Economic Hardship, Sleep and Self-Rated Health: Evidence from the Supplemental Nutrition Assistance Program (SNAP)*

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Abstract

The Supplemental Nutrition Assistance Program (SNAP) distributes vouchers for grocery shopping to around 43 million individuals across the United States to counteract food insecurity. In this study, we take advantage of the random interview day assignment of the American Time Use Survey (ATUS) and the variation in voucher issuance dates across states to identify changes in self-rated health and sleep over the monthly SNAP payment cycle. We find that the economic hardship experienced at the end of the payout period causes a significant and sizeable negative effect on self-assessed physical health and sleep quality. SNAP recipients were 18 percent more likely to report fair or poor physical health at the end of the payment cycle compared

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to the rest of the month. During this period of scarcity, recipients were also 50 percent more likely to report sleeplessness, with the number of minutes being sleepless more than doubling while total sleep duration remained unchanged. Drawing upon information on time use in the ATUS, we discuss evidence suggesting that higher levels of stress, changed eating patterns, and reduced sleep quality may be potential mechanisms of the adverse health effects. Our findings extend the literature on sleep quality as a mediator between low socio-economic status and self-rated health in the short run.

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JEL classification: I10, I18, I32, I38

I. Introduction

The far-reaching health and economic effects of the COVID-19 pandemic have made it even more difficult for many households to afford food and other needs. In the United States, the number of individuals who participate in the Supplemental Nutrition Assistance Program (SNAP) rose from 37 million in January 2020 to 43 million in June 2020 (US Department of Agriculture). Low-income individuals often face hardship in their everyday lives, struggling to make ends meet and lacking the resources to serve their individual needs, such as healthcare and nutrition, adequately (e.g., Barr 2012; Edin & Lein, 1997; Ouellette et al., 2004). Investigating the short-term causal consequences of such poor financial circumstances has recently become of interest in economics (see, e.g., Carvalho et al., 2016; Mani et al., 2013; Schilbach et al., 2016).[1] Understanding these consequences is highly relevant from a policy perspective. Healthcare spending on government programs is one form of subsidy for low-income individuals and makes up a large part of the US national budget.[2] Isolating the causal effects of economic hardship on health, however, poses some challenges. Causal effect estimates may be confounded not only by unobserved individual characteristics (such as the potentially worse health status of the financially strained in general) but also by reverse causality (i.e., health affecting financial circumstances).

This paper provides evidence of a causal effect of economic hardship on self-rated health and quality of sleep, based on a sample of low-income individuals in the US who participate in SNAP. Previous studies have documented that the financial resources of recipients of food assistance programs generally decrease over the monthly voucher payment cycle, leading to especially poor economic circumstances at the cycle's end. We use the term economic scarcity to denote this state at the end of the monthly cycle in which many SNAP recipients' monetary resources are especially scarce. We estimate the short-run effect of this shortage of economic means on self-assessed physical health and sleep by exploiting the random assignment of individuals to their interview day in the American Time Use Survey (ATUS) together with the period of SNAP issuance, which differs from state to state.

The main idea behind our empirical strategy is to compare SNAP recipients interviewed at the end of the monthly voucher payment cycle with recipients interviewed during the rest of the cycle. The random interview day assignment implies that the individuals are randomly

[1] The papers of Carvalho et al. (2016) and Mani et al. (2013) investigated the effects of economic scarcity in the short run using cognition and economic decision-making as outcome variables.

[2] For example, in 2019, US public expenditure amounted to approximately $409 billion for Medicaid and $644 billion for Medicare, together surpassing spending for Social Security (approximately $1 trillion). (cbo.gov)

assigned to one of these two groups. Balance checks confirm the success of the randomization. To account for confounding events that may occur simultaneously with economic scarcity and to protect against imperfect random assignment, we extend the initial estimation by using a difference-in-differences approach with two different control groups, exploiting variation in SNAP issuance periods across states. Given our empirical strategy and the temporary nature of the scarcity that is our focus, this study speaks to the short-run effect of a temporary economic strain among a group of low-income adults in the US.

Cotti et al. (2020) take a similar approach, using the monthly SNAP benefit distribution to investigate emergency room visits at the end of the SNAP payout cycle. They find that increased food insecurity at the end of the payout cycle leads to higher emergency room utilization, especially among older recipients. Bronchetti et al. (2019) also use the assignment of SNAP benefits to investigate the relationship between economic hardship and health outcomes. They use the fixed gross SNAP payouts at the federal level together with state-variation in purchasing power to estimate the effect of supplemental nutrition assistance on child health. They find that a real increase in the purchasing power of SNAP vouchers positively affects the utilization of preventive health care and leads to lower levels of absenteeism from school due to illness. No effect was found for adults.

Our results suggest that the experience of economic scarcity at the end of the SNAP payout cycle has a detrimental effect on an individual's self-assessed physical health and increases sleeplessness. SNAP recipients were around 18 percent more likely to report fair or poor physical health at the end than during the rest of the payout cycle. The number of SNAP recipients reporting any sleeplessness increased by over 50 percent and the duration of sleeplessness more than doubled at the end of the payment cycle compared to the rest of the cycle. The total duration of sleep does not change over the payment cycle. Several robustness checks and placebo tests support the validity of these findings.

In epidemiology and related fields, a number of studies have documented that living in poverty is associated with worse health outcomes. In doing so, they have focused primarily on the long-run implications (e.g., Deaton, 2008) and placed special emphasis on children and adolescents (e.g., Aber et al., 1997). Economic hardship is associated with poor self-assessed health, depression, illness symptoms, limitations in activities of daily living, serious chronic conditions, heart attacks, and mortality.[3] The role of sleep in the relationship between wealth

[3]Poor self-assessed health (Gunasekara et al., 2013; Kahn & Pearlin, 2006; Wickrama et al., 2006; Stronks et al., 1998), depression (Butterworth et al. 2009; Schulz et al. 2006), illness symptoms (Kahn & Pearlin, 2006; Stronks et al., 1998), limitations in activities of daily living (Szanton et al., 2010), serious chronic conditions (Kahn & Pearlin, 2006), heart attacks (Ferrie et al., 2005), mortality (Tucker-Seeley et al., 2009). The studies

and health is complex and has not been fully identified to date. Sleep quality and health have a strong relation (Buysse, 2014). Suboptimal sleep has a strong association with mortality and morbidity and is associated with various risk factors (Bixler, 2009), poverty and ethnicity (Patel et al., 2010). Over-average sleep duration is also associated with higher mortality, mainly through depression and low socio-economic status (Patel et al., 2006). Sleep has also been identified as a mediator between socio-economic status and health (e.g., Moore et al., 2002). Most of these links have been established for the long-run. In our paper, we extend these findings, looking at the monthly, short-term fluctuation of resources, changes in self-assessed physical health and the adjustment of sleeping patterns. Additionally, we provide insights into the potential mechanisms behind these changes.

