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

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Abstract

We estimate impacts of cash and in-kind transfers on the consumption of temptation goods 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. Additionally, fills of prescription drugs for new illnesses 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 argues 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; their primary explanation is 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). Policy is also influenced by such paternalistic concerns. 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).[2] Similarly, in 2021, then-Senator Joe Manchin reportedly expressed opposition

[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).

[2] Likewise, in Brazil, evidence that a large share of a cash transfer program for the poor (Bolsa Familia) was being spent on on-line gambling prompted the government to prohibit use of cash transfer program cards for this purpose (Reuters (2024); Pereira (2024)).

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 such as time-inconsistent preferences (e.g., Laibson 1997).[3]

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 reduce the consumption of temptation goods (specifically drugs and alcohol) and 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 policy 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 it covered about 7.4 million Americans (SSA 2024). SNAP provides food vouchers to low-income individuals; it 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 reach about 42.1 million Americans (Jones and Toossi 2024).

We analyze a customized data set that contains two decades of data 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, benefits are paid on a monthly schedule 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;[4] 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 focus is on 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 ED visits prescription drugs fills, our proxy for consumption of non-temptation, non-labelled goods; we focus on fills for new conditions or acute conditions in order to better capture consumption rather than merely the timing of purchases. Our

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

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

evidence is consistent with a higher marginal propensity to consume temptation goods out of cash transfers than out of food vouchers. Specifically, looking at impacts in the six days on and after benefit receipt, we find that receipt of SSI benefits each month 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 fills of new prescription drugs or drugs for acute conditions increase by about 40 to 100 percent following receipt of SSI but increase between 0 and 2 percent following receipt of SNAP, which 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; Hoynes et al. 2015; Hastings and Shapiro 2018).[5] We therefore extend the model in Hastings and Shapiro (2018) to allow for temptation goods and show that, if individuals engage in mental accounting, we can re-produce the non-fungibility results in the paper even when SNAP is infra-marginal.

We then consider a paternalistic social planner's choice of how to split an exogenous transfer budget between SNAP and cash when individuals over-consume temptation goods due to self-control problems. 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.[6] 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 weakly increasing as time-inconsistency increases, and weakly decreasing in the extent of mental accounting. As a result, if mental accounting is strong enough, the planner will choose a SNAP share that preserves the infra-marginality of SNAP benefits that currently exists.[7] A (very) rough calibration suggests that

[5] 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. 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).

[6] 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).

[7] 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 reduces the negative consequences of their over-consumption of temptation goods.

the optimal level of SNAP benefits is about 10 to 20 percent of food spending for SNAP recipients; given estimates that SNAP benefits are about 40 percent of food spending for SNAP recipients (Hastings and Shapiro 2018), this suggests that the current level of SNAP benefits may be overly paternalistic. 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.[8] 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. 2019; Farhi and Gabaix 2020), as well as optimal income taxation in the presence of present bias (Lockwood 2020).

Our empirical work goods 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.[9] 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) find a much higher MPCf out of SNAP than out of cash when examining detailed data on grocery store purchases and Song (2022) similarly find a very high MPCf out of SNAP; 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).[10]

[8] Another widely-conjectured but relatively-understudied rationale for in-kind transfers is based on a political economy argument (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), or, in low-income countries, limited state capacity for preventing misdirection or theft of cash.

[9] 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).

[10] 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 impacts of cash on temptation goods, cash on health, and SNAP 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*.[11]

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. In every state, SSI benefits are paid on the first of the month, 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 timing of SNAP benefit payments varies across states and time (Cotti et al. 2016). In South Carolina, SNAP benefits are 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 are 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 are 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). This schedule is not adjusted if the payment date happens to fall on a weekend (USDA (2023))

Our empirical strategy will examine how various outcomes change relative to the day of benefit *receipt*. In practice, the date of benefit receipt and benefit payment are the same. SNAP benefits have been distributed via electronic benefit transfer over our sample period (Tiehen et al. 2024),

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).

[11] 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.

and SSI payments have been distributed electronically starting in 2013 (SSA 2014). Prior to 2013, 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 wis a weekend or federal holiday (SSA 2013); the share of SSI recipients in South Carolina who received checks by mail declined from roughly two-thirds in 1998 to one-quarter in 2013 (SSA 2019).

2.2 Estimating equations

We use within-month variation in the timing of benefit receipt to identify its impact.

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

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

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-day is 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.[12] We let SSI_g denote an indicator variable for whether the person-day is on SSI (vs. not) and allow the coefficients on the relative day indicators to vary based on this; we also control for fixed outcome differences between groups (SSI_g).

In what follows, we will report two sets of estimates for how outcomes change around the timing of SSI payout: the ($\alpha_r + \beta_r$) coefficients, which show the within month pattern for SSI recipients, and the β_r coefficients, which show the within month pattern for SSI recipients *relative to* other low-income adults who are not SSI recipients. A priori, we expect that this 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 benefits or of monthly paychecks; in this case, while our estimates might represent the impact of liquidity, we would be incorrect in attributing all of the liquidity impact to SSI. 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 SSI effect as some of the pattern in the 'likely not on SSI' group may in fact reflect the impact of *unmeasured* receipt of SSI; as we discuss in the next section, our 'likely not on SSI' sample is not receiving Medicaid via SSI eligiblity, but they might still be on SSI and simply eligible for Medicaid via a different channel.. Moreover,

[12] 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.

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, such an effect may not be present in the SSI group. Together, we think the two approaches likely provide bounds on the impact of SSI benefit receipt.

The regression also includes a number of indicator variables as controls, Ω_d. Specifically, following the approach of Evans and Moore (2012) we include indicator variables for calendar month, calendar year, day of the week, and 21 "special days".[13] We assume that these various calendar time controls 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.

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

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

Here, d once again denotes a specific calendar date, but now group c denotes one of the 10 possible last digits for one's SNAP case number, and s denotes whether one's SNAP case number was assigned before or during/after September 2012, when the mapping rule from SNAP case number to payout day changed. The SNAP payout day is determined by c and s together (Appendix Table OA.1). We expect that case numbers are randomly assigned and therefore, conditional on s, SNAP payout days will be uncorrelated with beneficiary characteristics; this is confirmed by balance tests (Appendix Tables OA.4 and OA.5). We therefore control for a series of indicator variables for the last digit c of an individual's case number (ψ_c), and allow the coefficient on this last digit of the case number to vary based on whether the case was assigned before or after September 2012 ($\delta_{c,s}$). [14]

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.

[13] 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.)

[14] More broadly, because SNAP payout day is randomly assigned within assignment regime s, we allow the effect of all covariates to vary by s; in practice, we show in the robustness analysis below that results look very similar if we impose the same relationship between covariates across assignment regime.

We include the same set of indicator variable controls Ω_d for calendar month, calendar year, day of the week and special days as in equation (1), but now allow their coefficients to vary for separate indicators based on whether the case was assigned before or after September 2012 (γ_s). 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; the $\kappa_{k,s}$ are a series of indicators for which day of the month it is (from the 1st potentially through the 31st), and again we allow their effect to vary by case assignment timing s. We report standard errors clustered at the date (day-month-year) 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. This consists of about a half million unique individuals in total. 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: Medicaid enrollment and utilization records; emergency and hospital discharge data for all payers; vital statistics death certificate data, and Department of Social Services (DSS) records on SNAP and TANF recipients. [15]

The DSS records contain the months that each individual receives SNAP and the months that they receive TANF. For each person-month receiving SNAP (and likewise for TANF), we also observe the benefit amount and benefit type (i.e. regular, supplemental, expedited, corrected). For SNAP, we also observe the last digit of the case number which we use to impute the day-of-the-month in which benefits are received. To identify SSI recipients, we use the Medicaid data which contains information on the months each individual was enrolled in Medicaid and her eligibility category at the beginning of each eligibility spell. The Medicaid data also provide basic demographics for our sample including year of birth, gender, race, and a household ID that allows us to identify members of the same household within our sample.

Our main source for outcomes is the all-payer hospital and ED records 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. We also use the Medicaid health care utilization data to measure Medicaid-covered prescription drug fills both overall and by type of drug. Unlike the other outcome variables, prescription

[15] 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.

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. The Vital Statistics death certificate data contain year of death for individuals who died between 1998 and 2019.

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, but instead, as in Dobkin and Puller (2007), define an indicator for SSI receipt based on whether the person-month received Medicaid through an SSI-related eligibility category;[16] this approach to identifying person-months on SSI is unlikely to generate false positives, but likely creates false negatives, since individuals can be on SSI but receive Medicaid through a different eligibility category. Therefore, for some of our empirical analyses of the impact of SSI receipt we use 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 individuals who are likely not SSI recipients. To reduce the chance of false positives when classifying someone as likely not on SSI, we drop any individual who at any point from 1998-2019 belongs to a household whom we ever see receiving SSI (i.e. receiving Medicaid through an SSI-related eligibility category). This does not, however, eliminate the possibility that this individual is on SSI. If the individual enrolled in SSI but their Medicaid eligibility is not via SSI, we will miss the fact that they are SSI; for this reason we refer to this group as "likely not on SSI."

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 use the emergency room data to proxy for consumption of temptation goods based on drug and alcohol related ER visits. 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).[18]

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 diagnosed conditions, where the timing of purchase more likely corresponds to the timing of con-

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

[17] Appendix B provides additional details on how we code the various outcomes.

[18] 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.

sumption. 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, 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; we do this so that we can interpret benefit receipt as an anticipated income 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.2 shows the impact of each of these restriction.

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 ER visits per day overall (34.18 per 10,000 person-days compared to 29.25 per 10,000) as well as drug or alcohol related ER visits (1.90 per 10,000 compared to 2.36 per 10,000).

For the SSI analysis we conduct a difference-in-differences analysis between person-months on SSI (column 2) and likely not on SSI (column 3). The differences between these samples are more pronounced. 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 ER visits both overall (39.25 vs 15.65 per 10,000 person-days) as well as drug or alcohol related ER 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 people both on and not on SSI, and likewise the SSI sample (column 2) includes people 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).[19] 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. Outcomes for those on SSI and SNAP are thus, by construction, the same.on SNAP. In this sample, ER 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 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. This causes us to lose between 60 and 75 percent of our person-months, because in order to observe drug fills the person-month must both be on Medicaid and also not be covered by Medicare Part D prescription drug coverage.[20] The bottom panel of

[19]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.

[20]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 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

Appendix Table OA.2 shows the impact of each of these restriction and Appendix Table OA.3 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. Note that because we are restricting to person-months on Medicaid, we may have a higher share of the 'likely not on SSI' sample that is actually on SSI.

4 Empirical Results

4.1 Graphical Evidence

Consumption of Temptation Goods. Figure 1 shows the impact of SSI and SNAP on emergency room 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 ER visits. By contrast, panel (b) shows a sharp increase in the number of a drug-or-alcohol related ER visit immediately following receipt of SSI; more specifically, there is an increase of approximately 0.26 visits on day the of SSI payout (day 0), rising to an increase of about 0.86 by the day after receipt (day 1), that stays elevated for another several more days before gradually declining. Relative to an average number of ER visits for drug and alcohol use of about 2.36 per day in this population (Table 1 column 2), these represent an approximately 11 percent increase in ER visits on day 0 and an approximately 36 percent on day 1. This finding of a cash-benefit cycle in drug and alcohol use is consistent with an existing literature (reviewed in more detail in Appendix A) of this type of cycle in ER 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), as well as evidence from tax rebates that on the extensive margin as well, the 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 ER visits rise by about 20 percent following SSI receipt in California. Unlike the link between cash transfers and alcohol and drug use, we are not aware of prior work examining the impact of SNAP on these temptation goods.

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. To control for potential factors that are correlated with the timing of SSI receipt and the consumption of drugs and alcohol, we 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 a sample of low-income adults who are likely not on SSI. Panel (c) compares the estimated

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.'

pattern of ER 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 an increase in ER 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 that receipt of SSI increases ER visits for drug and alcohol use is essentially the same as what we estimated when examining just the SSI group (panel b).

Consumption of non-labeled non-temptation goods. Figure 2 shows the impact of SNAP And SSI for fills of new prescription drugs, our proxy for non-labeled, non-temptation consumption. One again, panel (a) shows no evidence that such fills increase following SNAP benefit receipt. In contrast, figures (b) through (d) suggest that there is 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 146 (more than doubling the average daily rate of first fills of 141 in the SSI population; see Appendix Table OA.3) in the within-month analysis (panel b) and of about 96 (about a two-thirds increase) in the difference in difference analysis (panel d). This higher rate of first fills persists - albeit at a lower rte of increase - in the subsequent days. 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.[21] 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 - whose consumption may be unaffected by when the refill occurs. Interestingly, Appendix Figure OA.3 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 (or about 3 percent relative to the mean of 751), 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

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

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 3.4 to 4.0 (USDA). 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 just 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.[22] 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 surprisingly, reduces precision, but have not much impact on the point estimates; Appendix figures OA.1 and OA.2 report the analogous event studies for the overlap sample as those shown in the full sample for ER visits for drug and alcohol use (i.e. figure 1) and first fills of a prescription for a new illness (i.e. figure 2).

Figure 3 summarizes the results for ER visits for drug and alcohol use. We focus on the estimates of average impact in the week (7 days) after payout, but results are similar over other durations. We report one-fourth of 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, 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; as discussed, we suspect that these bound the impact of SSI. We also report the estimated impact of SNAP.

In the full sample, we estimate the average 7-day impact of SNAP on ER visits for drug and alcohol use is to decrease visits by a statistically insignificant -0.006 visits (standard error of 0.043) per day per 10,000. By comparison, one-fourth of the estimate of the average 7-day impact of SSI is a statistically significant increase of 0.176 (standard error = 0.009) visits per day per 10,000 people if we use the within-month variation in SSI only (column 2), and of 0.160 (standard error =0.010) if we use the difference in difference specification. 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 of the differences between SSI and SNAP impacts on ER visits for drug and alcohol use are similar (0.169 using the within-month variation in SSI only and 0.126 using the DD variation in SSI), but due to the substantial reduction in sample

[22] Ideally we would use the benefit payments received by our participants. However, while we observe SNAP benefit payments directly in our data, but unfortunately 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.

size (see Table 1), the results are less precise (p-values of 0.008 and 0.030, respectively). 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 results for both the full sample, as well as results for the overlap sample, and once again we report results for the first week, 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 (standard error = 7.99) or about 6 percent relative to the daily mean of 143 new first fills per 10,000 people. By contrast, one fourth of the SSI impact over the first week ranges from a statistically significant increase of 100 first fills (standard error = 5.33) or about 71 percent relative to the daily mean, to 45.6 first fills (standard error = 5.33). 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). We estimate that 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, the difference in estimates is now slightly larger (116 and 54 rather rather than 91 and 36) and 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 for 'bads' (i.e. temptation goods) but also to optimize over 'goods' that are not provided by the in kind transfer.

Robustness These fungibility tests are generally robust to a number of alternative specifications. In the overlap sample, we report an alternative specification in which in the SSI analysis we control for SNAP payout day and in the SNAP analysis we control for SSI payout day (rather than 'only' calendar day since SSI payout day is not always on the first of the month). We also show results in which we impose that the effect of all of the covariates in equation 2 do not vary by the SNAP assignment regime s, in which we remove or add additional covariates to both analysis, in which we limit SSI analysis to 2013 and later (when we know for sure that all benefits are paid electronically so received on the payment date), in which we estimate a proportional rather than a linear effect of SNAP and SSI benefit receipt, in which we present an alternative calculation of standard errors, and a variety of other specifications. For the prescription drug analysis, we also show that results are similar when we 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 C provides more details on these robustness analyses.

4.3 Heterogeneity and Additional Outcomes

Heterogeneity In the normative framework below, we model the consumption of temptation goods (which we proxy for by ED visits for drug and alcohol use) as increasing 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).[23] 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 as having behavioral health issues based on whether or not they had an ER 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.[24]

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. Individuals with prior behavioral health issues experience an average daily increase of 2.9 (standard error = 0.25) ER visits per 10,000 for drug and alcohol use (about a one-third increase relative to baseline), while individuals without prior behavioral health issues experience an average increase of only 0.36 (standard error = 0.037) visits. 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.15). We view these results as consistent with interpreting the increase in ER 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.[25]

[23]We are grateful to Sheena Tan for this suggestion. Specifically, we following Agarwal et al. (2024)'s definition for ED visits for behavioral health issues, which 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 it is far from 1-for-1: the behavioral health measure includes other types of visits tha 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 ER 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.

[24]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).

[25]Appendix Table OA.14 repeats our fungibility tests on the combined (smaller) sample as well as for the two

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 ER 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 ER visits for nutrition sensitive conditions, which may proxy for a (lack of) food consumption. Appendix D 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 ER 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). Tables OA.12 and OA.13 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 0.1 visits) and injuries and poisonings (a statistically significant increase of 0.15 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 muscuoloskeletal conditions, suggesting that SNAP may be having beneficial health effects relative to SSI.

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 infra-marginal 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, which can generate the empirical findings of a higher marginal propensity to consume temptation goods and non-food goods out of cash than out of infra-marginal SNAP. We then explore the normative implications for the optimal mix of in-kind and cash transfers for a paternalistic social planner facing individuals with self-control problems, which leads them to over-consume temptation goods such as drugs and alcohol, and compare the use of in-kind transfers to other policy instruments such as a food subsidy or a

sub-samples 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.

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.

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

$$p_f * f + n + p_b * c_1^b \leq y_1 + b_1$$
$$n + p_b * c_1^b \leq y_1$$

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.[26]

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 $b_1 = 0$); it 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

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

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. β), while her optimal choice of food and non-food are increasing in self-control (see Appendix for proof). Intuitively, a consumer with more self-control (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.[27]

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 ($\phi_0 y_1 + b_1$).[28] Target food consumption is determined by the sum of SNAP benefits (b_1) and the amount the consumer would choose to spend on food in the absence of mental accounting (i.e. $\phi_0 y_1$). Intuitively, the individual treats SNAP income as "food money".

The following 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. $b_1 < \frac{\phi_0}{1-\phi_0} y_1$.*

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 infra-marginal, mental accounting ($\kappa > 0$) is necessary and sufficient for SNAP and cash to be non-fungible:

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

[27] Note, however, that even when $\beta = 1$, the individual will choose to consume some temptation good (since $0 < \gamma < 1$).

[28] 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 straightforward first-order approach. In the Appendix, we discuss the functional form in more detail and also show that the quadratic functional form allows the model to more closely match the existing empirical evidence on fungibility of SNAP and cash.

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.

Proposition 1 says that if SNAP is infra-marginal, in the absence of mental accounting ($\kappa = 0$), individuals' consumption responses to cash transfers and infra-marginal 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 infra-marginal; this leads to a lack of fungibility and 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. The consumption (or lack of consumption) of food, non-food, and the temptation good were proxied in the empirical work by emergency room visits for nutrition-sensitive conditions, purchases of prescription drug medication for new illnesses, and emergency room visits for drug and alcohol use, respectively. Our key empirical results were a rejection of fungibility between cash and SNAP; more specifically, we found a higher marginal propensity to consume temptation goods and prescription drugs out of cash than SNAP, but higher marginal propensity to consume food out of SNAP than cash. Given the existing evidence that SNAP benefits are infra-marginal 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 having mental accounting.

However, the model is one in which cash and in-kind transfers can be thought of as permanent income, and the theoretical results concern the uncompensated responses that would arise from permanent policy changes that would provide recurring transfers each month, while our empirical results reveal the individual's response to anticipated inter-temporal fluctuations in the timing of these benefits. In Appendix E.8, therefore, we show that with self-control problems, mental accounting and borrowing constraints, evidence of non-fungibility in response to within-month timing of benefit receipt is informative of the presence of non-fungibility in response to permanent changes in benefit amounts. Specifically, in response to the permanent introduction of a small cash transfer or a small SNAP transfer, the consumption of all three goods will increase following the (regular) benefit payment; however, relative to the regular cash payment, the regular SNAP payment will trigger a bigger immediate increase in food consumption and a smaller immediate increase in consumption of the temptation good and the non-labeled non-temptation good. Intuitively, if the reason why consumption "spikes" immediately after receipt of cash transfer or SNAP comes from a combination of present bias and borrowing constraints, then our "within-month" estimates are informative about the degree of mental accounting as well as the extent to which cash and SNAP have "permanently" different effects of consumption.

