}$*SSI DD - SNAP)	(6) SNAP Estimate	(7) SSI Estimate, On SSI	(8) SSI Estimate, DD	(9) P-value of difference ($\frac{1}{4}$*On SSI - SNAP)	(10) P-value of difference ($\frac{1}{4}$*SSI DD - SNAP)
Baseline	9.066	400.931	182.597	< 0.001	< 0.001	0.807	465.319	217.148	< 0.001	< 0.001
	(7.985)	(21.342)	(21.305)			(10.537)	(23.041)	(21.355)		
Drop special days	8.143	377.400	182.597	< 0.001	< 0.001	< 0.001	440.302	217.148	< 0.001	< 0.001
	(7.982)	(21.739)	(21.298)			(10.546)	(23.488)	(21.349)		
Drop year	8.172	377.610	182.597	< 0.001	< 0.001	-0.033	440.454	217.148	< 0.001	< 0.001
	(7.988)	(22.529)	(21.294)			(10.551)	(24.547)	(21.344)		
Drop month	5.120	375.528	182.597	< 0.001	< 0.001	-3.299	438.153	217.148	< 0.001	< 0.001
	(7.991)	(23.062)	(21.290)			(10.571)	(25.054)	(21.341)		
Drop day of week	5.037	252.573	182.597	< 0.001	< 0.001	-3.519	303.781	217.148	< 0.001	< 0.001
	(8.114)	(31.087)	(21.288)			(10.686)	(33.449)	(21.339)		
Drop day of month from SNAP	-97.436	-	-	< 0.001	< 0.001	-143.646	-	-	< 0.001	< 0.001
	(11.818)	-	-			(15.031)	-	-		

Notes: This table shows point estimates and standard errors for the sum of effects of the SSI and SNAP cycles as we sequentially (and cumulatively) drop covariates to our estimating equations, from relative days 0 through 6 on first fills. Covariates dropped are given by row headers, and each row builds on the last (that is, rows represent an *additional* covariate dropped). Row 1 shows the baseline estimates for the full sample (columns 1 through 5) and overlap sample (columns 6 through 10); see notes to Table 4 for more details. In final row ("drop day of month from SNAP"), SNAP estimates are compared to SSI estimates from previous row ("drop day of week"). Standard errors are clustered at the date (day-month-year) level.

Table OA.16: Sample size changes

	ER Samples			Drug Fills Samples		
	On SNAP	On SSI	Likely Not On SSI	On SNAP	On SSI	Likely Not On SSI
Panel A: Full Samples						
Baseline Samples	29,016,217	19,236,048	109,240,417	7,877,590	9,288,812	7,377,659
SSI 2013 and later		5,749,456	29,202,098		1,799,781	1,145,132
Aged 61 and below	19,668,279	11,062,895	71,003,355	6,097,421	6,656,957	5,175,069
Early SNAP Payouts	22,672,890			6,860,040		
Panel B: Overlap Samples						
Baseline Samples	9,794,149	9,794,149	12,815,630	4,568,532	4,568,532	2,441,425
SSI 2013 and later	3,292,220	3,292,220	4,697,588	1,045,523	1,045,523	514,374
Aged 61 and below	5,486,967	5,486,967	9,138,172	3,270,442	3,270,442	2,067,286
Early SNAP Payouts	7,806,477	7,806,477	9,619,218	3,950,760	3,950,760	2,107,283

Notes: This table shows the change in number of person-months in the SNAP, on-SSI, and likely-not-on-SSI samples when we apply sample restrictions for two robustness checks. "SSI 2013 and later" refers to a robustness check where we restrict the SSI sample to span the years 2013 to 2019, when SSI payments were made electronically. "Aged 61 and below" is designed to remove individuals who may be receiving Social Security income (which begins at the earliest at age 62). "Early SNAP payouts" refers to a robustness check where we restrict the SNAP sample to individuals who are assigned their case number before 9/2012, and therefore receive SNAP payments on days 1 through 10 of the month.