The remainder of this paper is structured as follows. Section II. describes SNAP and recipients financial circumstances over the payment cycle. Section III. explains our empirical strategy. Section IV. describes the data and gives the results from randomization checks. Section V. presents the main results. Section VI. discusses two potential mechanisms through which the effects of interest may occur. Section VII. presents the results from robustness checks and placebo tests. Section VIII. concludes.

II. Background

A. SUPPLEMENTAL NUTRITION ASSISTANCE PROGRAM

SNAP is one of the central elements of the social safety net in the United States.[4] In 2014 the program provided assistance to 46.5 million people at a cost of $74.2 billion (Gray and Kochhar, 2015). Up to February 2020, participation in SNAP had steadily decreased to fewer than 37 million individuals, mainly due to enduring economic growth and a resulting decline in eligibility. Since March 2020, SNAP has been used to distribute subsidies from the Families First Coronavirus Response Act, leading to a significant increase in participation to over 43 million individuals in June 2020. The USDA's total budget for the program was expanded by 40 percent. Households with children eligible for free school lunches were awarded additional money for periods of school closings through the Pandemic Electronic Benefit Transfer (P-

typically measure poor financial circumstances by using indices that combine questions about whether individuals experience various hardships (such as the ones mentioned above).

[4]The Supplemental Nutrition Assistance Program was previously called the Food Stamp Program (FSP), which was relabeled SNAP and revised as part of the Food, Conservation and Energy Act of 2008, otherwise known as the Farm Bill.

EBT) program. Benefits for unemployed individuals, which had been limited to three months, were extended and, in many states, raised to the maximum amount. The recertification process was suspended and the option was introduced to apply for the program by phone. Under the Biden administration, further extensions of the program have been announced, such as a 15 percent increase in the maximum SNAP allowance.

The main goal of SNAP is to reduce food insecurity. The program distributes vouchers to eligible households to buy most food items at grocery stores and other authorized retailers (e.g., alcohol and prepared foods cannot be purchased). Although these are in-kind benefits, studies have shown that SNAP recipients treat the monthly subsidy similarly to cash transfers of the same amount (Hoynes & Schanzenbach, 2009). The SNAP is federally funded, and its rules are set mostly at the federal level. There is little variation in the program across states, and its characteristics have not varied much over the past few decades (Hoynes & Schanzenbach, 2016).

In contrast to other welfare programs, eligibility for SNAP is universal. It is not restricted to specific groups in the population, such as the disabled or families with children. Generally, for a household to qualify for SNAP, three criteria must be satisfied with respect to monthly gross income, net income (calculated by making permitted deductions from the gross income), and countable resources. For example, one criterion is that the gross monthly household income must not be greater than 130 percent of the poverty line. In addition, there are households that are categorically eligible for food vouchers (e.g., because they receive specific additional government assistance) and therefore do not have to fulfil the three criteria.

The amount a household receives in SNAP benefits is calculated by subtracting 30 percent of the household's net income from a maximum benefit amount, which depends on the size of the household and is adapted annually to reflect changes in food prices. In 2007, the average SNAP-receiving household of 2.2 individuals received $212 in monthly SNAP vouchers. This household had a gross monthly income of $691, a net monthly income of $330, and countable resources amounting to $144 (Wolkwitz & Leftin 2008). Although the median benefit amount of $212 may not seem large in absolute terms, SNAP vouchers are an important contribution to the monthly resources a low-income household has at its disposal.

Each SNAP-receiving household in every state receives its vouchers once a month. However, the monthly date of receipt varies across states. Supplementary Table 1 lists the issuance periods for all states during the sample period. Whereas some states issue all of their vouchers on one day of the month, such as New Hampshire and Virginia, most states stagger their issuance dates, i.e., they distribute the benefits over a period of days. Among the states that

do so, there is variation in the starting date and duration of the issuance period. For example, California transfers SNAP subsidies between the first and tenth day of each month, whereas Mississippi distributes the benefits between day 5 and day 19.[5] Within the given issuance period, each state determines the SNAP transfer day for a household quasi-randomly, based on Social Security numbers or a case number. The payout date of the SNAP benefits are determined for each household and remains the same from month to month.

Since 2004, all states have issued SNAP benefits via an electronic transfer system called Electronic Benefit Transfer (EBT). On the assigned transmission day, a household's monthly benefits are transferred to its EBT card, which works similarly to a conventional debit card. The benefits are therefore instantly available at the day of payout and can be used for purchasing food items right away. A positive balance on the card from the previous month is carried over to the current month, similar to a bank account.

B. FINANCIAL CIRCUMSTANCES OVER THE SNAP DISTRIBUTION CYCLE

A number of studies have investigated the financial circumstances and consequential behaviors of SNAP-receiving households over their monthly payout cycle, i.e., the time from one voucher issuance day to the subsequent one.

Using data from retailers (e.g., Castellari et al., 2017; Goldin et al., 2016; Hastings & Washington, 2010) and surveys (e.g., Shapiro, 2005; Wilde & Ranney, 2000), researchers have found evidence that the expenditures of SNAP households decrease over the voucher payment cycle. For example, based on panel data containing 1.13 million observations over the period 2004–2011, Goldin et al. (2016) estimate a 27 percent drop in food expenditures between the first and last week of the monthly SNAP cycle for eligible households relative to non-SNAP households.[6] Beatty et al. (2019) provide evidence that this spending behavior over the SNAP cycle is relatively stable at different levels of wealth and can also be observed for other income streams. Along these lines, Cole and Lee (2005) examine food stamp redemption patterns

[5]Foley (2011) investigates which factors influence how states set their welfare payment schedules. He finds that common considerations include monthly budget processes, administrative factors, and requests from retailers to reduce monthly demand fluctuations by staggering welfare payments. However, he also finds that, for many programs and jurisdictions, the payment schedules were set long ago and without any documentation as to why they were set in this way. Overall, Foley's (2011) findings suggest that there are no clear systematic reasons for the variation in issuance periods across states.