A related concern is that our empirical results could reflect severe liquidity constraints rather than mental accounting. In particular, if people have no cash on hand prior to receipt of SNAP, it is possible that they could treat SNAP and cash as fungible over the course of the month, but our within-month strategy strategy would detect what looks like non-fungibility because on the day SNAP arrives, people have no cash on hand. In this case, we would not see an increase in temptation goods and in new prescription fills associated with the date of SNAP benefits, because the individual would literally have no cash to purchase temptation goods or prescriptions, but SNAP and cash could be fungible over the course of the month. Consistent with a role for liquidity, 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.

In practice, however, it is not likely that our results can be explained solely by a lack of liquidity. Pooling data from the 1998 through 2019 SCFs, we estimate that among people who received aid of some form (SNAP, SSI, TANF or other), only about one-fifth report having no liquid assets. Moreover, we find that when we limit to individuals who both SSI and SNAP (i.e. the overlap sample), and receive SNAP within the first 10 days of the month (so that they still have cash-on-hand from SSI) we continue to find no impact of SNAP receipt on either of our main outcomes (Appendix Figure OA.17), suggesting that a lack of liquidity cannot be a full explanation.

5.2 Benefit Design: Optimal Mix of SNAP vs Cash

We consider the problem faced by a paternalistic social planner choosing y_1 and b_1 subject to a total budget available $\bar{y}$ 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's optimal transfer is all cash, while in the presence of self-control problems ($\beta < 1$), the planner will always choose a strictly positive amount of both SNAP and cash. 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.

Intuitively, if the consumer has no self-control problems, so there is no reason in the model for the planner to use SNAP benefits to try to distort the consumer's consumption choices. However, when individuals have self-control problems ($\beta < 1$), the individual chooses to over-consume the temptation good relative to the social planner's $\beta = 1$ benchmark; 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, is when the planner keeps the SNAP share sufficiently low that it is infra-marginal, 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 social planner uses SNAP to increase food consumption directly by increasing the amount of SNAP above the infra-marginal amount, hence decreasing consumption of the bad. As we will see in the next result, which case we end up in depends on the strength of the mental accounting parameter κ. 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 necessary nor sufficient for this.[29]

We now show that, all else equal, 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*

[29]The fact that, for any value of κ, the planner will never choose only SNAP benefits is a consequence of our assumption 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.

the optimal SNAP share is such that SNAP benefits are inframarginal.
Proof: See Appendix.

These two comparative static results establish the role of SNAP in the safety net in the presence of self-control problems ($\beta < 1$). The optimal SNAP share is larger the greater the self-control problems of the individual; intuitively, the farther β is from 1, the farther the individual's choices are from what the planner would choose, and the planner therefore chooses a larger SNAP benefit share in order to have the consumer to make larger consumption responses 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 is needed to induce a given increase in food consumption. In other words, if κ is large, then the individual's mental accounting behavior is very strong, so 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 infra-marginality 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 transfer were in cash; below this point 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. This is why the planner chooses a constant optimal SNAP share that is independent of κ and β for $0 \leq \kappa \leq \kappa^*$: in this range, the planner is instead targeting food spending directly using the kinked budget constraint; the consumer's food consumption will now exactly equal the SNAP benefit because the planner's choice of SNAP is above what they 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 infra-marginality of SNAP benefits.

Normative benchmark It is worth noting that the above results assume a particular normative paternalistic benchmark for the social planner. Specifically, she considers the individual's utility at $\beta = 1$ and $\kappa = 0$ rather than at the individual's actual β and κ parameters (O'donoghue and Rabin 1999). This is known as the long-run utility criterion. Naturally one could choose other benchmarks; (Laibson 1997), for example, proposes a Pareto criterion under which a policy is said to increase welfare only if both the time consistent and time inconsistent self is made at least as well off. We show in the Appendix that if we apply an alternative normative criterion that takes a weighted average of consumer welfare viewed from the perspective of the time-consistent and time-inconsistent consumer's utility, the social planner's optimal SNAP share of the total transfer is simply a weighted average of what the social planner would choose using the long-run utility criterion and what the consumer herself would choose.

Finally, our results concerning optimal paternalistic policy do not require time-inconsistency (i.e. $\beta - \delta$ preferences) per se.[30] Rather, as we show in the Appendix as long as the social planner has an optimal level of food consumption that exceeds that of the consumer's, our above results concerning the planner's optimal use of SNAP still apply.

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 other policy instruments and how they 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). We consider two other policy instruments: the optimal Pigouvian tax on the temptation good, which seems a more natural and direct way to correct the "internality" of over-consumption of the temptation good due to self-control problems, and an optimal (linear) food subsidy.[31]

5.3.1 Representative agent

We first consider the case of a representative agent. In the Appendix, we show that if $\beta < 1$, the optimal Pigouvian tax on the temptation good is positive, and that the government would not use subsidies on other goods or SNAP if a Pigouvian tax on the temptation good is available.[32] We also show that if a linear food subsidy is the only policy instrument available alongside a cash transfer (i.e., the government can only transfer cash and subsidize food), then there is an equivalence result between the optimal food subsidy and the optimal SNAP policy. Specifically, if the planner has to choose to allocate money between a cash transfer and a food subsidy, then for $\beta < 1$, the optimal food subsidy (which is positive) causes the individual to make the exact same consumption choices as in the optimal SNAP share planner problem, and at the same share of the planner's transfer spent on the food subsidy and SNAP. In other words, for a government designing an income transfer, the two policy instruments (choosing the optimal SNAP benefit share and choosing the optimal food subsidy) lead the consumer to make the same choices.

5.3.2 Heterogeneous agents

In the remainder of this section we relax the representative agent assumption and allow for heterogeneity across consumers in both their self-control (β) and the extent of mental accounting (κ).

[30]Nor do our empirical results directly establish the presence of such time-inconsistency. Although we have interpreted the increase in increase in ER visits for drug and alcohol use in response to receipt of a cash transfer - and the greater increase in these visits for those with prior behavioral health issues - as indicative of time inconsistency (i.e. $\beta < 1$), it is possible to interpret these responses as those of a fully rational, time-consistent consumer.

[31]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 ˙1, and 0% beyond that.

[32]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 that here.

This has implications not only for optimal SNAP but for the performance of SNAP compared to other potential policy instruments.

To explore this, we consider a "two-by-two" heterogeneity structure. That is, individuals can either have a β parameter of $\beta = 1$ or $\beta = \bar{\beta}$ (with $\bar{\beta} < 1$) and can either have a κ parameter of $\kappa = 0$ or $\kappa = \bar{\kappa}$ (with $\bar{\kappa} > 0$). Suppose there is a unit mass of individuals, with population shares defined by $s_{\beta,\kappa}$, with $s_{\bar{\beta},\bar{\kappa}} + s_{\bar{\beta},0} + s_{1,\bar{\kappa}} + s_{1,0} = 1$. In what follows, we will often focus on the case in which β and κ are *negatively* correlated, sometimes by restricting to two types: $(\bar{\beta}, \bar{\kappa})$ and $(1, 0)$. In other words, individuals with self-control problems ($\beta = \bar{\beta}$) tend to engage in mental accounting ($\kappa = \bar{\kappa}$). This would be consistent with the original thinking of mental accounting as a way that agents may attempt to mitigate their own self-control problems (Thaler 1985).

Optimal mix of cash and SNAP If the individual "types" are observable, then the planner would choose group-specific transfers. Specifically, theorem 1 tells us that the individuals with $\beta = 1$ would receive only cash and the individuals with $\beta < 1$ would receive SNAP. Moreover, theorem 2 tells us that within the $\beta < 1$ sub-group, the planner would want to have a (weakly) greater share of SNAP benefits for the $\kappa = 0$ sub-group compared to the $\kappa > 0$ sub-group.

If the social planner cannot identify the individual "types", then the social planner will maximize social welfare by choosing a safety net that balances out the paternalistic benefits of using SNAP for the $\beta < 1$ types against the welfare costs of using SNAP for the $\beta = 1$ types. In the special case where there are only two types - individuals with no self-control problems and no mental accounting, and individuals with self-control problems and mental accounting (i.e. $s_{\bar{\beta},\bar{\kappa}} + s_{1,0} = 1$) the planner will optimize the safety net only for the $\beta < 1$ types as long as $\bar{\kappa}$ is large enough; for sufficiently large $\bar{\kappa}$, the optimal SNAP share for the $\beta < 1$ type preserves infra-marginality of SNAP, and there is therefore no welfare cost for the ($\beta = 1$,$\kappa = 0$) type from substituting SNAP for cash.

Comparison to alternative policies. In the Appendix we show that with heterogeneous agents, 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 starting observation is that the optimal (uniform) Pigouvian tax on the temptation good can not longer achieve the first best because the first best policy would distort the behavior of the $\beta = \bar{\beta}$ types but not the behavior of the $\beta = 1$ types, while the optimal (uniform) Pigouvian tax will distort both types' behavior.[33] To see the intuition for how SNAP can outperform the Pigouvian tax, consider the two type case $s_{\bar{\beta},\bar{\kappa}} + s_{1,0} = 1$. Once again, SNAP can be used to only affect the behavior of the individuals with self-control problems, since the individuals without self-control problems do not engage in mental accounting, while the Pigouvian tax on the temptation good will affect the behavior of both

[33] This is the "internality" version of the classic (Diamond 1973) result that in the presence of heterogenous agents, the optimal (uniform) Pigouvian tax for externalities can no longer achieve the first best.

types. Of course, the Pigouvian tax directly addresses consumption of the temptation good while SNAP does so only indirectly, by affecting food consumption; however for sufficient substitutibility between food consumption and the temptation good, the decrease in consumption of the temptation good through SNAP-induced consumption of food may be able to achieve the first best.

In addition, with heterogeneous agents, the optimal mix of SNAP and cash is no longer equivalent to the optimal (linear) food subsidy. In the perfectly negatively correlated two type case, SNAP will outperform the food subsidy for the same reason it can outperform the tax on temptation goods: it only distorts consumption for the individuals with self-control problems. Using a mix of SNAP and cash strictly dominates the combination of cash and food subsidies, since the latter would distort food consumption choices for the ($\beta = 1$,$\kappa = 0$) type as well. Of course, in the case of perfectly positively correlated types (i.e. the agents who engage in mental accounting have $\beta = 1$ and the agents with self control problems do not engage in mental accounting) then SNAP will do worse than the optimal linear food subsidy since SNAP only distorts the behavior of individuals with $\beta = 1$, which is counter-productive.

More generally, as long as β and κ are "sufficiently negatively correlated", we show that the optimal safety net will always include a mix of SNAP and cash and will not use food subsidies or Pigouvian taxes on the temptation good even if they are available to the planner; such corrective subsidies or taxes distort consumption on the margin for *all agents*. By using SNAP to reduce the consumption of temptation goods for the low β individuals (since they also have high mental accounting), SNAP provision can avoid distorting consumption choices for those without self-control problems.[34]

5.4 Calibration

To get a quantitative sense of the model's implications, we calibrate the the preference parameters in order to match several empirical targets. The Appendix provides the full details , which we briefly summarize here. We begin with a representative agent and then allow for heterogeneity in β and κ.

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 expenditure shares of food (both at home and away from home) and temptation goods (alcohol,

[34]Of course, conversely, if the correlation structure is reversed so that the only individuals who engage in mental accounting are the ones who are time consistent, providing some transfers in SNAP can be worse for social welfare than all cash. In this sense, our results are reminiscent of the Allcott et al. (2019) findings that whether or not the redistribution and corrective properties of sin taxes work in tandem or are in tension varies based on whether self control problems are decreasing or increasing with income.

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 existing empirical evidence on the $MPCf$ out of cash and SNAP, which gives a range of $0.043 < \kappa < 0.080$ to match the $0.5 < MPCf^{SNAP} < 0.6$ estimated range in Hastings and Shapiro (2018). Lastly, we calibrate γ to match a 7.5-fold higher rate of spending on temptation goods for individuals with $\beta = 1$ compared to those with $\beta = 0.7$.[35] . This results in an implied value of $\gamma = 0.95$.[36] Since γ scales the negative health consequences of consuming temptation goods, we evaluate sensitivity to this parameter in the Appendix.

Using the calibrated parameters, we numerically solve for the optimal SNAP share, which we express as the optimal SNAP benefit as a share of the individual's total food spending. Our simulations reproduce the comparative static in Proposition 2 that the optimal SNAP share of food spending is 100 percent of food spending for small values of κ (including $\kappa = 0$), because in this range SNAP benefits induce the individual to bunch at the kink in the budget constraint, and the optimal SNAP share is strictly decreasing in κ for $\kappa > \kappa^* = .0026$. For our assumed values of κ ($0.043 < \kappa < 0.080$), we calculate an optimal SNAP share of 8.8-11.4 percent of food spending, which is considerably below the current SNAP share of food spending. For example, Hastings and Shapiro (2018) report that SNAP households receive SNAP benefits that are roughly 40 percent of food spending. This implies that SNAP benefits are "overly paternalistic" given our calibrated parameters when we assume a representative agent.

Heterogeneous agents. We use the "two-by-two" heterogeneity structure described above, 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 $\beta = \bar{\beta} = 0.4$ (i.e. $s_{\bar{\beta},\bar{\kappa}} + s_{\bar{\beta},0} = 0.5$) 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 $\bar{\kappa} = 0.043$. This leaves the population shares, $s_{\beta,\kappa}$, as the only unknown parameters. Since we do not have any direct information on how β and κ are correlated in the population, we examine the optimal SNAP share under different assumed values of this correlation, ρ, and we use the assumed value of ρ to back out the population shares.

We begin with the two polar cases. First, if $\rho = -1$ then we are in the "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 ($\beta = \bar{\beta} = 0.4$, $\kappa = \bar{\kappa} = 0.043$), with $s_{\bar{\beta},\bar{\kappa}} = s_{1,0} = 0.5$. In this case, we calculate an optimal SNAP share of food spending to be 0.24, which is also the same optimal SNAP share if $s_{\bar{\beta},\bar{\kappa}} = 1$ (i.e., we are back in

[35] This 7.5 higher rate of consumption of temptation goods comes from the ratio of the average rate of drug and alcohol ER visits for individuals on SSI with prior behavioral health issues relative to the those on SSI wihtout prior behavioral health issues, as shown in Panel A of Appendix Table OA.15.

[36] Note that α_g and α_f are pinned down by the assumed expenditure shares and an assumed value of γ; using $\gamma = 0.95$ we calculate $\alpha_g = 0.779$ and $\alpha_f = 0.211$.

representative agent model but with everyone having $\beta = 0.4$ and $\kappa = 0.043$). Intuitively, in this case the planner is able to choose the optimal SNAP share for the $\beta = \bar{\beta}$ type at no cost to the "rational" type.

Second, 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 ($\beta = 1$, $\kappa = \bar{\kappa} = 0.043$), with $s_{\bar{\beta},0} = s_{1,\bar{\kappa}} = 0.5$. Then 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 infra-marginal SNAP transfer to increase social welfare.[37]

Appendix Figure OA.19 shows that, as expected, the optimal SNAP is decreasing in ρ between these two polar cases. If $\rho = 0$ (so that β and κ are completely uncorrelated in the population), then we calculate an optimal SNAP share of 0.140, which is slightly larger than the representative agent scenario.[38] Naturally, all of these estimates rely on parameters that have substantial uncertainty around them, but regardless of the value of ρ that we assume, we continue to calculate an optimal SNAP share that suggests SNAP is "overly paternalistic", just 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 ER 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 recept, and suggestive evidence that nutrition-sensitive ER visits rise slightly in response to SSI but fall slightly in response to SNAP.

Given the existing empirical evidence that SNAP is infra-marginal for most individuals, we show that allowing for mental accounting can generate our empirical findings of a higher marginal propensity to consume temptation goods and non-food goods out of cash than out of infra-marginal

[37] Given our parameter values, the social planner does not want to set the SNAP share at a non-infra marginal level but that is of course possible for other parameters for example, if $\bar{\kappa}$ and/or $\bar{\beta}$ were sufficiently small, the social planner could prefer to exploit the budget set to get the 'behavioral' types to consume more food even at the cost of distorting the food consumption of the $\beta = 1$ types.

[38] 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.

SNAP, and a higher marginal propensity to consume food out of infra-marginal SNAP than out of cash. We then explore the normative implications of providing transfers in cash vs. in-kind for a paternalistic social planner. 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; moreover 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. A (very) rough calibration suggests that the current level of SNAP benefits may be overly paternalistic. Work-in-progress suggests that with heterogeneous agents, the optimal mix of SNAP and cash transfers may outperform an optimal Pigouvian tax on the temptation good when present biasedness and mental accounting are positively correlated, suggesting that additional empirical work estimating the covariance between these two phenomena would be valuable.

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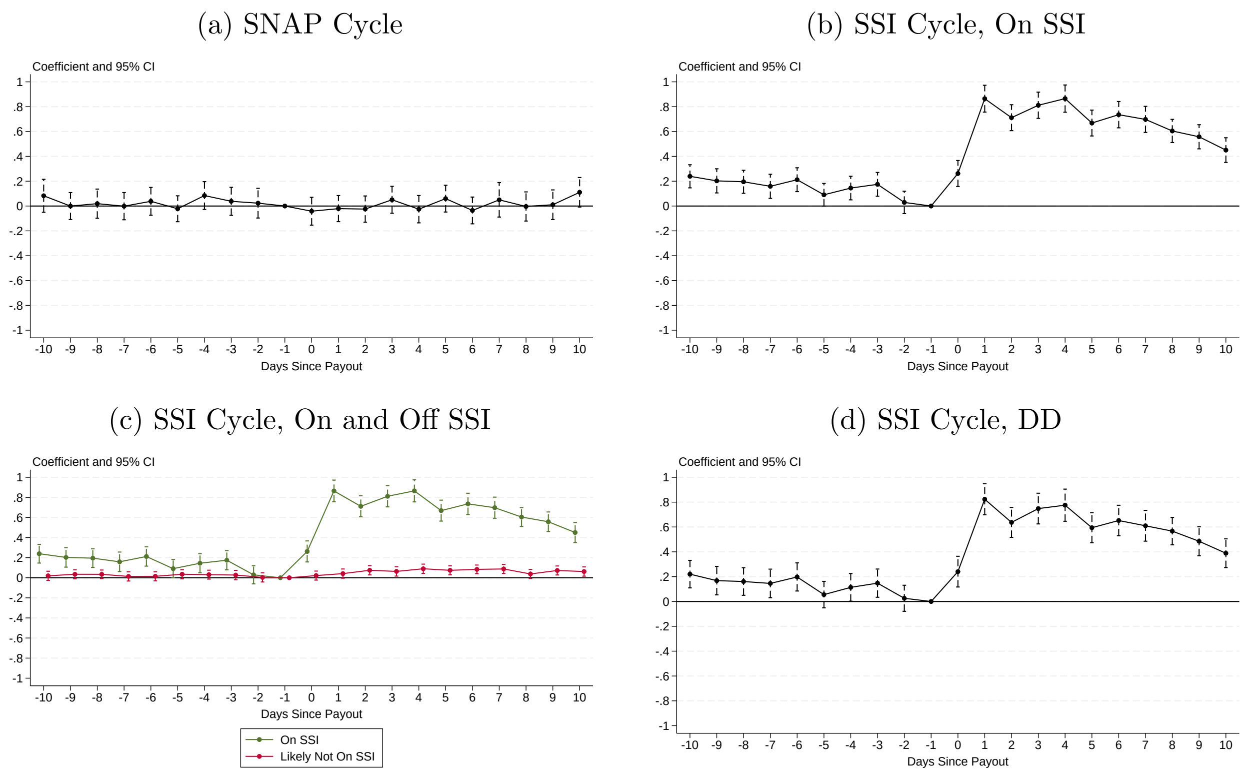
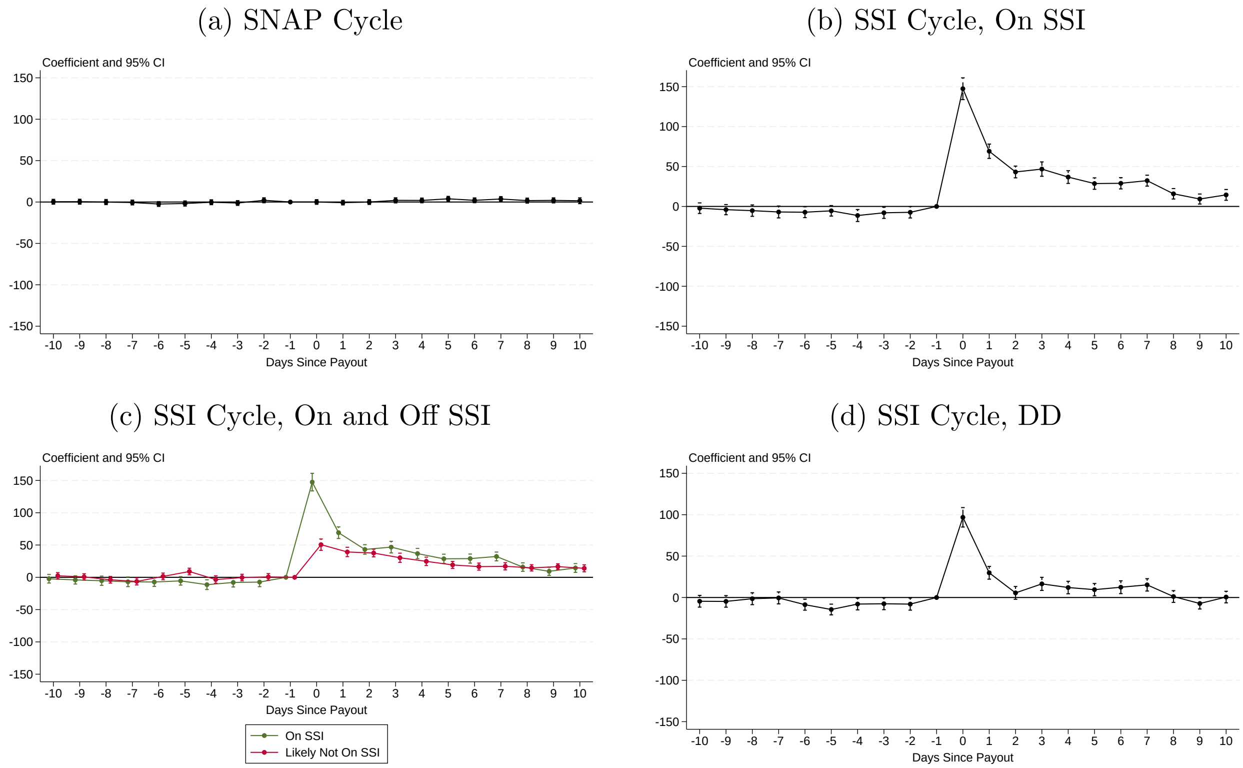
7 Figures

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



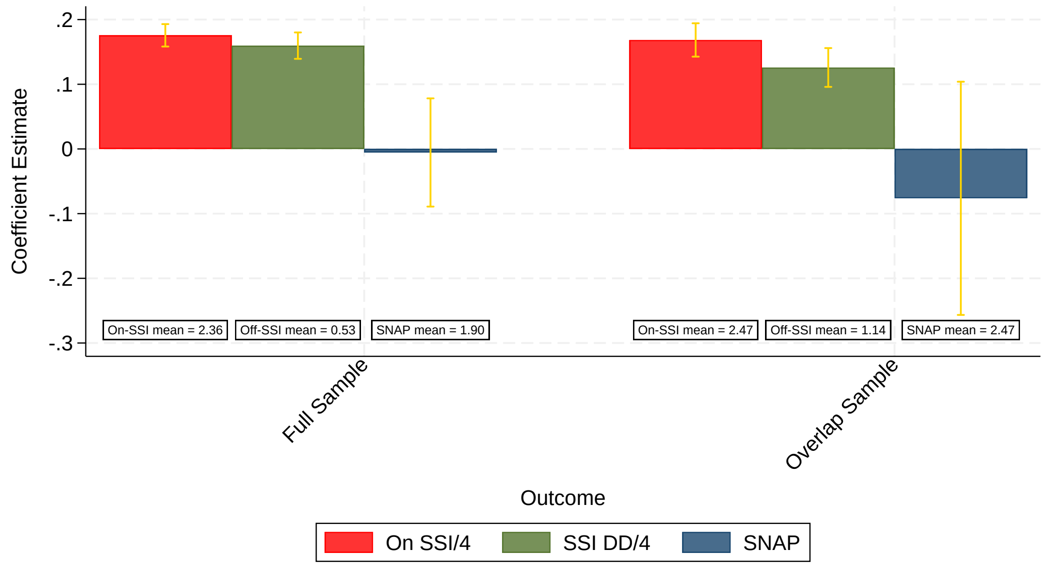
Notes: This figure shows estimates of (a) β_r from equation 2, (b) $\alpha_{r'} + \beta_{r'}$ from equation 1, (c) $\alpha_{r'} + \beta_{r'}$ from equation 1 (in green) overlaid with $\alpha_{r'}$ from equation 1 (in red), and (d) $\beta_{r'}$ from equation 1. The outcome variable is ER visits for drug-and-alcohol-related 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 2: Effects of SNAP and SSI on First Fills



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 = 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.

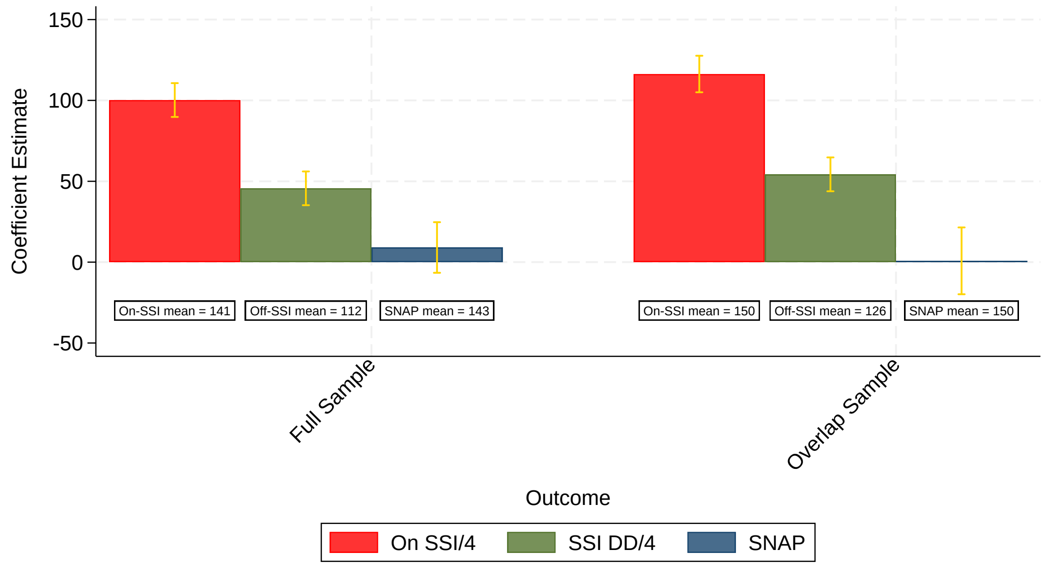
Figure 3: Examining Fungibility, Drug and Alcohol ER Visits



		(1) SNAP Estimate	(2) SSI Estimate $\frac{1}{4}$*On SSI	(3) SSI Estimate $\frac{1}{4}$*SSI DD
Full Samples	Estimate	-0.006	0.176	0.160
		(0.043)	(0.009)	(0.010)
	Difference, SSI - SNAP	-	0.181	0.165
		-	(0.044)	(0.044)
	P-value of difference	-	< 0.001	< 0.001
	Scaling factor		9.09	8.33
Overlap Samples	Estimate	-0.076	0.169	0.126
		(0.092)	(0.013)	(0.015)
	Difference, SSI - SNAP	-	0.245	0.202
		-	(0.093)	(0.093)
	P-value of difference	-	0.008	0.030
	Scaling factor		6.67	5.00

Notes: Exhibit shows fungibility test results for drug-and-alcohol-related ER visits. Figure shows point estimates and confidence intervals for the average effects of SNAP receipt and one-fourth the average effects of SSI receipt on drug and alcohol related ER visits over the first week (relative days 0 through 6) following equations 2 and 1 respectively. Red bars show one-fourth of the average first week on-SSI effect from equation 1. Red bars show one-fourth of the average first week SSI DD effect from equation 1. Navy bars show the average first week SNAP effect from equation 2. "Means" in figure represent mean number of DA ER 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 one-fourth of the average first week effect of SSI receipt, as well as the difference in these estimates. "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 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.

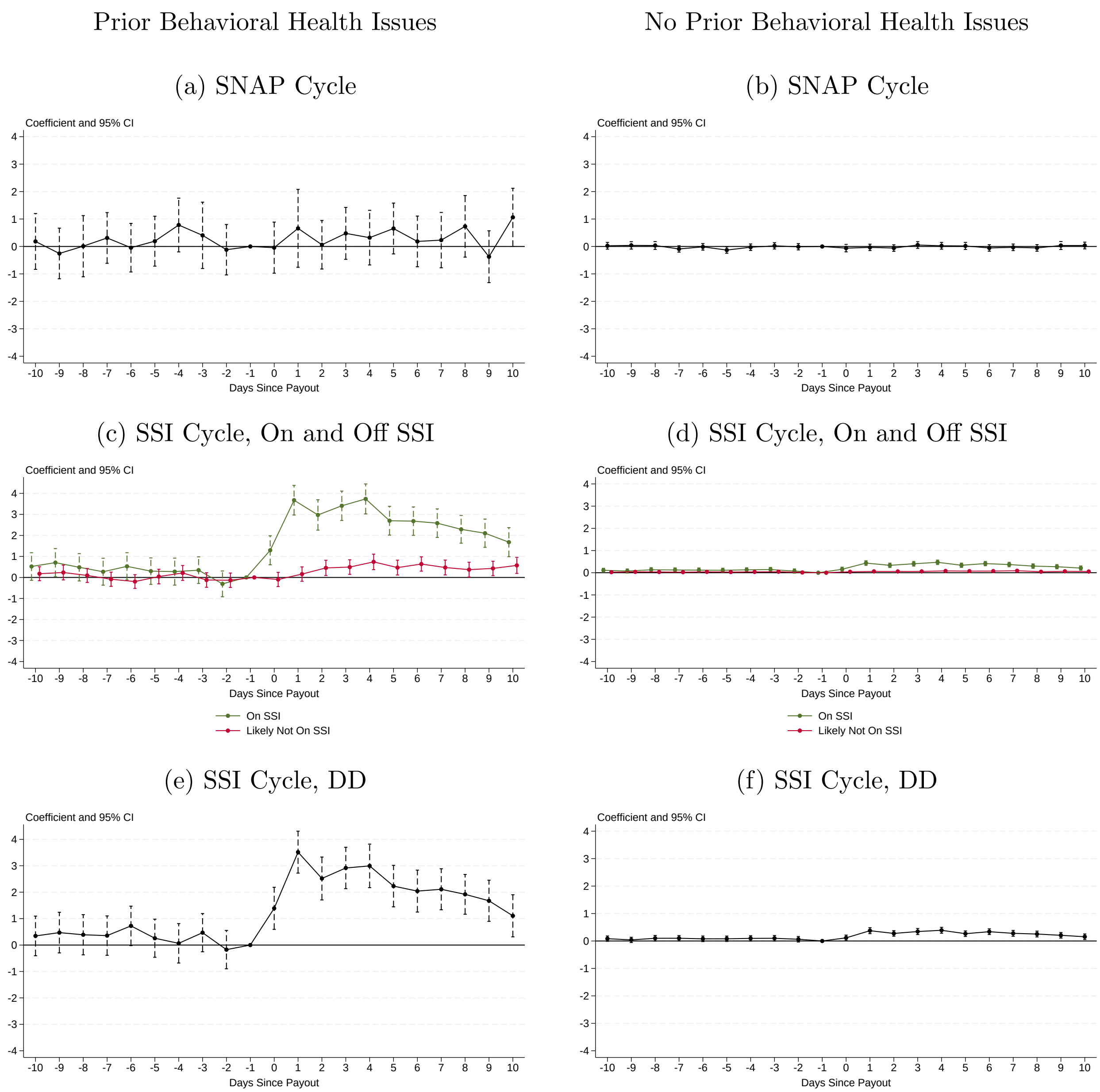
Figure 4: Examining Fungibility, First Fills



		(1) SNAP Estimate	(2) SSI Estimate $\frac{1}{4}$*On SSI	(3) SSI Estimate $\frac{1}{4}$*SSI DD
Full Samples	Estimate	9.066	100.233	45.649
		(7.985)	(5.335)	(5.326)
	Difference, SSI - SNAP	-	91.167	36.583
		-	(9.628)	(9.641)
	P-value of difference	-	< 0.001	< 0.001
	Scaling factor		16.67	7.14
Overlap Samples	Estimate	0.807	116.330	54.287
		(10.537)	(5.760)	(5.339)
	Difference, SSI - SNAP	-	115.523	53.480
		-	(12.081)	(11.891)
	P-value of difference	-	< 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 one-fourth the sum of effects of SSI receipt on first fills over the first week (relative days 0 through 6) following equations 2 and 1 respectively. Red bars show one-fourth of the sum of first week on-SSI effects from equation 1. Red bars show one-fourth of the sum of first week SSI DD effects from equation 1. Navy bars show the sum of first week SNAP effects from equation 2. "Means" in figure represent mean number of first fills per day 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 one-fourth of the sum of first week effects of SSI receipt, as well as the difference in these estimates. "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 ER visits, by Behavioral Health Issues



Notes: 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), and panels (e) and (f) show estimates of β_l from equation 1. The outcome variable is ER 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 observed in years five and later. In (a), N person-months on SNAP = 1,637,081. In (b), N person-months on SNAP = 15,016,753. In (c) and (e), N person-months on SSI = 1,515,591 and N person-months likely not on SSI = 2,809,981. In (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, ER 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: ER Visits Per Day (Per 10,000)					
Drug/alcohol-related (DA)	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. ER visits per day per 10,000 are calculated by averaging the number of ER 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 - peeks 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.[39]

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

[39] 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).

ER 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, a result they hypothesize is due to families being more likely to eat at home on these days. 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.[40] However, there are distinct literatures looking separately at the imnpact 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, there is also evidence of positive health impacts of cash transfers for low-income individuals, suggesting that the impacts of liquidity may be nuanced. For example, a randomized evaluation

[40] 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.

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 room visits, including reductions in visits related to behavioral health and substance use (Agarwal et al. 2024).[41] Moreover, several recent papers have also found a cash benefit cycle in which low-income individuals increase their prescription drug fills upon benefit receipt; these 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).[42]

A.2.2 SNAP

Most closely related to our work is the literature on SNAP benefit cycles and health.[43] Several (although not all) papers find evidence consistent with receipt of SNAP reducing hospital or ER 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 ER 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 ER 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 ER 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.[44] Our findings that SNAP receipt is associated with an immediate but short lived decline in ER 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; **?**).

[41] 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).

[42] Looking beyond liquidity per se, a much larger income has examined the causal impact of income on health, with very mixed results across studies; Lleras-Muney (2022) reviews some of this evidence.

[43] 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).

[44] 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 ER visits. Our coding of drug and alcohol related ER 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*, 3065*), opioid (3040*, 3047*, 3055*), amphetamine (3044*, 3057*), residual drug dependence (admissions for dependence on other drugs) (292*, 304*), and alcohol only (291*, 303*, 3050*).[45]

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 ER Visits. We code ER 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 ER visits using an algorithm developed in Ginde et al. (2008). The algorithm defines hypoglycemia ER 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*.

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 ER 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 ER claims, arguing that it is an indication of food insecurity. We follow their definition of ER 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 Table OA.11 shows the share of ER visits which correspond to each component of nutrition-sensitive ER 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

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

hard to be confident that they are picking up effects of nutritional intake per se.

Major Causes of ER 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 ER visit has a primary diagnosis code falling into any of the above groups, we code it as such. Any ER 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 Tables OA.12 and OA.13 shows the share of ER visits which correspond to each major cause of ER visits.

C 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.6 and OA.7 summarize the results for, respectively, ER 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 controls for SNAP payout day to the baseline SSI analysis and controls for SSI payout day to the SNAP analysis. We focus this test on the overlap sample where controlling for the other benefit's payout day is most relevant. Note that the SNAP analysis already controls for calendar day but this is not quite the same as 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). .

In the third row, we relax the assumption in the baseline SNAP analysis in equation 2 that the effects of all the covariates (specifically 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).[46]

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.8 shows the (quite substantial) reductions

[46]We explored the sensitivity of results to the choice of covariates more broadly. In Appendix Tables OA.9 and OA.10 we sequentially (and cumulatively) drop the various covariates included in Ω_d in equations 1 and 2; i.e. we sequentially (and cumulatively) drop the controls for 'special days', for calendar year, for calendar month, and day of the week from both analyses and then finally the day of the month controls from the SNAP analysis.

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.

Finally, 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 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.

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.18, 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.

D Analysis of 'Nutrition Sensitive' Conditions

We attempt to proxy for ER 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 ER 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 ER 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.9 through OA.16 show the underlying event studies. Appendix table OA.11 Column (1) shows evidence that, for all definitions, nutrition-sensitive ER visits decline following receipt of SNAP.[47] Columns (2) and (3) show evidence

[47]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 ER visits for nutrition-sensitive conditions following receipt of SNAP (e.g., Ojinnaka and Heflin 2018;

that, by contrast, ER 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 ER visits for nutrition sensitive conditions 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 ER 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.

E Proofs and Derivations

E.1 Definitions Used in the Formal Proofs

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 makes the individual's utility function, U, 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:

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

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.

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 $\theta(\alpha_g, \alpha_f, \beta, \gamma, \kappa) \equiv \frac{p_b(c_1^{b*})}{y_1+b_1}$

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.

- 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. $b_1 < \frac{\phi_0}{1-\phi_0} y_1$
- Marginal propensities to consume food ($MPCF$), non-food ($MPCN$), and the "bad" temptation good ($MPCB$) out of cash and SNAP are:

$$MPCF^{cash} \equiv \frac{d(p_f f^*)}{dy_1} \qquad MPCF^{SNAP} \equiv \frac{d(p_f f^*)}{db_1}$$
$$MPCN^{cash} \equiv \frac{d(n^*)}{dy_1} \qquad MPCN^{SNAP} \equiv \frac{d(n^*)}{db_1}$$
$$MPCB^{cash} \equiv \frac{d(p_b(c_1^{b*}))}{dy_1} \qquad MPCB^{SNAP} \equiv \frac{d(p_b(c_1^{b*}))}{db_1}$$

E.2 Deriving the $MPCF$, $MPCN$, and $MPCB$ Expressions

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

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

Differentiating the utility function gives the following marginal utilities:

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

We define ϕ as the share of the individual's total income spent on food expenditures ($\phi = \frac{p_f f}{y_1 + b_1}$) and θ as the share of expenditures on the temptation good ($\theta = p_b c_1^b 1 y_1 + b_1$). This (further) reduces the problem to two unknown parameters: ϕ and θ. 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 then 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 in the main text:

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

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

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

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

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

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. 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 to the difference in the $MPCF$ 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 get $(\frac{d\phi}{db_1}-\frac{d\phi}{dy_1})$ as:

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

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:

$$\begin{aligned} &MPCB^{SNAP}-MPCB^{cash} = \left(\frac{d\theta}{db_1}-\frac{d\theta}{dy_1}\right)(y_1+b_1) \\ &= \frac{-(1-\alpha_g)(1-\beta\gamma)}{(1+\beta)\alpha_g(1-\alpha_f)+(1-\alpha_g)(1-\beta\gamma)}(MPCF^{SNAP}-MPCF^{cash}) \end{aligned} \tag{4}$$

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

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

E.3 Characterizing Food Spending as κ Varies

It is useful to think of the individual's optimal food spending for any $\kappa \geq 0$ as falling between the food spending characterized by the $\kappa = 0$ and $\lim_{\kappa \to \infty}$ cases:

- When $\kappa = 0$, the individual chooses the optimal food consumption absent mental accounting. This is the lower bound on the individual's food consumption: $f^*_{\kappa=0} = \phi_0(y_1 + b)$.
- 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: $f^*_{\kappa\to\infty} = \phi_0 y_1 + b$
- 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 $\frac{\partial f}{\partial \kappa} > 0$.