[6]Studies based on other populations have also found that individual spending behavior is sensitive to the timing of income receipt (see, e.g., Johnson et al. 2006; Shapiro and Slemrod 1995; Stephens 2003; 2006).

using actual transaction data from the EBT system. The results of their analysis indicate that food stamp households spend, on average, 80 percent of their food stamp benefits within the first 14 days of the payout cycle, 91 percent after 21 days, and 97 percent by the last day. Cole and Lee (2005) also find that food stamp redemption patterns vary very little across states, community characteristics and household characteristics. Additionally, the patterns appear to be relatively stable over time (U.S. Department of Agriculture, 2006). These spending patterns also express themselves in the perception of food insecurity, which is the chief reason that the food stamp program and SNAP were initiated. Gregory et al. (2018) find that SNAP recipients are 20 percent more likely to report food insecurity at the end of the payout cycle, and that the recent experience of food hardship around the voucher issuance day increases sensitivity to all questions related to food insecurity.

Going beyond the analysis of expenditure patterns, Shapiro (2005) provides further evidence of monthly variation in SNAP households' financial circumstances by exploiting exogenous variation in the time since last voucher receipt across individuals in survey data. In addition to a decline in food expenses as the SNAP cycle progresses, Shapiro (2005) estimates that the caloric intake of SNAP household members declines by 10 to 15 percent between the beginning and end of the cycle. Furthermore, he finds evidence that SNAP recipients show an increasing present-bias fueled by their growing desperation for money over the monthly cycle. The further away participants are from their last SNAP payment, the more money they are willing to forgo for an immediate payout instead of a larger amount in a month's time. These preferences over the payout cycle suggest that the established relationship between poverty and present-bias in the literature (e.g., Haushofer & Fehr, 2014) can also be observed among SNAP recipients. In summary, the results of the studies outlined above indicate that the financial resources of households receiving food vouchers decrease as the monthly payout cycle progresses, leading to particularly poor financial circumstances at the end of the cycle.[7]

III. Empirical Strategy

This section describes our empirical strategy to estimate the short-run effect of economic scarcity at the end of the SNAP payout cycle on self-assessed physical health and on sleeplessness. The strategy exploits the random interview day assignment in ATUS and the variation across states in the issuance periods for SNAP benefits. The subsequent section describes in

[7]This notion is further supported by a large qualitative study of the lives of SNAP recipients by Edin et al. (2013).

greater detail the data we use and reports results from randomization checks.

The ATUS data do not contain information on the actual day on which SNAP benefits are received. For our first estimation approach, we therefore select all SNAP recipients from states that issue their SNAP vouchers at the beginning of each month. We call this group of states the *early states* and define a state as such if its SNAP issuance period starts before the fifth day of each month and lasts no more than 10 days.[8] Appendix Table 1 lists all of the *early states* with their respective payout periods. Due to the payment of SNAP benefits early in the month, we know that in the *early states* the SNAP payout cycle coincides approximately with the actual calendar month. Therefore, individuals in the *early states* experience economic scarcity approximately at the end of the calendar month.

Our first estimation approach, which we call the *early states approach*, compares SNAP recipients from the *early states* interviewed at the end of the calendar month with SNAP recipients from the same states *not* interviewed at the end of the calendar month. We call the latter period the beginning of the month.[9] The estimated regression equation using a linear probability model is depicted by:

$$y_i = \alpha + \beta\, end_i + \gamma X_i + \epsilon_i, \tag{1}$$

where y_i is a dummy that equals one if individual i reported fair or poor physical health and zero otherwise (i.e., excellent, very good or good physical health). The dummy variable end_i is equal to one if individual i was interviewed at the end of the month, which we define in the main specification as the last 10 days of the calendar month, and zero otherwise. To improve precision and ensure that the randomization procedure of the survey was carried out correctly, Equation (1) also contains a vector of control variables X_i. Apart from standard demographic variables, X_i includes dummies for individual i's weight based on the Body Mass Index (BMI) and a dummy for whether he or she was disabled. Additionally, Vector X_i contains year$\times$month and state of residence dummies, as well as a dummy for whether the interview took place on the weekend. The notes for Table 3 list all of the covariates. ϵ_i is the zero-mean error term. The standard errors are clustered at the cross-sectional level of variation.[10] The coefficient of inter-

[8]When defining the *early states*, there is a trade-off between restricting the SNAP issuance period to a smaller time window at the beginning of the month and sample size. Our *early states* definition tries to balance this trade-off. Section VII. shows that the main results are robust to an alternative definition of *early states* .

[9]Because the individuals' SNAP payout cycle only approximately coincides with the calendar month, there may be individuals in the end-of-month group who had not actually reached the end of their monthly cycle, and vice versa. This may bias the effect estimates towards zero.

[10]The conclusions from the main analysis are robust to clustering at alternative levels, such as at the state–

est is β, which corresponds to the effect of end-of-cycle financial hardship on the probability of reporting fair or poor physical health.

In general, a major threat to obtaining an unbiased estimate for the effect of interest using Equation (1) is selection based on unobserved individual characteristics. For example, if individuals interviewed at the end of the month are generally more pessimistic about their health or generally have worse health, inducing them to report a health status that is worse than that reported by individuals interviewed at the beginning of the month, the effect estimate might be upward biased, overstating the detrimental effect of financial scarcity. However, the interview day randomization in ATUS breaks all correlations between the end-of-month dummy and characteristics of individuals that may determine their self-assessed physical health apart from the experience of financial scarcity. This being said, if there are factors besides financial scarcity that differ systematically between the end of the month and the beginning of the month, and that affect self-assessed physical health, then the estimation based on Equation (1) will give misleading results. For example, individuals interviewed at the end of the month might be exhausted from a long month's work, inducing them to report worse health than they would have reported if they had been interviewed earlier in the month.