In the case where $\kappa = 0$, 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 can also 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:

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

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

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

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

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

subject to $p_b c_1^b + n = (1-\phi)(y_1 + b_1)$. This gives the following 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:

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

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:

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

The numerator is given by

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

The denominator is given by

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

Putting these two together gives $\frac{d\phi^*}{d\kappa} > 0$. Food consumption is strictly increasing in κ, so κ exactly pins down food consumption in the interval $\bar{f}^* \in [\phi_0(y_1+b), \phi_0 y_1 + b)$. It is also worth noting that the optimal food consumption ϕ^* depends on y_1 and b_1 only through U_B.

It will also be useful to sign $\frac{d\phi^*}{db_1}$ and $\frac{d\phi^*}{dy_1}$

$$\begin{aligned}\frac{d\phi^*}{db_1} &= -\frac{d^2U}{d\phi db_1} / \frac{d^2U}{d\phi^2}, \\ \frac{d\phi^*}{dy_1} &= -\frac{d^2U}{d\phi dy_1} / \frac{d^2U}{d\phi^2}\end{aligned}$$

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

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

so $\frac{d\phi^*}{db_1} > 0$ and $\frac{d\phi^*}{dy_1}$ could be positive or negative. $\frac{d\phi^*}{db_1} - \frac{d\phi^*}{dy_1} = 2\kappa(1-\phi_0)(y_1+b_1) > 0$: an increase in SNAP always increases ϕ^* more than an increase in cash.[48]

E.4 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 $(MPCb^{cash} - MPCb^{SNAP})$*

[48] In B.XXX, we explain why it is possible for $\frac{\partial\phi^*}{\partial y_1} < 0$, which is a consequence of the "quadratic" mental accounting functional form.

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:

$$\phi^* = \phi_0 = \frac{(1+\beta)\alpha_g \alpha_f}{\alpha_g(1+\beta) + (1-\alpha_g)(1-\beta\gamma)} > 0$$
$$\theta^* = \theta_0 = \frac{(1-\alpha_g)(1-\beta\gamma)}{\alpha_g(1+\beta) + (1-\alpha_g)(1-\beta\gamma)} > 0$$

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 $MPCN^{cash} = MPCN^{SNAP} = (1 - \phi_0 - \theta_0)$. ■

We can restate the first part of part 2 of the Proposition as follows: $\frac{\partial\phi}{\partial\beta} > 0$, $\frac{\partial\theta}{\partial\beta} < 0$, and $\frac{\partial(1-\phi-\theta)}{\partial\beta} > 0$. To prove this, 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 $\frac{dU}{d\phi}(\phi^*)$ 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 $d(1-\phi^*-\theta^*)/d\beta > 0$.

To prove the last part of Part 2 in 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 (4) 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 (4):

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

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 (4) 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:

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

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 $\kappa > 0$:

$$\frac{\partial \phi^*}{\partial b_1} > 0, \quad \frac{\partial \phi^*}{\partial b_1} - \frac{\partial \phi^*}{\partial y_1} > 0$$

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

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

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 $\beta = 1$. The Theorem 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.[49]

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

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

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 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 perspective of the planner. 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:

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

[49] 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 $\bar{y}$.

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

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

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 $\frac{b^*}{\bar{y}}$:

$$\frac{b^*}{\bar{y}} = \frac{\alpha_g(1+\beta)+(1-\alpha_g)(1-\beta\gamma)}{2\kappa\bar{y}^2(1-\phi_0)}\left[\frac{1-\phi_0}{1-\phi_{SP}} - \frac{\phi_0}{\phi_{SP}}\right] + \frac{\phi_{SP}-\phi_0}{1-\phi_0} \tag{5}$$

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 reduce 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

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

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:

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

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 6. Over the full range of κ, the social planner would implement the exact same allocation for the consumer.

Over the range $0 \leq \kappa < \kappa^*$, 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:

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

For $\kappa > \kappa^*$, the social planner's preferred food consumption is implemented by the "interior" value $\frac{b^*}{\bar{y}}$ given by equation 6. 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 6.

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 6.

- 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 6, 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 6 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:

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

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:

$$\frac{\alpha_g(1-\alpha_f) - \gamma(1-\alpha_g)}{1-\phi_{SP}} - \frac{\alpha_g\alpha_f}{\phi_{SP}} < 0$$
$$\frac{(\alpha_g(1-\alpha_f) - \gamma(1-\alpha_g))\phi_{SP} - \alpha_g\alpha_f(1-\phi_{SP})}{(1-\phi_{SP})\phi_{SP}} < 0$$
$$(\alpha_g(1-\alpha_f) - \gamma(1-\alpha_g))\phi_{SP} - \alpha_g\alpha_f(1-\phi_{SP}) < 0$$
$$\alpha_g(1-\alpha_f)\phi_{SP} - \gamma(1-\alpha_g)\phi_{SP} - \alpha_g\alpha_f + \alpha_g\alpha_f\phi_{SP} < 0$$
$$\alpha_g\phi_{SP} - \gamma(1-\alpha_g)\phi_{SP} - \alpha_g\alpha_f < 0$$
$$\alpha_g(\phi_{SP} - \alpha_f) - \gamma(1-\alpha_g)\phi_{SP} < 0$$

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

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

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

E.5 Alternative Policy Instruments: 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.[50]

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:

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

[50] 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.

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

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

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. Government 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:

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

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:

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

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:

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

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:

$$\frac{\phi_0}{\phi^{\mathrm{SP}}} = 1 - \frac{\tau_b\theta_0}{1+\tau_b}. \tag{7}$$

The result above is useful for simplifying the expression for D.[51] After inserting the above definitions and collecting logarithms we obtain the following expression for D:

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

with

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

[51] 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:

$$2D_0 - (1-\alpha_g)(1-\beta)(1+\gamma) = 2[\alpha_g(1+\beta) + (1-\alpha_g)(1-\beta\gamma)] - (1-\alpha_g)(1-\beta)(1+\gamma) = (1+\beta)[2\alpha_g + (1-\alpha_g)(1-\gamma)]$$

The first log equals zero because of (7). Set

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

Hence

$$D = (c_1 + c_2)\,\log R_2 \;-\; c_2\,\log(1+\tau_b). \tag{8}$$

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 (8):

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

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 $\frac{c_1}{c_2} + 1 \geq 1 + \frac{2\alpha_g}{1-\alpha_g} > 2$, 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

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

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

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

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:

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

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:

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

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.

E.6 Alternative Policy Instruments: 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 2. *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 3. *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 consumers as a function of* β *if the* $\beta = \bar{\beta}$ *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. ■

E.7 Technical Notes on "Quadratic" and "Absolute Value" Functional Forms for Mental Accounting

In the proofs, we found that $\frac{\partial \phi^*}{\partial y_1} < \frac{\partial \phi^*}{\partial b_1}$ for all $\kappa > 0$, and that $\frac{\partial \phi^*}{\partial b_1} > 0$. However, we also have the somewhat counter-intuitive result that at low ϕ, $\frac{\partial \phi^*}{\partial y_1} > 0$. The reason for this lies in our quadratic mental accounting formula.

Recall that the consumer's optimality condition is:

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

Rewriting to put the mental accounting component of utility ($\kappa \frac{\partial U_B}{\partial \phi}$) on the LHS and neoclassical utility ($\frac{\partial U_A}{\partial \phi}$) on the RHS:

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

From the LHS, we can see that an increase in y does two things:

1. Pulls mental accounting towards ϕ_0 (this is the $(y+b)$ term)

2. Increases the absolute size of the mental accounting penalty (this is the $((\phi_0 - \phi^*)y + (1-\phi^*)b)$ term)

The RHS doesn't depend on y because Cobb-Douglas implies constant expenditure shares.

Holding fixed ϕ^*, the derivative of the LHS with respect to y is :

$$\begin{aligned} \frac{\partial}{\partial y_1}[2\kappa((\phi_0 - \phi^*)y + (1-\phi^*)b)(y+b)] &= 2\kappa[(\phi_0 - \phi^*)y + (1-\phi^*)b + (\phi_0 - \phi^*)(y+b)] \\ &= 2\kappa[2(\phi_0 - \phi^*)y + (1 + \phi_0 - 2\phi^*)b] \end{aligned}$$

1. If $\phi^* = \frac{1}{2}[\phi_0 + \frac{\phi_0 y + b}{y+b}]$, then $\frac{\partial LHS}{\partial y_1} = 0$: ϕ^* does not have to adjust to an incremental change in y, and $\frac{\partial \phi^*}{\partial y_1} = 0$.

2. If $\phi^* < \frac{1}{2}[\phi_0 + \frac{\phi_0 y + b}{y+b}]$, $\frac{\partial LHS}{\partial y_1} > 0$. In words, a marginal increase in y increases the marginal utility of food consumption through mental accounting without changing the consumer's neoclassical utility. The consumer adjusts ϕ upwards to reach the new equilibrium ϕ^*, and $\frac{\partial \phi^*}{\partial y_1} > 0$ (this was the puzzling result from before). The increase in the overall importance of mental accounting $(y+b)$ outweighs the importance of the pulling the mental account back towards ϕ_0 $((\phi_0 - \phi^*)y + (1-\phi^*)b)$

3. If $\phi^* < \frac{1}{2}[\phi_0 + \frac{\phi_0 y + b}{y+b}]$, we have the opposite of the previous bullet point, and $\frac{\partial \phi^*}{\partial y_1} < 0$, which is what we expected/what we find with absolute value mental accounting.

Note that this same thing doesn't happen under absolute value mental accounting (as in Farhi-Gabaix or Hastings-Shapiro). If we rewrite the mental accounting component of utility as $-\kappa|\phi_0 y + b - \phi^*(y+b)|$, the consumer's optimality condition becomes:

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

Rearranging as before:

$$\kappa(y+b) = \frac{\alpha_g(1-\alpha_f)(1+\beta) + (1-\alpha_g)(1-\beta\gamma)}{1-\phi^*} - \frac{\alpha_g \alpha_f (1+\beta)}{\phi^*}$$

The LHS no longer has a squared term in y, so everything is monotonic and we don't have to do all the gymnastics from before.

Main Takeaways

- Quadratic mental accounting unexpectedly generates that $\frac{\partial \phi^*}{\partial y_1} > 0$ for small ϕ. For small ϕ, $MPCF^{cash} > \phi$, which is greater than $MPCF^{cash} = \phi$ that log utility would generate. This does not happen with absolute value mental accounting.
- However, we always have $\frac{\partial \phi^*}{\partial b_1} > \frac{\partial \phi^*}{\partial y_1}$ when $\kappa > 0$ ($MPCF^{SNAP} > MPCF^{cash}$). For the social planner who is considering the tradeoffs of SNAP vs Cash, this doesn't substantively change any of the points we are trying to make about cash vs. in-kind transfers.
- The functional form of mental accounting matters beyond first derivatives.

E.8 Dynamic Model to Compare Within-Month Effects to Effects of Permanent Policy Changes

Our empirical results are based on estimating individuals' responses to *anticipated* transfers each month (either cash transfers or in-kind transfers). The two-period model in the main text makes it difficult to distinguish inter-temporal responses to anticipated transfers from uncompensated responses that would arise from permanent policy changes that would provide recurring cash transfers and/or in-kind transfers each month.

This section clarifies the mapping between the "within-month" estimated effects that represent the behavioral response to an anticipated transfer (which is what we estimate in the empirical analysis) and the "total" uncompensated effects of permanent policy changes. To do this, we extend the two-period model to a four-period model so that the consumer can respond to anticipated future transfers while receiving (and consuming) transfers in the current period.

Model setup

As in the main model, we allow for self-control problems ($\beta < 1$) as well as mental accounting ($\kappa > 0$). There are four periods $t = 1...4$. The consumer receives either cash transfers y_t in periods $t = 1$ and $t = 3$ or SNAP benefits b_1 and b_3 in $t = 1$ and $t = 3$, and receives a constant wage $w_t = w$ every period. The purpose of the wage income is so the consumer can have baseline consumption prior to the transfer to study the impact of introducing the tranfer.

We will work with a β-δ utility function and will assume $\delta = 1$ so that the individual at the start of period 1 maximizes the following:

$$\begin{aligned} U &= U_1 + \beta * (U_2 + U_3 + U_4) \\ &\quad -\kappa * (\phi_0(4 * w + y_1 + y_3) + b_1 + b_3 - (f_1 + f_2 + f_3 + f_4))^2 \end{aligned}$$

where κ governs the strength of mental accounting as in the main model, 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 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 (PIH)

If $\kappa = 0$ and $\beta = 1$ and the consumer can freely borrow and save at an exogenous interest rate $r = 0$ between periods, then the individual will have constant consumption for all of the goods in every period because of full consumption smoothing for all vlues of y, b, and w. This means there would be no observed change in consumption in any of the goods following the transfer in $t = 3$ relative to $t = 2$.

Benchmark: Present Bias With Saving and Borrowing

If we now assume $\beta < 1$ but continue to assume $\kappa = 0$ and $r = 0$, then instead of observing constant consumption as in the PIH benchmark above, the individual will instead choose strictly declining consumption for all goods over time. In other words, whether the consumer receives a cash transfer (y) or SNAP (b) or both, the individual will not increase consumption between $t = 2$ and $t = 3$ because the present-biased consumer chooses to borrow in anticipation of the receipt of future transfer income. In other words, present bias alone is not sufficient to observe an increase in consumption between $t = 2$ and $t = 3$.

Present Bias With Saving But No Borrowing

We now introduce strict borrowing constraints, so that the consumer can save between periods but cannot borrow, and we continue to assume $\beta < 1$.

If $y_1 = y_3 = b_1 = b_3 = 0$, then in this case we have perfect consumption smoothing because the individual is consuming hand-to-mouth and wage income is constant. The consumer would prefer to borrow from future wage income because of present bias, but is unable to do so because of the strict borrowing constraints.

Now suppose that a cash transfer program is introduced ($y_1 = y_3 = \bar{y}$) which is assumed to be small relative to the wage income (i.e., $\bar{y} << \bar{w}$). In this case, the consumer will increase consumption in $t = 3$ relative to $t = 2$ for all goods. If β is sufficiently low and the transfer is small, then the consumer will continue to be hand-to-mouth because they would prefer to borrow from the future transfer income to finance consumption, but the consumer is unable to borrow.

Finally, suppose that SNAP transfers are introduced instead ($b_1 = b_3 = \bar{b}$) which are also assumed to be small relative to the wage income (i.e., $\bar{b} << \bar{w}$). In this case, the consumer will again increase consumption in $t = 3$ relative to $t = 2$. If $\kappa = 0$ and SNAP is infra-marginal (which is likely to be the case when $\bar{b}$ is small), then SNAP has the same effect on consumption as the cash transfer program. If $\kappa > 0$, however, then the consumer will increase food consumption between $t = 2$ and $t = 3$ by relatively more than the consumer would if the same amount had been transferred as cash. The consumer will also increase consumption of the temptation good between $t = 2$ and $t = 3$ by relatively less than the consumer would if the same amount had been transferred as cash.

In simulations, we find that the $t = 2$ to $t = 3$ increase in consumption of each good (after introduction of cash tranfser program or SNAP benefit) is related to the "lifetime" MPC from the introduction of the cash transfer program or SNAP benefit, which provides the mapping between the within-month estimates and the total uncompensated effects that are needed for the optimal policy calibrations. In the special case where $w_t = w$ for all periods prior to the introduction of the recurring cash transfer or SNAP benefit, the $t = 2$ to $t = 3$ increase in consumption for each good is identical to the "lifetime" MPC for each good; that is, the change in consumption is exactly equal to the marginal propensity to consume each good across all periods relative to the total transfer across distributed across all periods.

Intuitively, if the reason why consumption "spikes" immediately after receipt of cash transfer or SNAP comes from a combination of present bias and borrowing constraints, then our "within-month" estimates are informative about the degree of mental accounting as well as the extent to which cash and SNAP have "permanently" different effects of consumption.

Dynamic Model Simulation

To quantitatively illustrate the results described above, we simulate the dynamic model with the following parameters:

- $w_t = w = 10$
- $\beta = 0.7$, $\delta = 1$
- $\alpha_g = 0.8$, $\alpha_f = 0.15$
- $\gamma = 0.75$

We solve the model assuming the consumer is a naive hyperbolic discounter, which means solving the model sequentially.[52] Solving the model gives the following consumption choices:

[52]Specifically, we have the consumer maximize $U = U_1 + \beta * (U_2 + U_3 + U_4) - \kappa(\cdot)^2$ and make period 1 consumption choices. Then with remaining income, the consumer maximizes $U = U_2 + \beta * (U_3 + U_4) - \kappa(\cdot)^2$ and then maximizes $U = U_3 + \beta * U_4 - \kappa(\cdot)^2$. One technical issue is how to model mental accounting considerations dynamically. We assume that the consumer only cares about mental accounting during the periods that the SNAP benefits are distributed (in $t = 1$ and $t = 3$). This corresponds to the consumer spending all of their SNAP benefits in $t = 1$ and $t = 3$ and then no longer considering mental accounting in $t = 2$ and $t = 4$.

- $f_1 = f_2 = f_3 = 1.34,\ f_4 = 1.5$
- $n_1 = n_2 = n_3 = 7.60,\ n_4 = 8.5$
- $c_1^b = c_2^b = c_3^b = 1.06$

Note that there is full consumption smoothing (except for the fact that the temptation good is not consumed in the last period and that amount is then proportionally divided between food and non-food consumption based on α_f).

Cash transfers. Now we introduce a recurring cash transfer $y_1 = y_3 = 1$. We re-solve the model and find the following consumption choices:

- $f_1 = f_3 = 1.47,\ f_2 = 1.34,\ f_4 = 1.5$
- $n_1 = n_3 = 8.36,\ n_2 = 7.60,\ n_4 = 8.5$
- $c_1^b = c_3^b = 1.17,\ c_2^b = 1.06$

The change in consumption between $t = 2$ and $t = 3$ are given by the following:

- $f_3 - f_2 = 0.13$ (equal to lifetime $MPCF$)
- $n_3 - n_2 = 0.76$ (equal to lifetime $MPCN$)
- $c_3^b - c_2^b = 0.11$ (equal to lifetime $MPCB$)

It is straightforward to show that these consumption changes are the same as the implied "lifetime" marginal propensities to consume each good out of the additional cash transfers.

SNAP Transfers. Now we introduce a recurring SNAP transfer $b_1 = b_3 = 1$, and assume $\kappa = 0.025$ so that the consumer engages in mental accounting. We re-solve the model and get the following:

- $f_1 = f_3 = 1.93,\ f_2 = 1.34,\ f_4 = 1.5$
- $n_1 = n_3 = 7.96,\ n_2 = 7.60,\ n_4 = 8.5$
- $c_1^b = c_3^b = 1.11,\ c_2^b = 1.06$

The change in consumption between $t = 2$ and $t = 3$ are given by the following:

- $f_3 - f_2 = 0.59$ (equal to lifetime $MPCF$)
- $n_3 - n_2 = 0.36$ (equal to lifetime $MPCN$)
- $c_3^b - c_2^b = 0.05$ (equal to lifetime $MPCB$)

As with the cash transfer, it is straightforward to show that these consumption changes are exactly the same as the implied "lifetime" marginal propensities to consume each good out of the SNAP transfers. This shows that the "within-month" ($t = 2$ to $t = 3$) increases in consumption following receipt of cash transfer or SNAP benefit are exactly the same as the "lifetime" MPCs in the special case of hand-to-mouth consumption with otherwise smooth consumption in the absence of the transfers.