To account for such potential factors, we extend the *early states approach* using a difference-in-differences (DID) approach. This additionally protects against bias that could result from an imperfect random interview period assignment. However, our randomization checks indicate that imperfect randomization is unlikely to be a concern in the estimations. The idea of the DID approach is to compare the 'beginning of the month–end of the month' change in self-assessed physical health between the SNAP participants from the early states and a suitable control group that is unlikely to experience scarcity at the end of the month, which we describe below. The regression equation that we estimate via OLS is:

$$y_i = \alpha + \delta\, end_i + \eta\, SNAP\_early_i + \beta\, end_i \times SNAP\_early_i + \gamma X_i + \epsilon_i, \qquad (2)$$

where, as in the *early states approach*, y_i is a dummy that is equal to one if individual i reported fair or poor physical health and zero otherwise, and dummy end_i equals one if individual i was interviewed during the last 10 days of the month and zero otherwise. The dummy $SNAP\_early_i$ takes on the value of one if individual i was a SNAP recipient from the *early states* and zero otherwise. Vector X_i contains the same variables as in the *early states approach*. ϵ_i is the zero-mean error term, and the standard errors are again clustered at the cross-sectional

quarter, state–month level, and to using unclustered (heteroscedasticity-consistent) standard errors.

level. Coefficient β is the effect of interest.

For estimations based on Equation (2) to yield an unbiased effect estimate, the parallel trends assumption must hold. In the present case, the assumption states that individuals from the *early states* would experience the same average change in self-assessed health between the beginning of the month and end of the month in the absence of scarcity as the average change in self-assessed health between the beginning of the month and end of the month for the control group (conditional on X_i). When we think about control groups for which the parallel trends assumption might hold, two groups of individuals come to mind: SNAP recipients who were not living in *early states* and inhabitants of *early states* who did not receive SNAP vouchers. We estimate Equation (2) with both of these groups separately.

The first control group consists of all SNAP recipients who were not from the *early states*. As Appendix Table 1 shows, many of the *'non-early' states* stagger their SNAP issuance days over a longer time span than the *early states*. For this reason, we call this group of states the *staggering states*. In addition, many of the *staggering states* start issuing SNAP vouchers more towards the middle of the month, later than the *early states*. The greater staggering and later issuance of SNAP vouchers imply that (a) the time since an individual has received his or her last voucher does not change as much on average between the beginning of the month and the end of month for individuals from the *staggering states* as it does for individuals from the *early states*, and (b) the SNAP payout cycle for individuals in the *staggering states*' has, on average, not reached its very end in either of the two periods of the month. Therefore, whether at the beginning or the end of the month, SNAP recipients from the *staggering states* are, on average, unlikely to experience the financial scarcity that the group of SNAP recipients from the *early states* faces at the end of the month. Furthermore, it is plausible that the parallel trends assumption holds because both groups consist of individuals who participate in SNAP. The estimator of interest compares both groups (SNAP recipients from *early* and *staggering states*) at the end of the month. In this way, other events or financial transfers (like wages or additional social benefits) coinciding with the SNAP payout period in *early states* (at the beginning of the month) are filtered out.

The second control group consists of all non-SNAP recipients from the *early states*. Because non-SNAP recipients are, on average, wealthier than recipients, it is unlikely that they experience the financial scarcity of the SNAP recipients. Moreover, it can be argued that the parallel trends assumption is fulfilled because both groups come from the same geographical areas. Any divergence at the end of the month is likely to be due to the timing along the payment cycle, which affects only the SNAP recipients. Inherent heterogeneity in self-rated health

and sleep between both groups is filtered out by the DID approach.

If there truly are factors other than the experience of economic scarcity that vary systematically between the beginning of the month and end of the month, it is a priori not clear which of the two DID estimations would yield more reliable effect estimates. The estimations based on the two controls groups do not necessarily need to give similar results, and there is some uncertainty as to which of the two control groups is more suitable. However, if such alternative factors are not present, then the DID approach using either of the two control groups, and the *early states approach*, should yield similar and valid effect estimates. Our estimations in the Results section of the paper suggest that this is indeed the case.

IV. Data

A. AMERICAN TIME USE SURVEY

For our empirical analysis, we use data from the ATUS. Among other variables, the survey records whether a subject takes part in SNAP and includes an indicator of self-assessed physical health (for selected years). Unlike other potentially suitable surveys, it assigns individuals randomly to an interview day. The random interview day assignment allows us to adopt the estimation strategy outlined above.

The main purpose of ATUS is to obtain nationally representative estimates of how individuals in the US spend their time. The survey is conducted by the US Census Bureau and is sponsored by the Bureau of Labor Statistics. Since 2003, annual ATUS waves have been published, containing 12,000–13,000 observations for most years. ATUS is based on a random sample drawn from households that have recently completed their last interview for the Current Population Survey (CPS). From every household drawn, one household member aged 15 or older is randomly selected to be questioned in ATUS. The interview is conducted via telephone and takes place 2–5 months after the last CPS interview. The interview day is randomly assigned in accordance with the following procedure: For a designated respondent, the month of the interview is randomly selected, and then the interview week during that month and, subsequently, the day of the week are randomly selected, as well.[11] Each designated re-

[11]The random assignment is performed by distributing the number of designated respondents evenly across the weeks of the year. Twenty-five percent of interviews are conducted on Sundays, a further 25 percent on Mondays, and 10 percent on each of the other days of the week. The respondents are asked how they used their time the day before the interview. The day-of-the-week allocation means that 50 percent of all individuals report about a weekend day.

spondent is notified in advance of the day on which the interview is scheduled to take place. If an individual is unable to partake in the interview on the designated date, he or she will be contacted and asked to partake in an interview at some point during the following seven weeks, but always on the same day of the week to which he or she had originally been assigned. Each ATUS respondent is interviewed only once.

Apart from information about how individuals use their time, ATUS includes some limited demographic information. The survey can be linked to the CPS, which increases the number of available variables. Additionally, in 2006–2008, all ATUS respondents were asked to assess their physical health as part of the supplementary Eating and Health module, which contains a small number of health-related questions. The wording of the question on self-rated physical health is as follows: 'In general, would you say that your physical health is Excellent, Very Good, Good, Fair, or Poor?' A popular outcome in health economics and epidemiological studies, self-rated health (SRH) is a subjective, short-term measure that is easy to administer because it does not require a medical examination. Moreover, instead of comprising a single medical parameter, it captures general health-related quality of life, including physical, mental and social factors (Quesnel-Vallée, 2007). Despite its subjectivity, self-rated health is a reliable predictor of morbidity and mortality, even when controlling for a large number of clinical measurements (Jylhä, 2009). It also shows consistent associations with objective health parameters like disease prevalence and laboratory testing results (Wu et al., 2013). Some of its predictive power is due to the behavioral factors it captures, including habits that are beneficial to health and may promote positive future health outcomes (Bombak, 2013). Measures concerning sleep were also collected in the ATUS. Participants are asked how many minutes they slept the previous night and how many minutes they had tried to but been unable to fall asleep. We use these two variables as outcome variables in our analysis of sleep quality.

The supplementary ATUS Eating and Health module additionally asked respondents whether they or anyone else in their household had received benefits from SNAP in the past 30 days. We refer to individuals who answered this question with 'yes' as SNAP recipients.[12]

[12]Survey participants tend to under-report government support, potentially biasing our estimates towards zero. Because such an effect is very likely to be non-systematic and not dependent on when the interview date falls within the month, however, it does not pose any limitations to our approach. Indeed, Courtemanche et al. (2019) have shown that self-reported survey data are as reliable as administrative data in recording participation in government assistance programs.

B. SAMPLE AND DESCRIPTIVE STATISTICS

The sample for our analysis consists of data from the ATUS waves 2006–2008, supplemented by data from the respondents' last CPS interview. We include all individuals who belonged to one of the three groups (SNAP recipients from *early states*, non-SNAP recipients from *early states* and SNAP recipients from *staggering states*) used in the empirical strategy and did not have missing data for the relevant variables. This selection procedure yields 1,322 SNAP recipients from the *early states*, 997 SNAP recipients from the *staggering states*, and 18,592 non-SNAP recipients from the *early states*.[13] In all three groups, the observations are evenly distributed over the three years.

Table 1 presents descriptive statistics of the variables used in the main analysis for each of the three groups of individuals separately. Overall, the two groups of SNAP recipients were very similar. The only notable differences in variable means are a nine percentage point lower share of black participants and an eight percentage point higher share of individuals living in metropolitan areas among recipients from the *early states* relative to recipients from the *staggering states*.

Conversely, there were distinct differences between non-SNAP and SNAP recipients . This is not surprising given that SNAP targets low-income individuals. Comparing the means for the three groups reveals that SNAP recipients were, overall, less educated, more likely to be disabled, and had lower levels of employment. Additionally, SNAP households were more often single households and the number of children was, on average, higher compared to non-SNAP households. There is also a marked difference in the average for the outcome variables. The share of SNAP recipients who assessed their physical health as fair or poor (as opposed to good, very good, or excellent) is approximately 40 percent. The corresponding share for the non-SNAP recipients is only about 14 percent. Recipients of SNAP benefits also differed with regard to their sleeping habits. On average, non-recipients slept eight hours and 37 minutes the night before the interview, whereas recipients slept on average 44 minutes longer. In general, this aligns with the general trend that wealthier and healthier individuals report less sleeping time (e.g., Bixler, 2009; Patel et al., 2006). SNAP recipients also reported more minutes of sleeplessness (6.12 on average) compared with non-recipients (3.94 on average).

To assess the notion that, overall, neither of the two groups of SNAP recipients experiences economic scarcity at the beginning of the month and that only the group of SNAP recipients

[13] Due to missing values, we dropped approximately 11 percent of all SNAP recipients from the *early states*, 14 percent of SNAP recipients from the *staggering states* and 9 percent of non-SNAP recipients from the *early states*.

from the *early states* experiences financial scarcity at the end of the month, Figure 1 displays the distribution of the mean number of days since receipt of the last SNAP voucher for both groups of SNAP recipients and both periods of the month.[14] Panel A suggests that most SNAP recipients interviewed at the beginning of the calendar month from both groups had not yet reached the end of their monthly SNAP issuance cycle. The mean time since receipt of the last SNAP voucher, averaged over all individuals, was 12.34 days for recipients from the *early states* and 14.76 days for recipients from the *staggering states*. Furthermore, for only nine percent of recipients from the *early states*' and for only 14 percent of recipients from the *staggering states*' recipients did the mean time since receipt of their last voucher equal or exceed 21 days. In contrast, Panel B suggests that for recipients from the *early states* who were interviewed at the end of the month, the SNAP payout cycle had progressed considerably further. The average mean time elapsed since receipt of the last SNAP voucher for these *early states*' recipients was 22.08 days. This interval equaled or exceeded 21 days for 62 percent of these individuals. Recipients from *staggering states*' who were interviewed at the end of the calendar month had also progressed further along the SNAP payment cycle, but the effect was smaller compared to recipients from the *early states*. For this group, the average time elapsed since receipt of the last SNAP voucher was 17.99 days, and the mean interval since receipt of the last voucher was 21 days or more for only 26 percent of them.

In sum, the conclusions drawn from Figure 1 support the empirical approach outlined in the previous section. For recipients from the *early states*, the SNAP payment cycle coincided approximately with the calendar month, whereas for SNAP recipients from the *staggering states*, the payment cycles are more evenly distributed over the whole month.

C. RANDOMIZATION CHECKS

In the following section, we assess whether the randomization of the interview period, resulting from the interview day randomization in ATUS, is successful in balancing the characteristics between the individuals interviewed at the beginning and the individuals interviewed at the end of the month. An imperfect interview period randomization could threaten the validity of our empirical analysis.