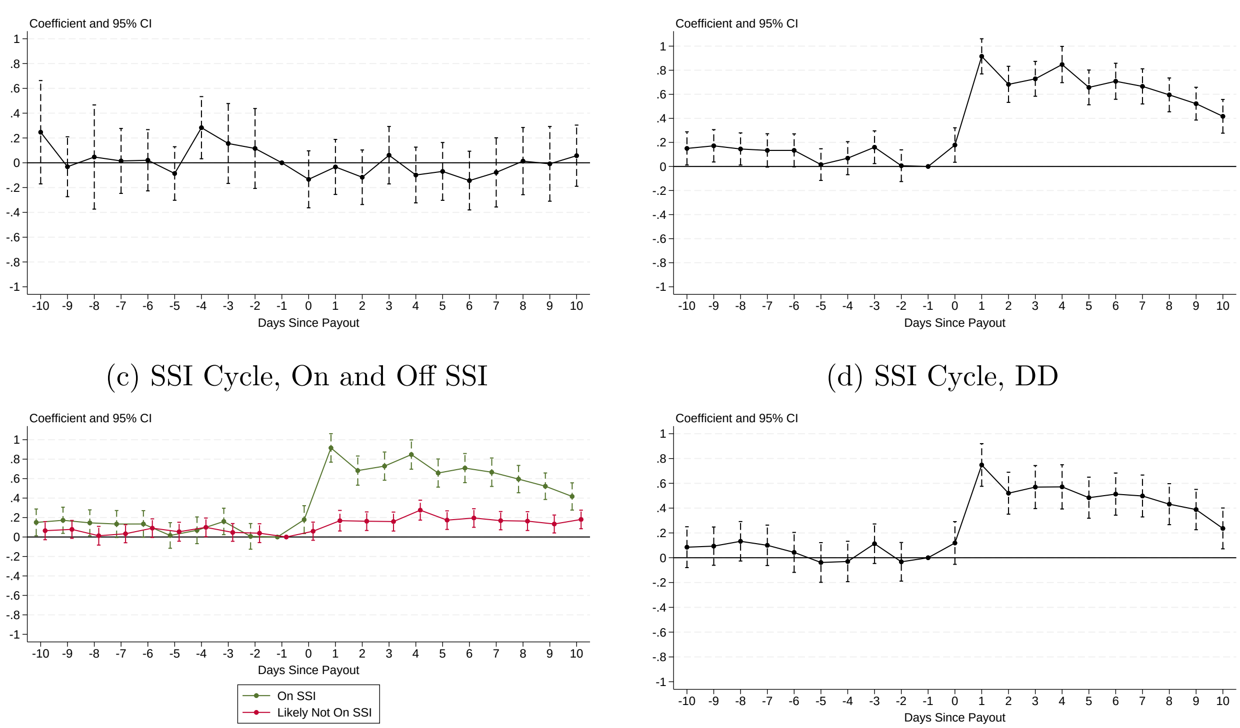
In additional simulations, we generally that the $t = 2$ to $t = 3$ increase in food consumption and consumption of temptation good is larger when the "lifetime" MPCF and MPCB values are larger, respectively, so that even when two values are not exactly the same they are generally informative about the relative magnitudes. That is, when the $t = 2$ to $t = 3$ increase in food consumption is larger for SNAP than for cash, the simulation also shows that $MPCF^{SNAP} > MPCF^{cash}$. Additionally, absent mental accounting the $t = 2$ to $t = 3$ increases in consumption of all goods is the same for cash and SNAP, which is what we expect when SNAP benefits are non-fungible.

Intuitively, the reason why the within-month estimate is identical to the total uncompensated effect in the simulation is that there is no effect of the cash transfer or SNAP benefits on consumption of any good in the period prior to the receipt of the transfer. This is because the transfer from the prior period (in $t = 1$) is already fully "spent" in $t = 1$ and none of it saved for $t = 2$, because the consumer consumes out of their wage income in $t = 2$. Additionally, consumption would otherwise be constant in absence of the transfer, so that the $t = 2$ to $t = 3$ increase is entirely coming from the transfer. This would be violated if, for example, there were other sources of income that also arrived in $t = 3$ that did not arrive $t = 2$. In our empirical work, both the SSI and SNAP research designs address potential confounding effects of other income arriving at the same time. The issue of the recurring transfers affecting consumption throughout the month, there is an existing literature on the "food stamp nutrition cycle" that generally finds that SNAP affects food consumption much more immediately after benefits are distributed and much less towards the end of each SNAP benefit monthly cycle. In this case, our within-month estimates may be quite close to the total uncompensated effects of introducing or increasing the value of recurring monthly transfers (whether cash or in-kind).

E.9 Welfare Calibration Details

F Appendix Figures

Figure OA.1: Effects of SNAP and SSI on Drug and Alcohol ER Visits, Overlap Sample



(a) SNAP Cycle

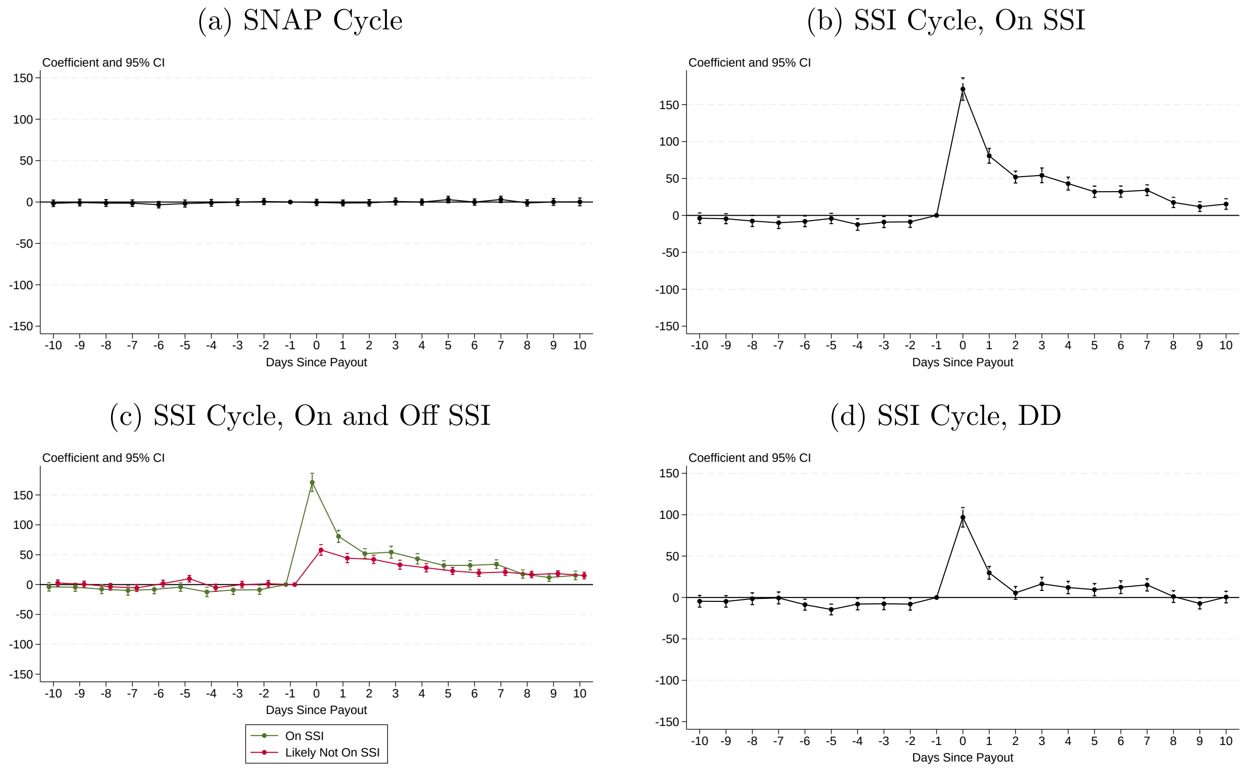
(b) SSI Cycle, On SSI

(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 ER 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.

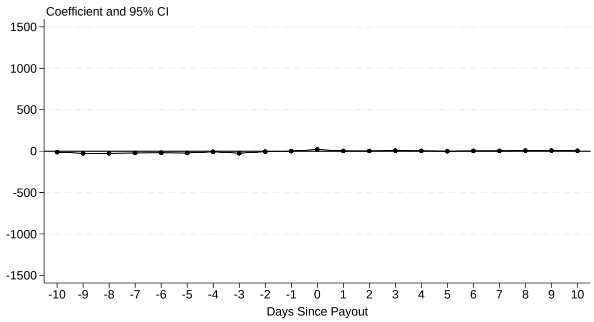
Figure OA.2: Effects of SNAP and SSI on First Fills, Overlap Samples



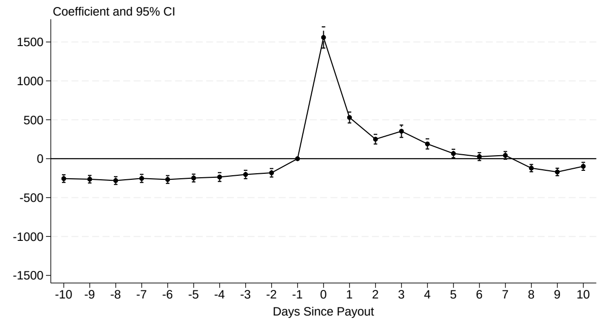
Notes: This figure shows estimates of (a) β_r from equation 2, (b) $\alpha_l + \beta_l$ from equation 1, (c) $\alpha_l + \beta_l$ from equation 1 (in green) overlaid with α_l from equation 1 (in red), and (d) β_l from equation 1. The outcome variable is first fills per day per 10,000. In (a), N person-months 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.3: Effects of SNAP and SSI on Refills, Full Samples

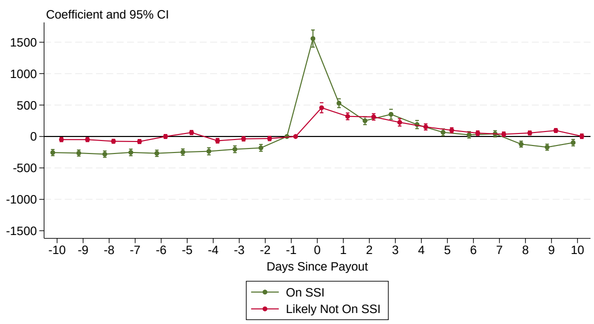
(a) SNAP Cycle



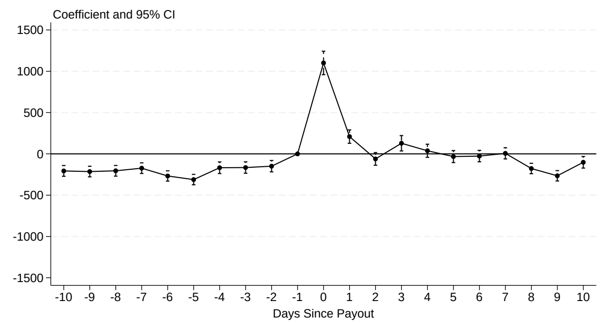
(b) SSI Cycle, On SSI



(c) SSI Cycle, On and Off SSI



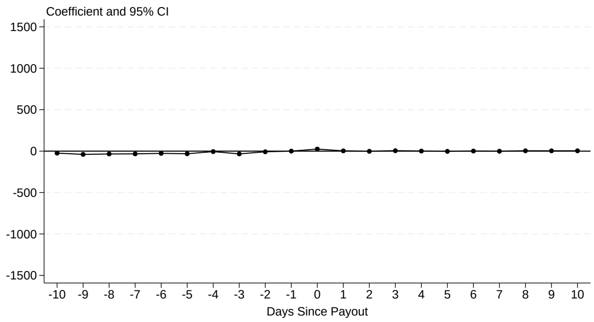
(d) SSI Cycle, DD



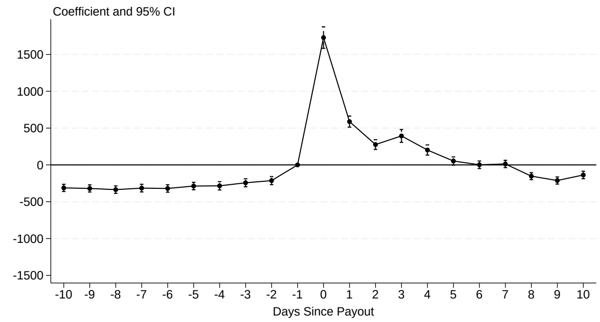
Notes: This figure shows estimates of (a) β_r from equation 2, (b) $\alpha_l + \beta_l$ from equation 1, (c) $\alpha_l + \beta_l$ from equation 1 (in green) overlaid with α_l from equation 1 (in red), and (d) β_l from equation 1. The outcome variable is refills per day per 10,000. In (a), N person-months 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.4: Effects of SNAP and SSI on Refills, Overlap Samples

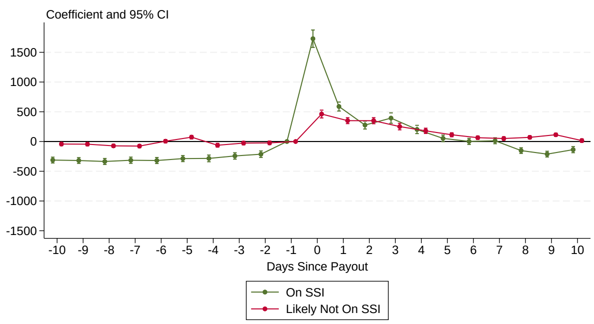
(a) SNAP Cycle



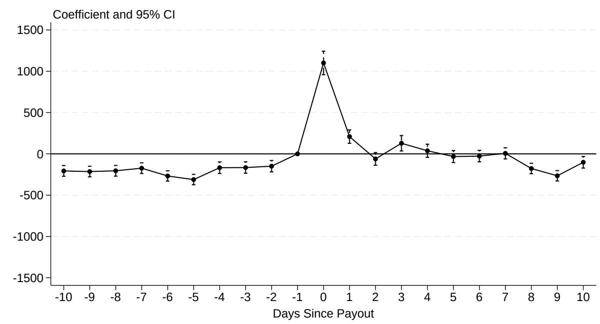
(b) SSI Cycle, On SSI



(c) SSI Cycle, On and Off SSI

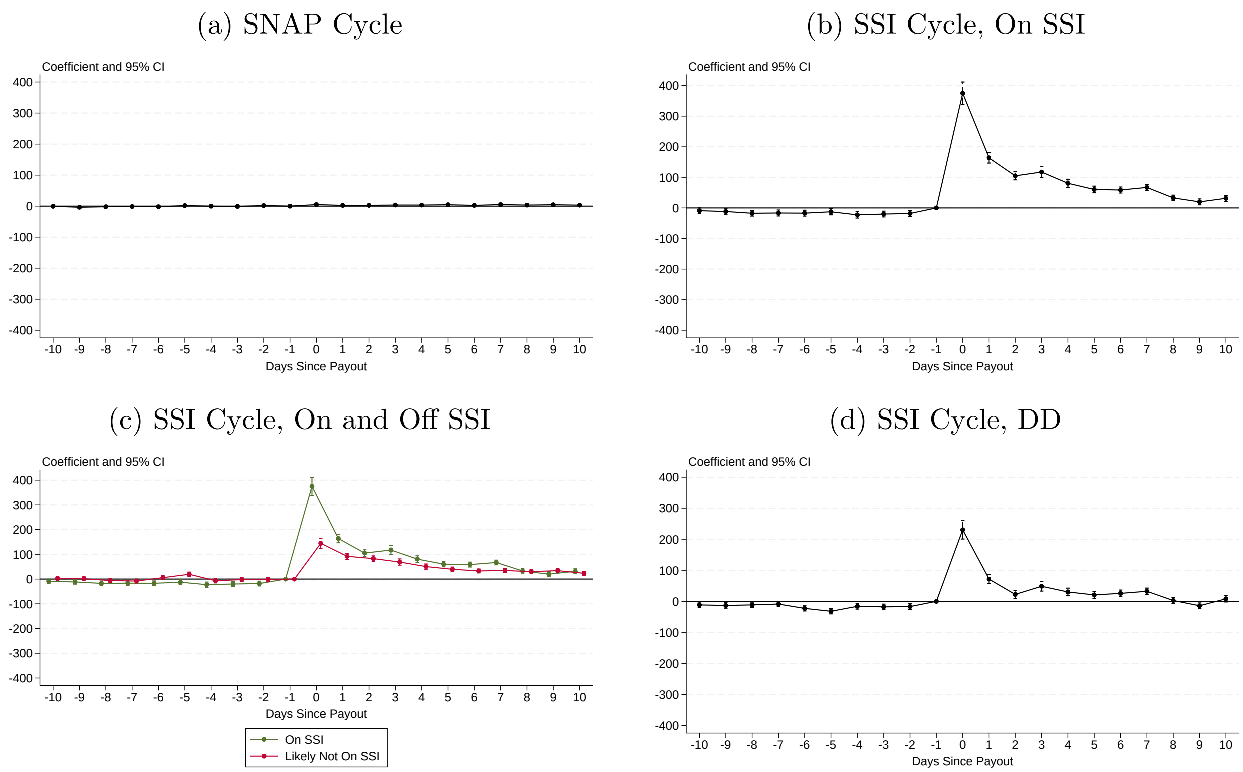


(d) SSI Cycle, DD



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 refills per 10,000. In (a), N person-months on SNAP (and on SSI) = 4,543,906. In (b)-(d), N person-months on SSI (and on SNAP) = 4,543,906, and N person-months likely not on SSI (but on SNAP) = 2,443,136.

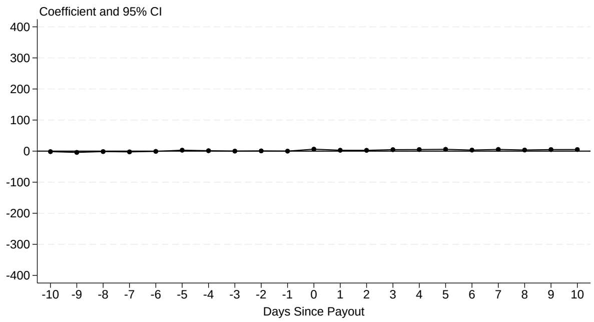
Figure OA.5: Effects of SNAP and SSI on Non-Maintenance Fills, Full Samples



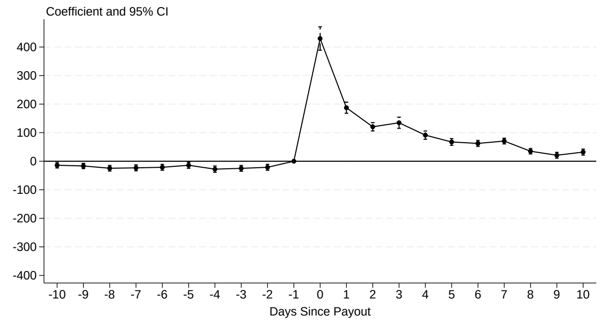
Notes: This figure shows estimates of (a) β_r from equation 2, (b) $\alpha_l + \beta_l$ from equation 1, (c) $\alpha_l + \beta_l$ from equation 1 (in green) overlaid with α_l from equation 1 (in red), and (d) β_l from equation 1. The outcome variable is non-maintenance fills per day per 10,000. In (a), 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.6: Effects of SNAP and SSI on Non-Maintenance Fills, Overlap Samples

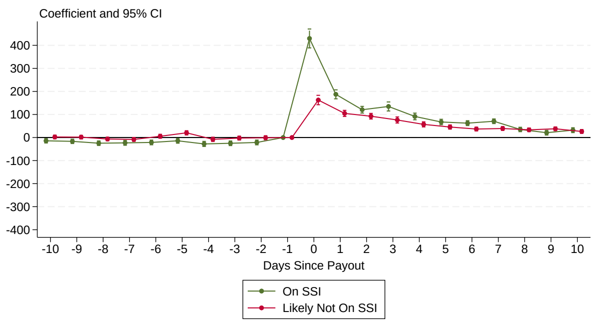
(a) SNAP Cycle



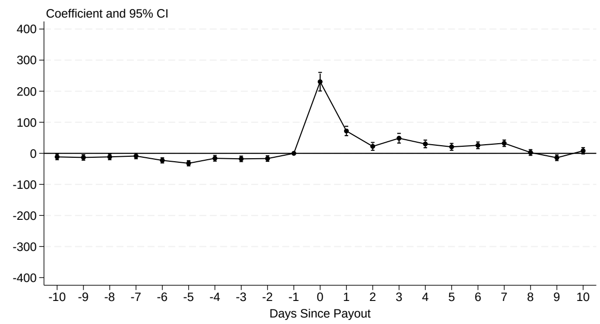
(b) SSI Cycle, On SSI



(c) SSI Cycle, On and Off SSI



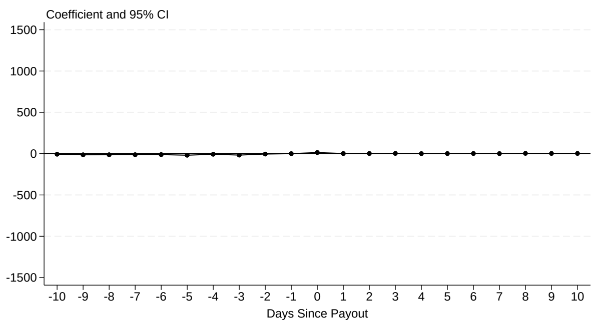
(d) SSI Cycle, DD



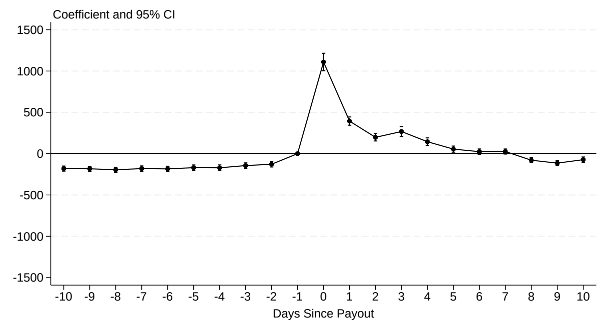
Notes: This figure shows estimates of (a) β_r from equation 2, (b) $\alpha_l + \beta_l$ from equation 1, (c) $\alpha_l + \beta_l$ from equation 1 (in green) overlaid with α_l from equation 1 (in red), and (d) β_l from equation 1. The outcome variable is non-maintenance fills per day per 10,000. In (a), 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.7: Effects of SNAP and SSI on Maintenance Fills, Full Samples

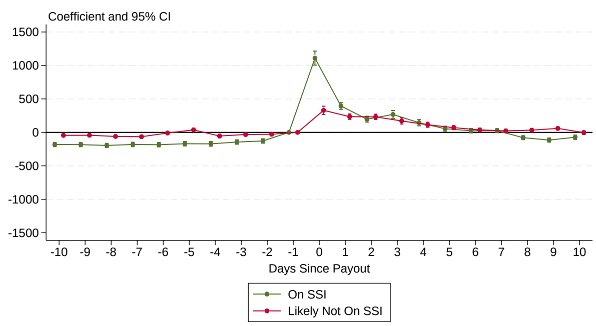
(a) SNAP Cycle



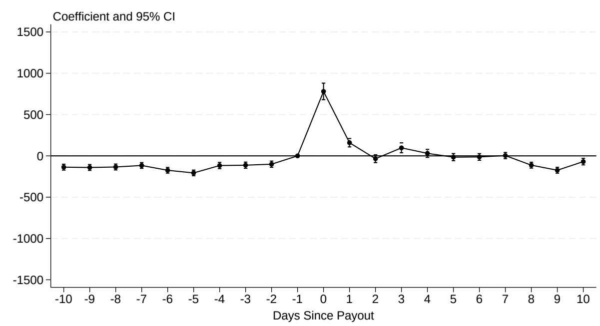
(b) SSI Cycle, On SSI



(c) SSI Cycle, On and Off SSI



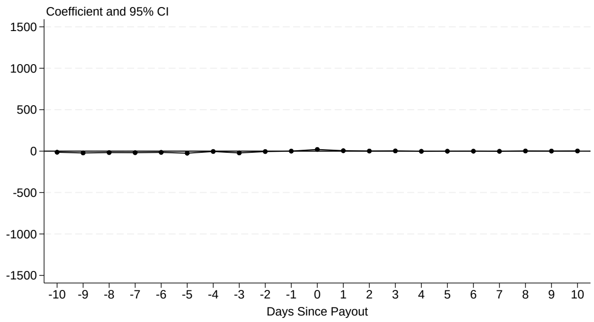
(d) SSI Cycle, DD



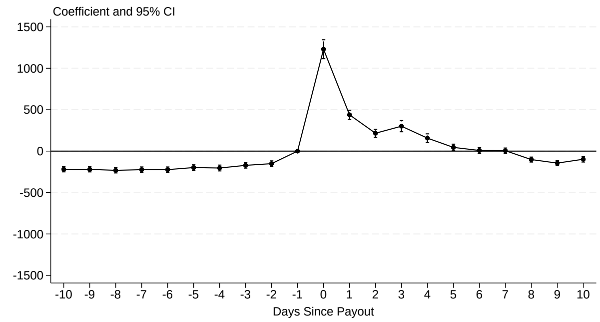
Notes: This figure shows estimates of (a) β_r from equation 2, (b) $\alpha_l + \beta_l$ from equation 1, (c) $\alpha_l + \beta_l$ from equation 1 (in green) overlaid with α_l from equation 1 (in red), and (d) β_l from equation 1. The outcome variable is maintenance fills per day per 10,000. In (a), N 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.8: Effects of SNAP and SSI on Maintenance Fills, Overlap Samples

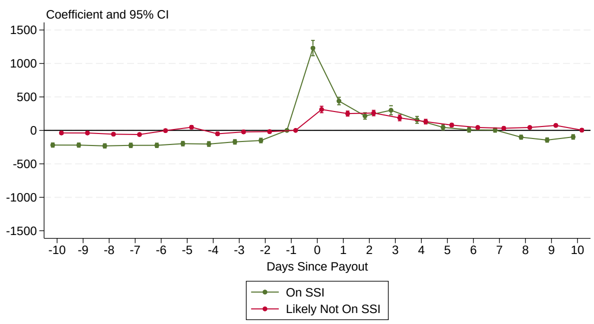
(a) SNAP Cycle



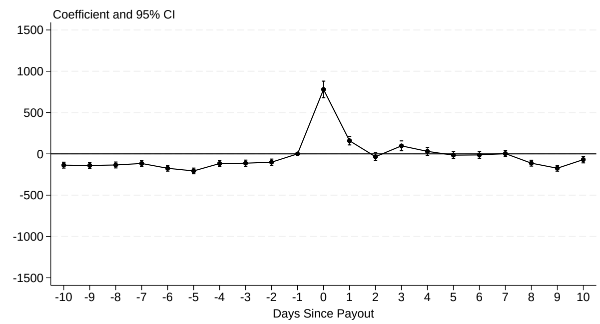
(b) SSI Cycle, On SSI



(c) SSI Cycle, On and Off SSI



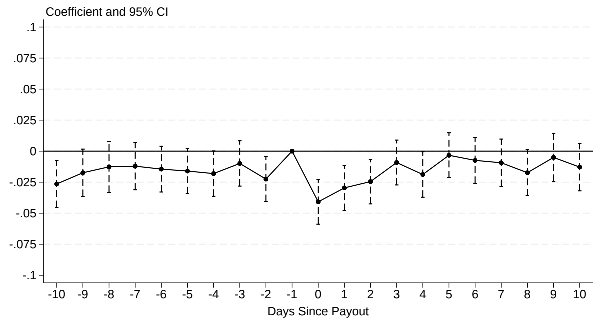
(d) SSI Cycle, DD



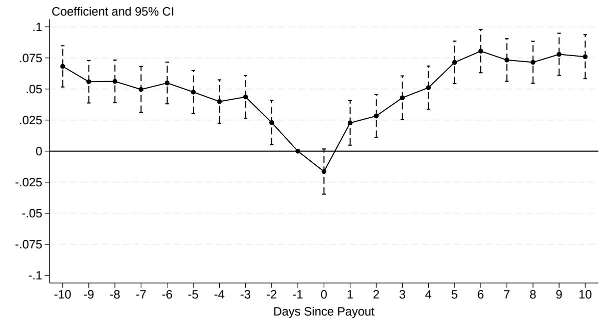
Notes: This figure shows estimates of (a) β_r from equation 2, (b) $\alpha_l + \beta_l$ from equation 1, (c) $\alpha_l + \beta_l$ from equation 1 (in green) overlaid with α_l from equation 1 (in red), and (d) β_l from equation 1. The outcome variable is maintenance fills per day per 10,000. In (a), N 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.9: Effects of SNAP and SSI on Nutrition-Sensitive ER Visits, Full Sample

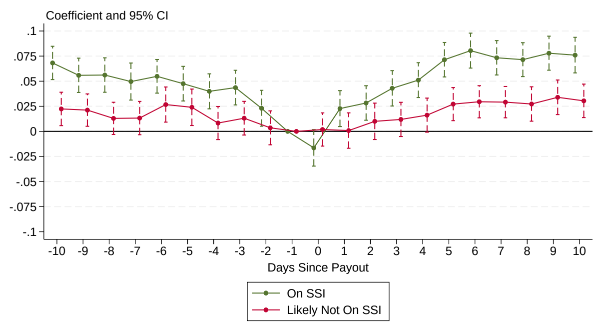
(a) SNAP Cycle



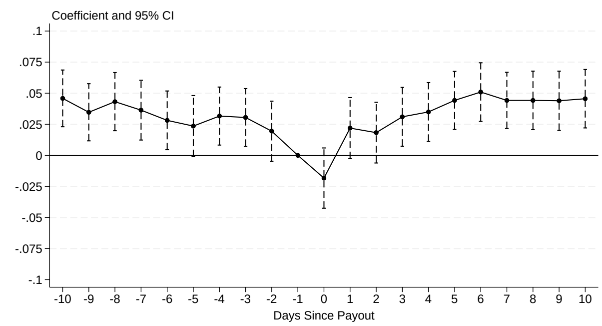
(b) SSI Cycle, On SSI



(c) SSI Cycle, On and Off SSI

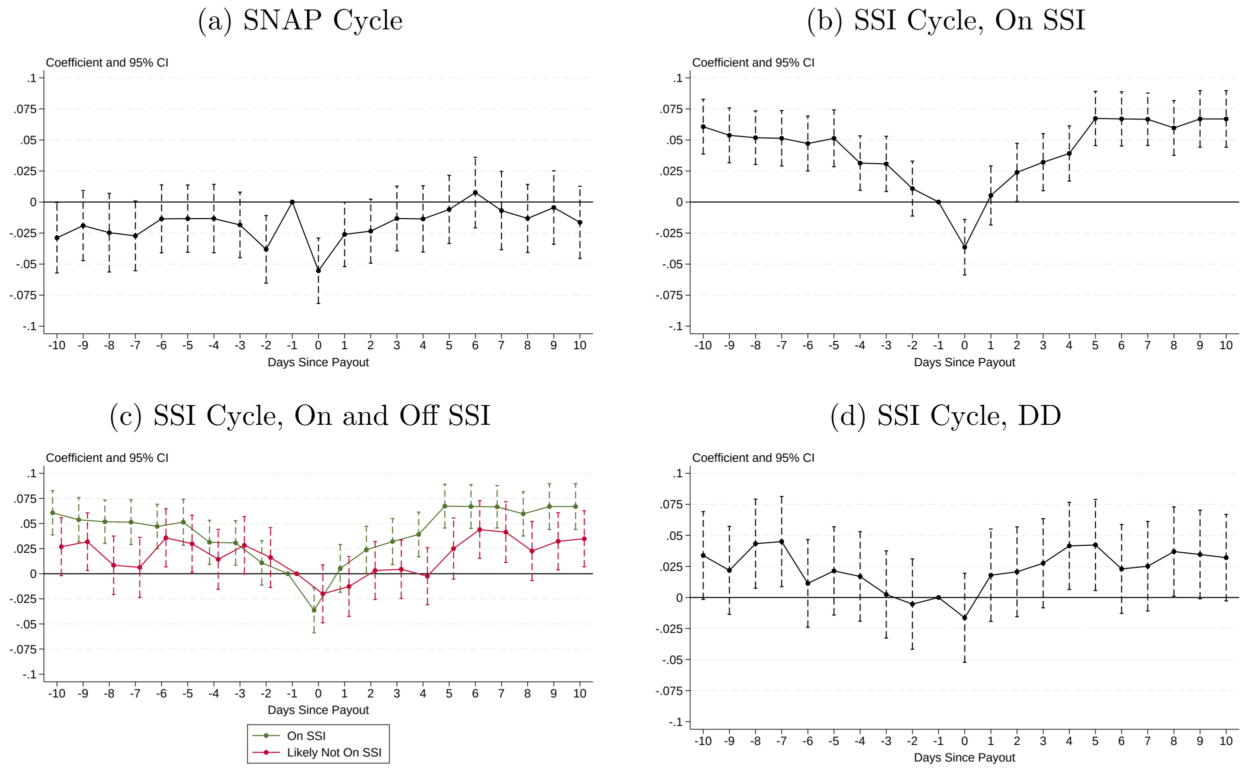


(d) SSI Cycle, DD



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 ER 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.

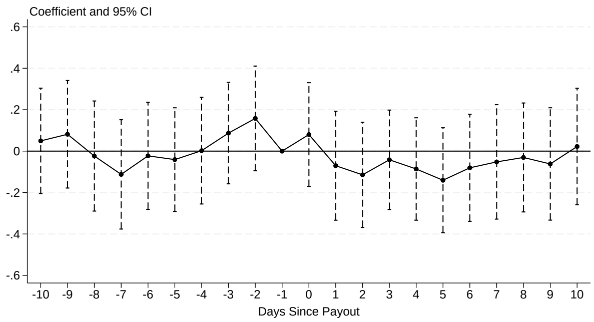
Figure OA.10: Effects of SNAP and SSI on Nutrition-Sensitive ER Visits, Overlap Sample



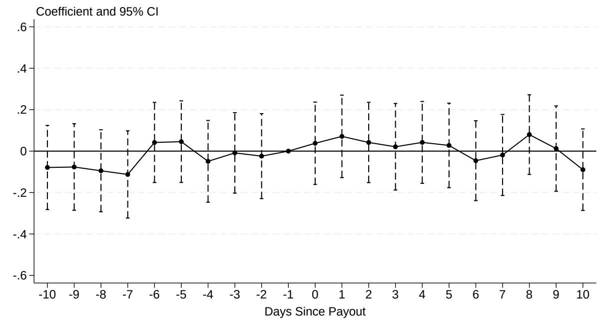
Notes: This figure shows estimates of (a) β_r from equation 2, (b) $\alpha_l + \beta_l$ from equation 1, (c) $\alpha_l + \beta_l$ from equation 1 (in green) overlaid with α_l from equation 1 (in red), and (d) β_l from equation 1. The outcome variable is ER visits for nutrition-sensitive conditions per 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.11: Effects of SNAP and SSI on ER Visits for Hypoglycemia, Full Sample

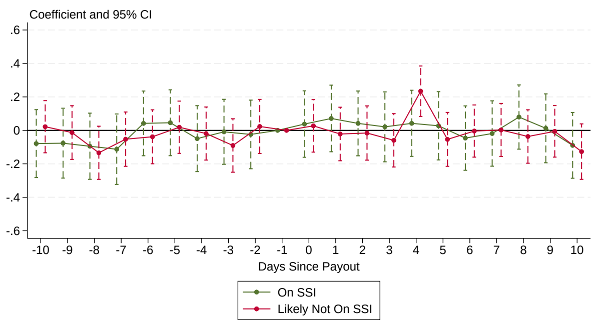
(a) SNAP Cycle



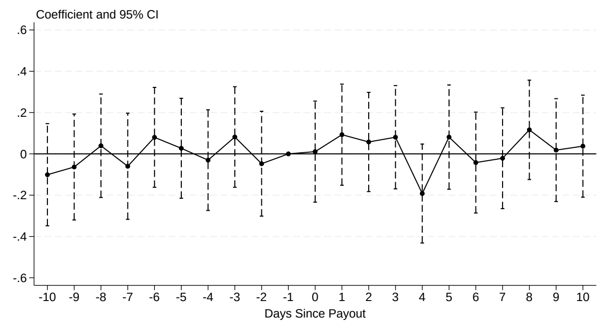
(b) SSI Cycle, On SSI



(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 ER 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.

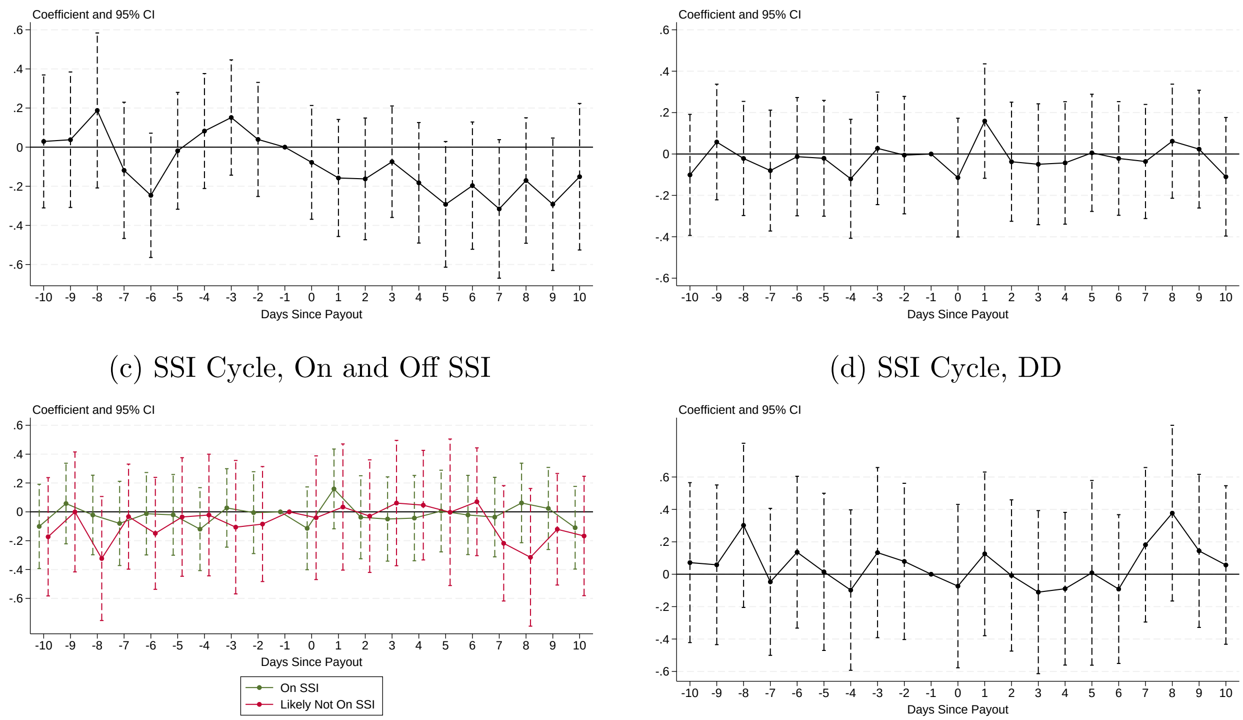
Figure OA.12: Effects of SNAP and SSI on ER Visits for Hypoglycemia, Overlap Sample