Table 2 reports means for individual and household characteristics by interview period for

[14] We compute the mean number of days since receipt of the last SNAP voucher for individual i by taking the average distance between i's interview day and each possible day he or she could have received his or her last voucher based on the SNAP issuance dates for his or her state of residence. We use this relatively imprecise measure because we cannot observe the actual issuance days for individual recipients.

each of the three groups (SNAP recipients and non-SNAP recipients from the *early states* and SNAP recipients from the *staggering states*) used in the analysis. In addition, the table displays p-values from t-tests for differences in means for the different interview periods for each listed variable, and F-tests of whether all mean differences within each group are jointly equal to zero. For each of the three groups, the table shows only small overall differences in means between the individuals interviewed at the beginning and the individuals interviewed at the end of the month. For 57 of the 60 pairwise comparisons of averages, the t-tests fail to reject the hypothesis of equal means at the 10 percent level.[15] Furthermore, the F-tests do not reject the hypothesis that all mean differences within each group are jointly equal to zero at the 10 percent level, as the second to last row in the table shows. The corresponding p-values are 0.853, 0.475, and 0.652. The balance checks in Table 2 suggest that the interview period randomization successfully balances the characteristics between the two periods of the month. Figure 2 in the Appendix includes additional histograms of the distribution of interview days among survey participants, SNAP recipients and inhabitants of *early states*.

Furthermore, the DID approach protects against bias from imperfect random interview period assignment if the bias is equal in treatment and control groups. If the interview period randomization is, however, imperfect in any one of the three groups used in our analysis, this could pose a threat to the validity of the estimations. A concern might be that SNAP recipients from the *early states* refuse to participate in the survey at the end of the month due to economic hardship. However, the means for the dummy variable *end* in Table 1 indicate that almost exactly 30 percent of all individuals in each of the three groups were interviewed at the end of the month, suggesting that group-specific interview period selection is unlikely to threaten the validity of the analysis[16].

V. Main Results

Table 3 presents the main estimates for the short-run effect of economic scarcity at the end of the SNAP payment cycle on self-assessed physical health. Column (1) reports the effect estimate from the *early states* approach, which compares SNAP recipients from the *early states*

[15]The three exceptions are: the 5.7 percentage point difference in the share of retired people for the SNAP voucher recipients from the *staggering states* is significant at the 5 percent level; for the non-SNAP recipients, the 0.5 year age difference and 1.4 percentage point difference in the share of individuals who have a normal weight is significant at the 10 percent level. The set of covariates in the estimations includes these three variables.

[16]The shares are also close to the share of individuals assigned to the end-of-month period among all designated ATUS respondents, which is 29 percent.

interviewed either at the beginning or end of the calendar month, without controls. Although the probability of reporting fair or poor physical health was 5.3 percentage points higher for participants interviewed at the end of the month, the difference was not statistically significant. Adding various groups of control variables to the model in Column (2) increases the estimate moderately to 7.2 percentage points. The R^2 increases considerably, from 0.003 to 0.342, and the effect estimate becomes more precise and is now significant at the one percent level.

Columns (3)–(6) report the main estimates from the DID approach, first using SNAP recipients from *staggering states* and then non-SNAP recipients from *early states* as a control group. These groups of individuals are unlikely to experience economic hardship at the end of the calendar month from having exhausted their SNAP benefits. In the DID models, the coefficient of the dummy variable *End* indicates the change in the probability of reporting bad physical health between the beginning and the end of the month for each of the two control groups. For either of these control groups, including or excluding the control variables, the estimated coefficient is far from significant and close to zero. This suggests that there are no factors other than the experience of economic scarcity that influence individuals' self-assessed physical health at the end of the month.

The interaction term SNAP_early×end gives the effect estimate for economic scarcity in the DID estimations. Using SNAP recipients from the *staggering states* as the control group, the estimated effect without controls is 5.9 percentage points; however, this estimate is imprecise. After we add controls, the estimate becomes significant at the five percent level. It shows that the number of recipients from different states reporting fair or poor self-rated health due to economic hardship at the end of the month increases by 7.6 percentage points. The DID model using the non-SNAP recipients from the *early states* as the control group yields an effect estimate of 5.6 percentage points without controls, also estimated with imprecision. With control variables, the model yields an estimate of 6.7 percentage points and is significant at the five percent level. The DID estimates with and without controls are very similar to the estimates from the *early states* approach. This was to be expected considering the small estimated changes in the probability of reporting bad physical health between the beginning and end of the month for both control groups.

In summary, all of the specifications from both estimation approaches indicate that there is a detrimental short-run effect of economic scarcity at the end of the payout cycle on self-assessed physical health. After we add controls, the regressions suggest that the economic scarcity increases the probability of reporting fair or poor physical health by around seven percentage points. The probability of reporting fair or poor physical health for the SNAP recipients from

the *early states* interviewed at the beginning of the month is 38.3 percent. Relative to this baseline value, the effect appears quite sizeable, corresponding to an increase of around 18 percent. While self-rated health is a useful measure of general health, it is limited in how much it can tell us about magnitudes of change. In this regard, studies that compare objective, clinically verified health data and subjective self-rated health outcomes can be helpful. A study of older adults by Fried et al. (1998) found that over a five-year period, lower self-rated health was associated with higher mortality. Wu et al. (2013) investigated the relationship between self-rated health and other objective health outcomes. They found that poorer self-rated health is associated with a higher prevalence of diseases, such as cardiovascular disorders or severe depression.

Table 4 presents estimates from regressions that are analogous to the ones on self-rated health (linear regressions in columns (1)-(2); DID approach in columns (3)-(6)) for the effect of financial scarcity on reported sleeplessness. Panel A depicts the estimated economic scarcity effect on the probability of reporting any sleeplessness, which is positive and significant at conventional levels in all estimations. Each regression yields a similar effect estimate between three and four percentage points. This magnitude appears sizable, with about 49 to 66 percent relative to the baseline probability of 6.1 percent reported by SNAP recipients from the *early states* at the beginning of the month. Panel B shows estimates for the financial scarcity effect on the number of minutes that an individual reports being sleepless. In all regressions, the estimated effect is approximately six minutes. This corresponds to a 130 percent increase relative to the average minutes of sleeplessness of 4.64 for the SNAP recipients from the *early states* at the beginning of the month. All of the estimates including controls are significant at the five percent level. In contrast to the results of our sleeplessness analysis, the difference in reported average sleep duration at the end (565 minutes) and the remainder (566 minutes) of the SNAP payout cycle is not statistically significant. There is, however, a large difference between SNAP recipients and non-SNAP recipients, with the latter sleeping on average 44 minutes less.