(a) SNAP Cycle

(b) SSI Cycle, On SSI

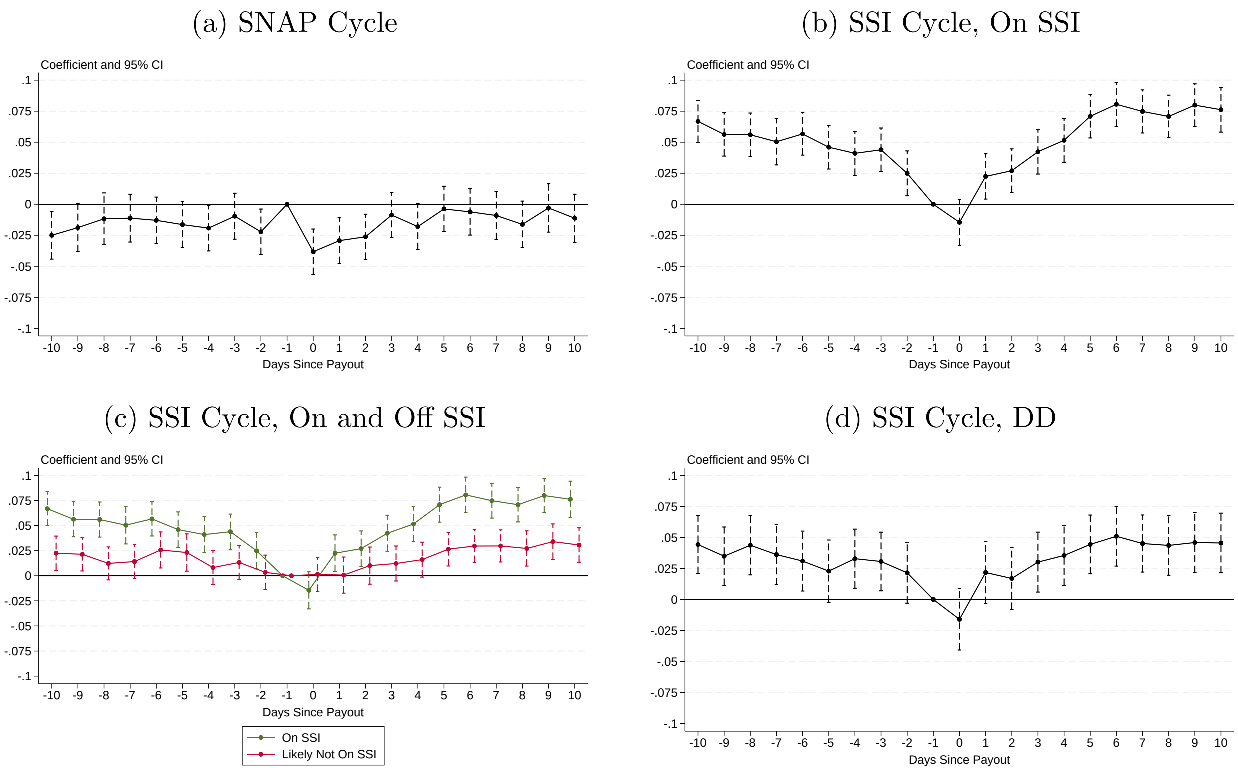
(c) SSI Cycle, On and Off SSI

(d) SSI Cycle, DD



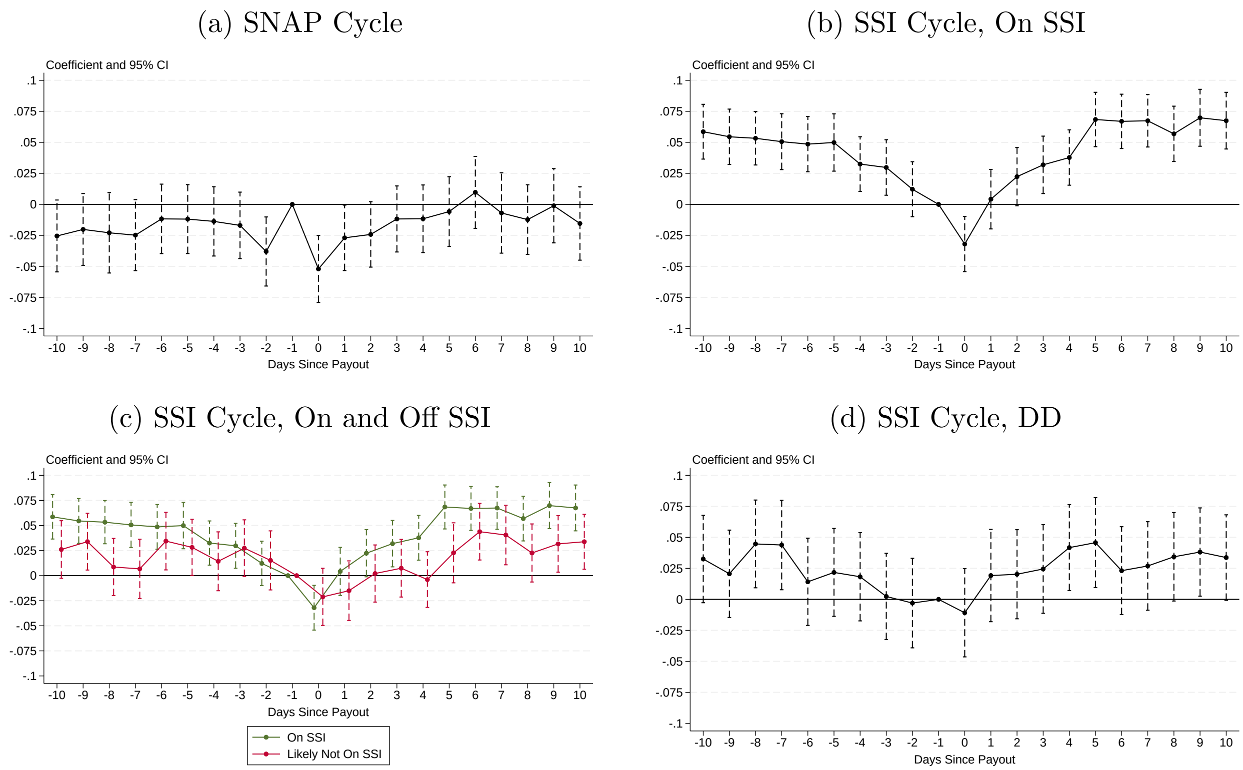
Notes: This figure shows estimates of (a) β_r from equation 2, (b) $\alpha_l + \beta_l$ from equation 1, (c) $\alpha_l + \beta_l$ from equation 1 (in green) overlaid with α_l from equation 1 (in red), and (d) β_l from equation 1. The outcome variable is ER visits for hypertension per day per 10,000. 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.13: Effects of SNAP and SSI on ER 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 ER 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.

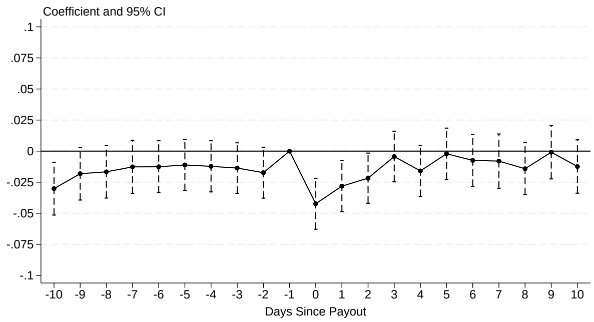
Figure OA.14: Effects of SNAP and SSI on ER Visits for Diabetes-Related Complications, Overlap Sample



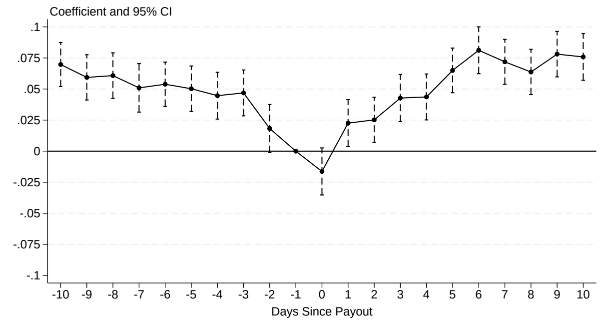
Notes: This figure shows estimates of (a) β_r from equation 2, (b) $\alpha_l + \beta_l$ from equation 1, (c) $\alpha_l + \beta_l$ from equation 1 (in green) overlaid with α_l from equation 1 (in red), and (d) β_l from equation 1. The outcome variable is ER visits for diabetes-related complications per 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.15: Effects of SNAP and SSI on ER Visits for Hypertension, Full Sample

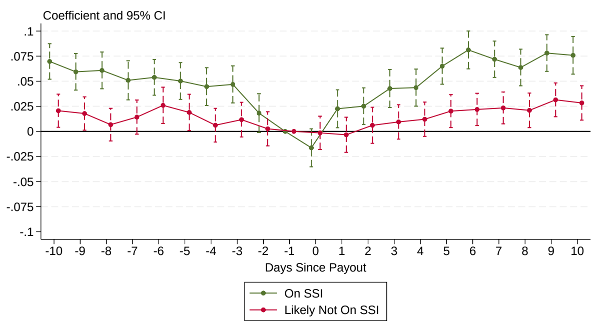
(a) SNAP Cycle



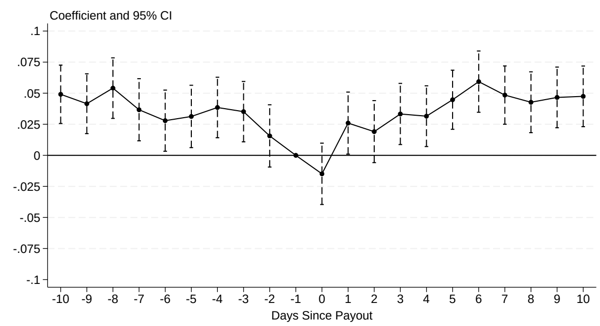
(b) SSI Cycle, On SSI



(c) SSI Cycle, On and Off SSI

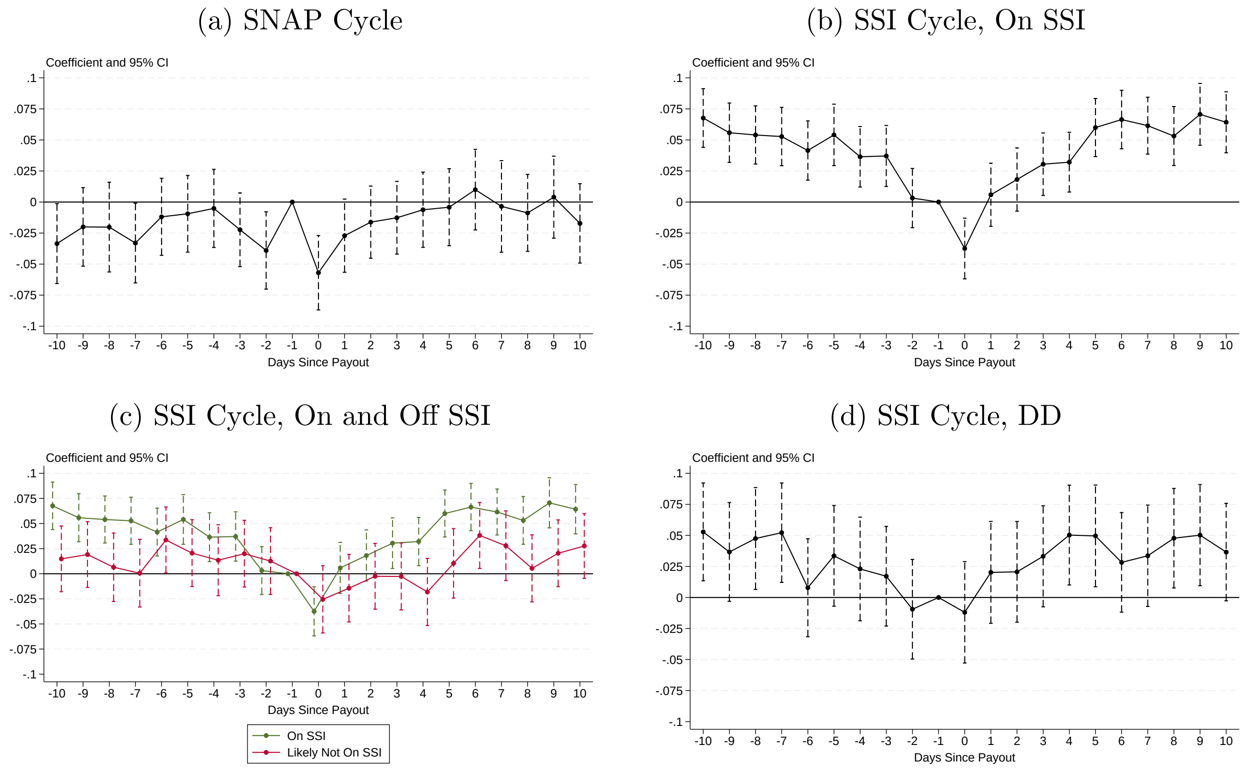


(d) SSI Cycle, DD



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 ER visits for hypoglycemia 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.

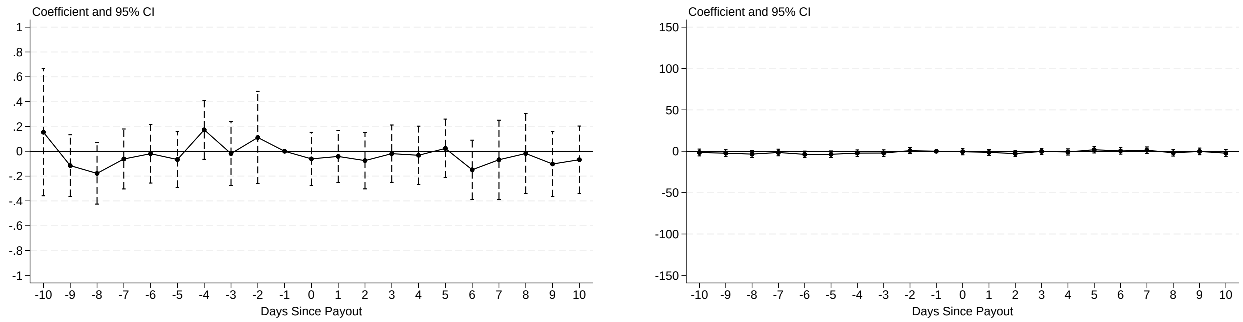
Figure OA.16: Effects of SNAP and SSI on ER Visits for Hypertension, Overlap Sample



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 ER visits for hypoglycemia 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.

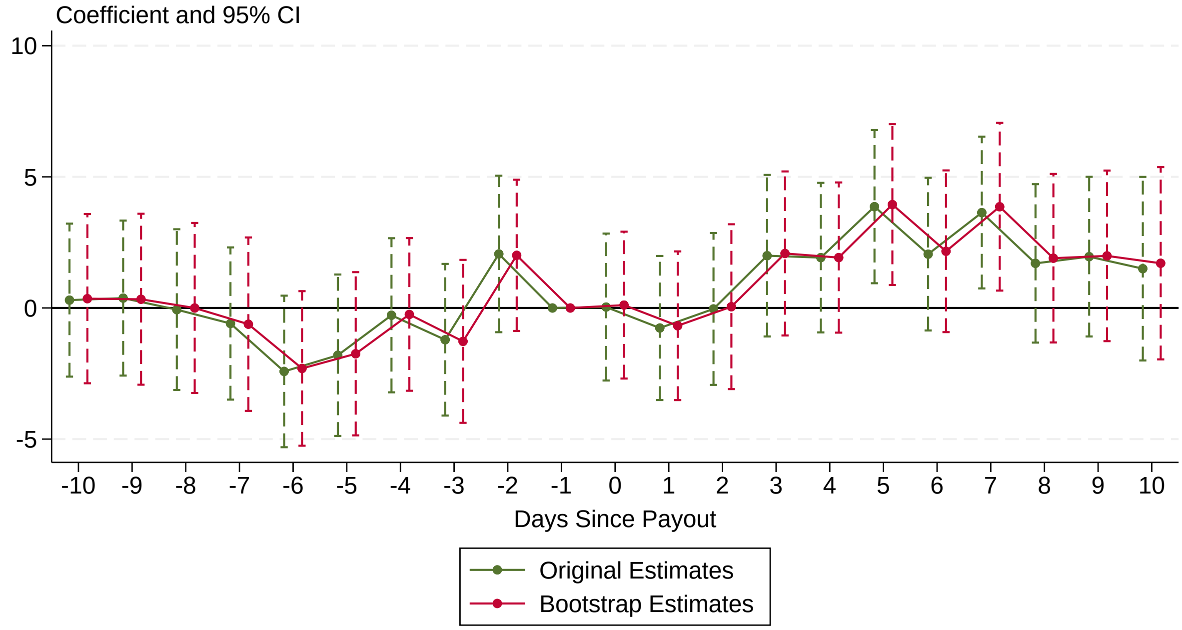
Figure OA.17: Effects of SNAP on Drug and Alcohol ER Visits and First Fills, Early Payouts Only

(a) DA ER Visits (b) First Fills



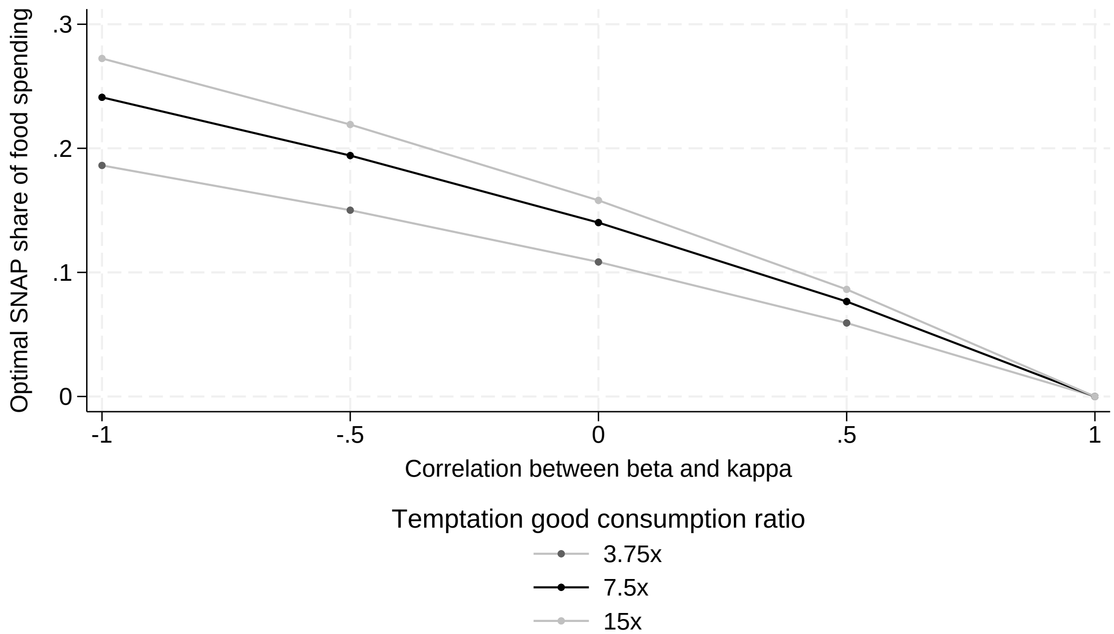
Notes: This figure shows estimates of β_r from equation 2, estimated using only person-months corresponding to individuals who are paid from the 1st to the 10th and who were assigned a SNAP case number before September 2012. Subfigure (a) uses the union of this restriction and the overlap ER sample, while subfigure (b) uses the union of this restriction and the overlap drug fills sample. The outcome variables are (a) ER 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.18: 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.19: 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 (dark gray), 7.5-fold (black), and 15-fold (light gray) 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, $\gamma = 88$; under a 7.5-fold higher rate it is .95; under a 15-fold higher rate it is .98.