VI. Potential Mechanisms

This section discusses potential mechanisms through which SNAP recipients' economic hardship may affect self-assessed physical health and sleep quality. One potential mechanism for the effect could be that the experience of economic hardship increases individuals' levels of stress. Edin et al. (2013) found evidence that a lack of resources may be a stressful experience for many SNAP recipients, and a number of studies have found that stress may lead to neg-

ative health consequences, such as headaches and back pain (see Benson and Proctor, 2010). Unfortunately, ATUS does not have any direct measure of stress to explore this mechanism. However, it does contain an outcome variable for 'sleeplessness', which captures the number of minutes that elapse before an individual falls asleep.[17] A number of studies have documented associations between stress and sleep difficulties (e.g., Åkerstedt, 2006; Kahn et al., 2013). If stress is a mechanism for the effect of economic scarcity, then an impact of economic scarcity on individuals' reported sleeplessness seems plausible.

The two outcome variables sleep and self-rated health might also affect each other directly. Worse sleep has been associated with poorer health outcomes (e.g., Luyster, 2014; Paiva et al., 2015). This relation also holds true for specific medical conditions. Lower quality of sleep and sleep abnormalities are associated with higher levels of obesity (e.g., Beccuti & Pannain, 2011), type 2 diabetes (e.g., Yaggi et al., 2006), cardiovascular disease (e.g., Wolk et al., 2005) hypertension (e.g., Nieto et al., 2000) and immune function (e.g., Besedovsky et al., 2012). The literature on the reverse relationship, the effects of poor health on sleep quality, is less yielding (e.g., Zee & Turrey, 2006).

SNAP was implemented to target individuals threatened by food insecurity. Another mechanism for the effect of interest may be that the SNAP voucher recipients experience hunger and are not meeting their nutritional needs due to a lack of financial resources. As discussed in Section B., Shapiro (2005) estimates that there is a decline in caloric intake for food stamp recipients between the beginning and end of the monthly food stamp cycle. This finding suggests that hunger could also play a role. Unfortunately, ATUS does not include any suitable measure for hunger. However, the American Time Use Survey does include the cumulative time spent eating and drinking over the previous day. Even though this does not provide information about the nutritional intake or the amount of food in terms of calories, it might serve as an approximation for hunger. In general, time spent eating and drinking is positively correlated with income. On average, SNAP recipients spend 55 minutes per day eating and drinking compared to 69 minutes for non-SNAP recipients. Comparing SNAP voucher recipients at different times of the payment cycle reveals that in the last 10 days before the next payout period, recipients spent an average of 5.1 fewer minutes eating and drinking compared to recipients earlier in the cycle [18].

The survey further divides eating time into the two groups primary and secondary eating.

[17]The measurement has to be seen as rough estimate since it is unlikely that individuals recall the exact time they tried to fall asleep.

[18]To look at eating patterns during time of economic hardship at the end of the SNAP cycle, the 10 days before the next payout period are compared to the rest of the cycle in states that pay their benefits over 10 or fewer days

Primary eating constitutes eating as ones sole activity at a particular time, whereas secondary eating describes eating while engaging simultaneously in another activity, e.g., driving. The data show that the difference in eating time for SNAP recipients at the end of the payment cycle is entirely due to a reduction in primary eating. This might be another indicator that food subsidy vouchers are depleted at the end of the cycle and participants are more likely to buy prepared foods, which are excluded from SNAP. A closer investigation of this potential mechanism, with a more precise measurement of hunger, may therefore represent a fruitful opportunity for future research.

VII. Robustness Analysis and Placebo Tests

A. ROBUSTNESS ANALYSIS

All of the main estimations, which use two different approaches and two different control groups, yield similar results for the outcome variables self-rated health and sleep quality. To increase confidence in the findings from the main analysis yet further, we assess the robustness of the estimates to alternative model specifications.

One concern could be that the estimates might be sensitive to the definition of the end-of-month period. To address this issue, we re-estimate the models from the main analysis using alternative end-of-month definitions. Table 5 presents estimates with alternative end-of-month windows, adding and subtracting three days to the original 10-day definition. The table shows that the effect estimates remain stable and, if anything, generally behave as one might expect. Beginning with the self-rated health measure, Column (2) shows that the estimated effect based on the *early states approach* decreases from 7.2 percentage points in the main specification to 5.3 percentage points when the end of the month is defined as the last 13 days of the month. This moderate decrease appears plausible because increasing the end-of-month period from 10 to 13 days likely decreases the share of individuals experiencing financial scarcity during that time.

The only effect estimate that loses significance at conventional levels is the estimate in Column (3) from the DID approach that uses the SNAP recipients from the *staggering states* as the control group and the last seven days of the month as the end-of-month definition. Nevertheless, the 5.0 percentage point estimate still indicates the presence of a financial scarcity effect. The decrease in the estimate relative to the corresponding one from the main specifications also appears plausible. As the end-of-month window becomes narrower, the share of SNAP recipients from the *staggering states* that experience financial scarcity during the end-of-month

period is likely to increase, leading the DID approach to underestimate the effect of interest. This notion is supported by the increased but non-significant positive change in the probability of reporting bad health between the beginning and end of the month for the SNAP recipients in *staggering states'*, which is given by the coefficient estimate for the *End7* dummy.

Continuing with the second part of table 5, the alternative end-of-the-month definition has very little impact on the estimates of sleeplessness. Very similar to the estimates of the main analysis, respondents are around four percent more likely to report sleeplessness at the end of the SNAP payout cycle and all specifications remain significant at conventional levels.