G 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: Sample Size Restrictions

		On SSI	Likely Not On SSI	On SNAP
Original Samples		20,228,283	184,736,301	36,735,361
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	19,791,440	133,954,392	30,505,480
	No Observations from Year After Death	19,758,055	110,157,888	30,294,187
	Person-Months not on TANF	19,236,048	109,240,417	29,016,217
ER Analysis Samples		19,236,048	109,240,417	29,016,217
Drug Fills Restrictions	ER Analysis Sample	19,236,048	109,240,417	29,016,217
	Person-Months on Medicaid	19,236,048	27,162,770	19,333,909
	Not Dual After 2006	11,500,661	15,830,614	10,408,775
	Can Observe Drug Fill Dates	9,801,524	8,379,201	8,494,422
	≥6 Months into Medicaid Spell	9,288,812	7,377,659	7,877,590
Drug Fills Samples		9,288,812	7,377,659	7,877,590

Notes: This table tracks the change in number of person-months in the on-SSI, likely-not-on-SSI, and SNAP 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.3: 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.4: 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: ER Visits Per Month (Per 10,000)												
Drug/alcohol-related (DA)	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.5: 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: ER Visits Per Month (Per 10,000)												
Drug/alcohol-related (DA)	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.6: Robustness Table, Drug and Alcohol ER Visits

		Full Samples					Overlap Samples				
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		SNAP Estimate	SSI Estimate, $\frac{1}{4}$*On SSI	SSI Estimate, $\frac{1}{4}$* DD	Difference $\frac{1}{4}$*On SSI-SNAP	Scaled Difference $\frac{1}{4}$*SSI DD-SNAP	SNAP Estimate	SSI Estimate, $\frac{1}{4}$*On SSI	SSI Estimate, $\frac{1}{4}$*DD	Difference $\frac{1}{4}$*On SSI-SNAP	Difference $\frac{1}{4}$*SSI DD-SNAP
(1)	Baseline	-0.005	0.176	0.160	0.181	0.165	-0.076	0.168	0.126	0.245	0.202
		(0.043)	(0.009)	(0.010)	(0.044)	(0.044)	(0.092)	(0.013)	(0.015)	(0.093)	(0.093)
(2)	SNAP controlling for SSI and SSI controlling for SNAP	-	-	-	-	-	-0.068	0.165	-	0.233	-
		-	-	-	-	-	(0.089)	(0.028)	-	(0.095)	-
(3)	Uniform covariate effects across SNAP assignment time	-0.010	-	-	0.186	0.170	-0.118	-	-	0.286	0.244
		(0.042)	-	-	(0.043)	(0.043)	(0.091)	-	-	(0.092)	(0.092)
(4)	SSI in 2013 onwards	-	0.231	0.209	0.236	0.214	-0.044	0.206	0.161	0.250	0.204
		-	(0.018)	(0.018)	(0.046)	(0.046)	(0.151)	(0.027)	(0.029)	(0.154)	(0.154)
(5)	Non-social security (people aged ¡ 62)	0.037	0.239	0.222	0.202	0.185	0.009	0.237	0.193	0.227	0.184
		(0.061)	(0.014)	(0.015)	(0.062)	(0.062)	(0.134)	(0.021)	(0.024)	(0.136)	(0.136)
(6)	SNAP payouts on days 1-10 of month	-0.001	-	-	0.177	0.161	-0.051	-	-	0.197	0.164
		(0.049)	-	-	(0.050)	(0.050)	(0.091)	-	-	(0.094)	(0.094)
(7)	Poisson version of specifications	-0.003	0.075	0.045	0.078	0.048	-0.027	0.068	0.030	0.094	0.057
		(0.020)	(0.004)	(0.006)	(0.021)	(0.021)	(0.032)	(0.006)	(0.010)	(0.032)	(0.033)
		{-0.003}	{0.074}	{0.068}	-	-	{-0.031}	{0.068}	{0.051}	-	-

Notes: This table shows point estimates and standard errors for the average effects on ER 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.7: Robustness Table, First Fills

		Full Samples					Overlap Samples				
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		SNAP Estimate	SSI Estimate, $\frac{1}{4}$*On SSI	SSI Estimate, $\frac{1}{4}$* DD	Difference $\frac{1}{4}$*On SSI-SNAP	Scaled Difference $\frac{1}{4}$*SSI DD-SNAP	SNAP Estimate	SSI Estimate, $\frac{1}{4}$*On SSI	SSI Estimate, $\frac{1}{4}$*DD	Difference $\frac{1}{4}$*On SSI-SNAP	Difference $\frac{1}{4}$*SSI DD-SNAP
(1)	Baseline	9.066	100.233	45.649	91.167	36.583	0.807	116.330	54.287	115.523	53.480
		(7.985)	(5.335)	(5.326)	(9.628)	(9.641)	(10.537)	(5.760)	(5.339)	(12.081)	(11.891)
(2)	SNAP controlling for SSI and SSI controlling for SNAP	-	-	-	-	-	-28.395	110.802	-	139.198	-
		-	-	-	-	-	(11.525)	(5.975)	-	(13.125)	-
(3)	Uniform covariate effects across SNAP assignment time	10.907	-	-	89.326	34.742	2.729	-	-	113.601	51.558
		(7.799)	-	-	(9.470)	(9.477)	(10.318)	-	-	(11.905)	(11.699)
(4)	SSI in 2013 onwards	-	59.702	30.053	50.636	20.987	-2.137	64.602	32.091	66.739	34.228
		-	(9.519)	(9.010)	(12.533)	(12.161)	(16.887)	(10.118)	(8.753)	(19.885)	(19.258)
(5)	Non-social security (people aged ¡ 62)	10.673	98.488	50.837	87.815	40.164	3.374	116.453	58.602	113.079	55.228
		(8.309)	(5.118)	(5.285)	(9.759)	(9.858)	(10.818)	(5.544)	(5.346)	(12.199)	(12.111)
(6)	SNAP payouts on days 1-10 of month	3.194	-	-	97.039	42.456	-3.489	-	-	118.478	59.735
		(8.070)	-	-	(9.592)	(9.660)	(10.627)	-	-	(12.132)	(12.249)
(7)	Poisson version of specifications	0.060	0.619	0.222	0.559	0.163	0.014	0.658	0.249	0.644	0.235
		(0.049)	(0.034)	(0.038)	(0.060)	(0.062)	(0.060)	(0.034)	(0.035)	(0.069)	(0.069)
		{0.063}	{0.713}	{0.325}	-	-	{0.005}	{0.774}	{0.361}	-	-
(8)	Non-maint- -enance fills	24.018	240.340	112.608	216.322	88.590	30.364	273.387	129.572	243.022	99.208
		(7.200)	(8.681)	(7.927)	(10.910)	(10.273)	(10.335)	(9.527)	(8.210)	(13.615)	(12.621)

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.8: Sample size changes

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

Notes: This table shows the change in number of person-months in the on-SSI, likely-not-on-SSI, and SNAP 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.

Table OA.9: Results from dropping covariates, DA ER visits

	Full Samples					Overlap Samples				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	SNAP Estimate	SSI Estimate, $\frac{1}{4}$*On SSI	SSI Estimate, $\frac{1}{4}$* DD	Difference $\frac{1}{4}$*On SSI-SNAP	Scaled Difference $\frac{1}{4}$*SSI DD-SNAP	SNAP Estimate	SSI Estimate, $\frac{1}{4}$*On SSI	SSI Estimate, $\frac{1}{4}$*DD	Difference $\frac{1}{4}$*On SSI-SNAP	Difference $\frac{1}{4}$*SSI DD-SNAP
Baseline	-0.005	0.176	0.160	0.181	0.165	-0.076	0.168	0.126	0.245	0.202
	(0.043)	(0.009)	(0.010)	(0.044)	(0.044)	(0.092)	(0.013)	(0.015)	(0.093)	(0.093)
Drop special days	-0.004	0.173	0.160	0.177	0.164	-0.077	0.164	0.126	0.241	0.203
	(0.043)	(0.009)	(0.010)	(0.044)	(0.044)	(0.092)	(0.013)	(0.015)	(0.093)	(0.093)
Drop year	-0.005	0.173	0.160	0.178	0.165	-0.078	0.165	0.126	0.243	0.204
	(0.043)	(0.012)	(0.010)	(0.044)	(0.044)	(0.092)	(0.016)	(0.015)	(0.093)	(0.093)
Drop month	-0.004	0.173	0.160	0.178	0.164	-0.077	0.165	0.126	0.242	0.203
	(0.043)	(0.012)	(0.010)	(0.044)	(0.044)	(0.092)	(0.016)	(0.015)	(0.093)	(0.093)
Drop day of week	-0.005	0.175	0.160	0.180	0.164	-0.078	0.167	0.126	0.245	0.204
	(0.043)	(0.012)	(0.010)	(0.044)	(0.044)	(0.092)	(0.016)	(0.015)	(0.093)	(0.093)
Drop day of month from SNAP	-0.031	-	-	0.206	0.191	-0.140	-	-	0.308	0.266
	(0.041)	-	-	(0.043)	(0.042)	(0.084)	-	-	(0.086)	(0.085)

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 DA ER 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.10: Results from dropping covariates, first fills

	Full Samples					Overlap Samples				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	SNAP Estimate	SSI Estimate, $\frac{1}{4}$*On SSI	SSI Estimate, $\frac{1}{4}$* DD	Difference $\frac{1}{4}$*On SSI-SNAP	Scaled Difference $\frac{1}{4}$*SSI DD-SNAP	SNAP Estimate	SSI Estimate, $\frac{1}{4}$*On SSI	SSI Estimate, $\frac{1}{4}$*DD	Difference $\frac{1}{4}$*On SSI-SNAP	Difference $\frac{1}{4}$*SSI DD-SNAP
Baseline	9.066	100.233	45.649	91.167	36.583	0.807	116.330	54.287	115.523	53.480
	(7.985)	(5.335)	(5.326)	(9.628)	(9.641)	(10.537)	(5.760)	(5.339)	(12.081)	(11.891)
Drop	8.143	94.350	45.649	86.207	37.506	0.000	110.075	54.287	110.075	54.287
special days	(7.982)	(5.435)	(5.325)	(9.701)	(9.637)	(10.546)	(5.872)	(5.337)	(12.170)	(11.899)
Drop year	8.172	94.402	45.649	86.231	37.478	-0.033	110.114	54.287	110.146	54.320
	(7.988)	(5.632)	(5.323)	(9.852)	(9.641)	(10.551)	(6.137)	(5.336)	(12.326)	(11.890)
Drop month	5.120	93.882	45.649	88.762	40.529	-3.299	109.538	54.287	112.837	57.586
	(7.991)	(5.765)	(5.323)	(9.928)	(9.632)	(10.571)	(6.264)	(5.335)	(12.411)	(11.903)
Drop day of week	5.037	63.143	45.649	58.107	40.613	-3.519	75.945	54.287	79.464	57.806
	(8.114)	(7.772)	(5.322)	(11.071)	(9.690)	(10.686)	(8.362)	(5.335)	(13.492)	(11.986)
Drop day of	-97.436	-	-	160.579	143.085	-143.646	-	-	219.591	197.933
month from SNAP	(11.818)	-	-	(14.854)	(13.318)	(15.031)	-	-	(18.077)	(16.479)

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.11: Fungibility Tests on Nutrition-Sensitive ER Visits

	(1) SNAP Estimate	(2) SSI Estimate, $\frac{1}{4}$ * On SSI	(3) SSI Estimate, $\frac{1}{4}$ * DD	(4) Scaled Difference ($\frac{1}{4}$ * On SSI - SNAP)	(5) Scaled Difference ($\frac{1}{4}$ * SSI DD - SNAP)	Share of all ER visits
Panel A: Full Samples						
All nutrition-sensitive	-0.358	0.202	0.156	0.560	0.515	0.52
	(0.140)	(0.042)	(0.060)	(0.146)	(0.152)	
Hypertension	-0.260	0.151	0.126	0.411	0.386	0.39
	(0.125)	(0.037)	(0.057)	(0.131)	(0.138)	
Diabetes-related complications	-0.339	0.193	0.149	0.532	0.488	0.50
	(0.138)	(0.040)	(0.058)	(0.144)	(0.150)	
Hypoglycemia	-0.004	0.001	0.000	0.005	0.005	0.00
	(0.007)	(0.002)	(0.002)	(0.007)	(0.007)	
Panel B: Overlap Samples						
All nutrition-sensitive	-0.452	0.155	0.118	0.607	0.570	0.52
	(0.267)	(0.050)	(0.061)	(0.272)	(0.274)	
Hypertension	-0.323	0.108	0.099	0.431	0.422	0.39
	(0.246)	(0.043)	(0.055)	(0.250)	(0.252)	
Diabetes-related complications	-0.413	0.150	0.116	0.563	0.529	0.50
	(0.265)	(0.048)	(0.058)	(0.270)	(0.272)	
Hypoglycemia	-0.017	0.000	-0.001	0.016	0.016	0.00
	(0.012)	(0.003)	(0.004)	(0.012)	(0.013)	

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 ER visits (first row in each panel) as well as the components of nutrition-sensitive ER visits (hypertension + diabetes-related complications + hypoglycemia), using full and overlap samples. Column (1) shows one-fourth of the average first week on-SSI effect from equation 1. Column (2) shows one-fourth of the average first week SSI DD effect from equation 1. Column (3) shows the average first week SNAP effect from equation 2. Columns (4) and (5) show differences in the SNAP and SSI estimates. 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 ER visits which fall into each subcategory of nutrition-sensitive ER 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: Fungibility Tests on Major Causes of ER Visits, Full Samples

	(1) SNAP Estimate	(2) SSI Estimate, $\frac{1}{4}$ * On SSI	(3) SSI Estimate, $\frac{1}{4}$ DD	(4) Scaled Difference ($\frac{1}{4}$ * On SSI - SNAP)	(5) Scaled Difference ($\frac{1}{4}$ * SSI DD - SNAP)	Share of all ER visits
Ill-Defined	-0.046	0.055	0.043	0.101	0.088	0.21
	(0.083)	(0.021)	(0.021)	(0.085)	(0.085)	
Injury/Poisoning	0.100	0.154	0.148	0.055	0.048	0.17
	(0.066)	(0.015)	(0.016)	(0.068)	(0.069)	
Respiratory	-0.087	0.075	0.054	0.162	0.141	0.11
	(0.058)	(0.015)	(0.017)	(0.060)	(0.061)	
Musculoskeletal	-0.147	0.010	0.006	0.157	0.153	0.10
	(0.060)	(0.013)	(0.014)	(0.062)	(0.062)	
Circulatory	-0.001	0.017	0.001	0.018	0.002	0.08
	(0.048)	(0.011)	(0.011)	(0.049)	(0.049)	
Digestive	-0.048	0.034	0.024	0.081	0.072	0.07
	(0.046)	(0.011)	(0.011)	(0.047)	(0.047)	
Genitourinary	-0.070	0.008	0.007	0.077	0.077	0.06
	(0.041)	(0.009)	(0.009)	(0.042)	(0.042)	
Metabolic	0.033	0.007	0.006	-0.026	-0.027	0.04
	(0.033)	(0.009)	(0.009)	(0.034)	(0.034)	
Mental	0.013	0.102	0.092	0.089	0.079	0.04
	(0.037)	(0.009)	(0.009)	(0.038)	(0.038)	
Nervous	-0.029	-0.005	-0.004	0.023	0.025	0.04
	(0.035)	(0.009)	(0.011)	(0.036)	(0.037)	
Infectious	-0.024	-0.002	-0.002	0.022	0.023	0.03
	(0.028)	(0.007)	(0.007)	(0.029)	(0.029)	
Skin	-0.004	0.010	0.007	0.014	0.010	0.03
	(0.034)	(0.007)	(0.007)	(0.034)	(0.034)	
Supplementary	-0.013	0.012	0.008	0.025	0.020	0.02
	(0.026)	(0.006)	(0.006)	(0.026)	(0.026)	
Neoplasms	-0.006	0.005	0.004	0.011	0.010	0.01
	(0.014)	(0.003)	(0.003)	(0.014)	(0.014)	
Residual	0.006	0.000	0.000	-0.006	-0.006	0.01
	(0.015)	(0.004)	(0.004)	(0.015)	(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 major causes of ER visits (conditions defined by the row labels), using full samples. Column (1) shows one-fourth of the average first week on-SSI effect from equation 1. Column (2) shows one-fourth of the average first week SSI DD effect from equation 1. Column (3) shows the average first week SNAP effect from equation 2. Columns (4) and (5) show differences in the SNAP and SSI estimates. 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 ER visits which correspond to each major cause of ER visits.

Table OA.13: Fungibility Tests on Major Causes of ER Visits, Overlap Samples

	(1) SNAP Estimate	(2) SSI Estimate, $\frac{1}{4}$ * On SSI	(3) SSI Estimate, $\frac{1}{4}$ DD	(4) Scaled Difference ($\frac{1}{4}$ * On SSI - SNAP)	(5) Scaled Difference ($\frac{1}{4}$ * SSI DD - SNAP)	Share of all ER visits
Ill-Defined	-0.201	0.048	0.051	0.249	0.252	0.21
	(0.176)	(0.029)	(0.033)	(0.179)	(0.179)	
Injury/Poisoning	0.228	0.147	0.142	-0.080	-0.085	0.17
	(0.128)	(0.022)	(0.027)	(0.130)	(0.131)	
Respiratory	-0.180	0.077	0.053	0.256	0.232	0.11
	(0.120)	(0.019)	(0.022)	(0.122)	(0.123)	
Musculoskeletal	-0.263	0.022	0.017	0.285	0.280	0.10
	(0.130)	(0.019)	(0.023)	(0.131)	(0.132)	
Circulatory	0.052	0.025	-0.011	-0.027	-0.063	0.08
	(0.085)	(0.015)	(0.019)	(0.086)	(0.087)	
Digestive	-0.077	0.034	0.031	0.110	0.107	0.07
	(0.083)	(0.015)	(0.019)	(0.084)	(0.085)	
Genitourinary	-0.016	0.000	0.000	0.016	0.017	0.06
	(0.071)	(0.013)	(0.016)	(0.072)	(0.073)	
Metabolic	0.050	0.006	0.018	-0.044	-0.033	0.04
	(0.065)	(0.013)	(0.014)	(0.066)	(0.067)	
Mental	-0.100	0.096	0.070	0.196	0.170	0.04
	(0.100)	(0.012)	(0.013)	(0.100)	(0.100)	
Nervous	-0.063	-0.019	-0.021	0.044	0.042	0.04
	(0.065)	(0.012)	(0.015)	(0.066)	(0.066)	
Infectious	-0.002	-0.009	-0.015	-0.007	-0.013	0.03
	(0.052)	(0.009)	(0.011)	(0.053)	(0.053)	
Skin	0.045	0.009	0.020	-0.036	-0.025	0.03
	(0.058)	(0.009)	(0.012)	(0.059)	(0.060)	
Supplementary	0.041	0.009	0.007	-0.033	-0.034	0.02
	(0.042)	(0.008)	(0.010)	(0.042)	(0.043)	
Neoplasms	-0.011	0.005	0.006	0.016	0.017	0.01
	(0.023)	(0.004)	(0.005)	(0.023)	(0.024)	
Residual	-0.006	0.001	0.005	0.006	0.011	0.01
	(0.026)	(0.006)	(0.008)	(0.027)	(0.027)	

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 ER visits (conditions defined by the row labels), using overlap samples. Column (1) shows one-fourth of the average first week on-SSI effect from equation 1. Column (2) shows one-fourth of the average first week SSI DD effect from equation 1. Column (3) shows the average first week SNAP effect from equation 2. Columns (4) and (5) show differences in the SNAP and SSI estimates. 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 ER visits which correspond to each major cause of ER visits.

Table OA.14: Fungibility tests on ER visits for drug and alcohol use, by prior behavioral health issues

	(1) SNAP Estimate	(2) SSI Estimate, $\frac{1}{4}$ * On SSI	(3) SSI Estimate, $\frac{1}{4}$ * DD	(4) Scaled Difference ($\frac{1}{4}$ * On SSI - SNAP)	(5) Scaled Diffe ($\frac{1}{4}$ * SSI DD -
Has Prior Behavioral Health issues	0.331	0.731	0.629	0.400	0.298
	(0.376)	(0.063)	(0.074)	(0.382)	(0.385)
Does not have Prior Behavioral Health Issues	-0.015	0.091	0.075	0.106	0.090
	(0.047)	(0.009)	(0.010)	(0.048)	(0.048)
Combined sample	0.011	0.173	0.155	0.163	0.144
	(0.058)	(0.011)	(0.013)	(0.060)	(0.060)

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 DA ER visits, separately for individuals with and without M/B issues, as well as combined. Column (1) shows one-fourth of the average first week on-SSI effect from equation 1. Column (2) shows one-fourth of the average first week SSI DD effect from equation 1. Column (3) shows the average first week SNAP effect from equation 2. Columns (4) and (5) show differences in the SNAP and SSI estimates. 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.15: Heterogeneity in SSI effects on ER Visits for Drug and Alcohol Use

	Has prior behavioral health issues	Does not have prior behavioral
Panel A: Sample on SSI		
Share of sample	0.129	0.871
DA ER visits per day (per 10,000)	8.81	1.17
Estimated impact of SSI cycle	2.923	0.364
	(0.254)	(0.037)
Panel B: Sample Likely Not on SSI		
Share of sample	0.033	0.967
DA ER visits per day (per 10,000)	3.60	0.47
Estimated impact of SSI cycle	0.409	0.064
	(0.132)	(0.012)
Panel C: Difference-in-Differences		
Estimated impact of SSI cycle	2.515	0.300
	(0.297)	(0.039)

Notes: Table shows the difference in the impact of SSI between individuals with and without mental/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 mental/behavioral issues. The second row of Panels A and B shows the mean number of DA ER visits per day per 10,000 individuals in that sample. The third row of Panels A and B shows one-fourth of the average first week (relative days 0 through 6) effect of the SSI cycle from equation 1 on individuals with and without mental/behavioral issues, as well as the difference in effects between these groups. Panel C shows the difference-in-differences estimate for one-fourth of the average first week effect of the SSI cycle from equation 1, again separately for individuals with and without mental/behavioral health issues, as well as the difference in these estimates. Standard errors are clustered at the date (day-month-year) level.