Additional robustness checks are provided in Table6 for self-rated health and Table 7 for sleeplessness. Columns (2), (4), and (6) of Table 6 present estimates from regressions in which we include dummies for each week of the month instead of the end-of-month dummy to estimate the effect of economic scarcity. Based on the *early states approach*, Column (2) shows the probability of reporting fair or poor physical health rising moderately through weeks two and three, and then becoming markedly higher, by 9.1 percentage points, in week four, all relative to the first week of the month. This corresponds approximately to the definition of the end-of-the-month period in the main specifications. Estimating the financial scarcity effect by comparing the first and last week of the month thus increases the effect estimate by 1.9 percentage points relative to the corresponding estimate from the main analysis. Only the estimate for the coefficient of the week four dummy is significant at conventional levels. Similarly, the analogous DID models also yield significant effect estimates that are larger than the corresponding ones from the main analysis. In addition to the results for the specifications using week dummies, Table 6 displays estimates based on an alternative *early states* definition in Columns (1), (3), and (5). All states starting their SNAP issuance period on the first day of the month and with a duration of at most 10 days are defined as the alternative group of *early states*. All other states are defined as the alternative group of *staggering states*. Using this alternative *early states* definition does not change the effect estimates much relative to the respective main regressions, and all of the estimates remain significant at conventional levels.

Table 7 presents robustness checks for the sleeplessness analysis, taking the same approach. The estimates for the effect of economic scarcity are more imprecisely estimated but still yield increases of three to four percent at the end of the payout circle. Looking at the estimation of the week dummies, the results are similar to those for self-rated physical health. The largest effect can be seen in the last week before the recurring payout period, with estimates exceeding those of the main analysis.

B. PLACEBO TESTS

As discussed in Section III., the DID approach relies on the parallel trends assumption. In the DID model using the SNAP recipients from the *staggering states* as the control group, one factor that would violate the parallel trends assumption is the presence of a trend in self-assessed physical health between the beginning and end of the month, specific to individuals from either the *early states* or *staggering states*. Analogously, an exclusive trend in self-assessed physical health only for SNAP recipients or non-SNAP recipients would violate the parallel trends assumption when using the non-SNAP recipients from the *early states* as the control group in the DID approach.

To test for such group-specific trends, and thus for the validity of the parallel trends assumption, we conduct two placebo tests for both outcome variables self-rated health and sleeplessness. In both tests, we estimate the DID approach based on two groups of individuals who are unlikely to experience financial scarcity at the end of the month but would exhibit one of the two types of group-specific trends. In the presence of group-specific trends, one would expect the regressions to yield an estimate for the coefficient on the DID interaction term that is significantly different from zero.

To test for trends specific to either the *early states* or *staggering states*, we estimate the DID model based on the non-SNAP recipients from the *early states* and *staggering states*.

$$y_i = \alpha + \delta\, end_i + \mu\, SNAP_i + \beta\, SNAP_i \times end_i + \gamma X_i + \epsilon_i$$

To test for trends specific to SNAP-/non-SNAP recipients, we estimate the DID model based on the SNAP and non-SNAP recipients from the *staggering states*.

$$y_i = \alpha + \delta\, end_i + \xi\, early_i + \beta\, early_i \times end_i + \gamma X_i + \epsilon_i$$

Table 8 reports the results from the placebo tests. In each regression, the coefficients of the interaction terms early×end and SNAP×end, are close to zero and far from significant at the 10 percent level for self-rated health and sleeplessness. This suggests that no group-specific trends are present. Therefore, the placebo tests support the notion that the parallel trends assumption is valid in the DID estimations. In addition, the estimates for the end dummy coefficients are also close to zero and non-significant at the 10 percent level in all regressions. The placebo tests not only suggest that the parallel trends assumption holds, but also that none of the three placebo test groups experiences any change in the probability of reporting bad physical health

or sleeplessness between the beginning and end of the month.[19] This further increases confidence in the validity of the findings from our main analysis.

VIII. Conclusion

In this paper, we investigate the short-run effect of poor financial circumstances on self-rated health and sleep, using the variation in financial resources over the monthly payment cycle in a sample of recipients of the Supplemental Nutrition Assistance Program (SNAP). To isolate the causal effect of interest, we exploit the random interview day assignment in the American Time Use Survey and the variation in SNAP voucher issuance periods across states. Our empirical analysis suggests that poor economic circumstances can indeed have negative health consequences. We find that the economic scarcity experienced by SNAP recipients at the end of the monthly payout cycle increases the probability of reporting bad physical health by a considerable 18 percent relative to the baseline probability. Randomization checks, robustness checks, and placebo tests support the validity of this finding.

Looking at the sleeping patterns of SNAP recipients, we find that at the end of the payout cycle the average duration of sleep stays the same. The number of sleepless minutes, on the other hand, more than doubles from under five minutes to over 10 minutes at the end of the issuance period. Analyzing time use patterns for eating and drinking, we find that hunger or inadequate nutrition might be one of the mechanisms driving these effects. The two outcome variables, sleep and health, might also be affecting each other. Both outcomes might be negatively affected by an increased level of stress experienced by SNAP recipients at the end of the payout cycle. Quality of sleep can also be seen as a mediator, connecting poor socio-economic status and health.

From a policy perspective, our results suggest that measures taken to alleviate poverty may simultaneously improve the health and sleep quality of low-income individuals, potentially reducing the expenditures of publicly financed health care programs such as Medicaid. Furthermore, our results suggest that in the design of welfare programs, not only salient aspects (such as the benefit amount) but also more subtle features (such as the timing of payments) can be important. To mitigate particularly poor economic circumstances at the end of welfare payment cycles and their consequences, for example, it may be beneficial to distribute welfare payments at shorter time intervals (such as bi-weekly instead of monthly) to help individuals

[19] For all of the regressions, hypothesis tests also fail to reject at the 10 percent level that the two coefficients on the variables end, early×end and end, fsp×end, respectively, are jointly equal to zero.

smooth their consumption. In the case of SNAP, this could be a viable option because of the vouchers are issued using electronic cards. In addition, providing assistance to welfare recipients in managing their finances could also help mitigate especially poor end-of-cycle financial situations. This may include informing individuals explicitly about the exact purpose of a given welfare program to avoid a potential misjudgment of the benefit amount. In SNAP, for example, many households believe that their food subsidy vouchers are meant to cover all of the monthly food expenditures even though this is generally not the case (Edin et al. 2013).

The findings of this study suggest a number of avenues for future research. First, the effect suggested in this paper corresponds to a short-run response to a temporary and particularly poor economic situation. To gain a broader understanding of the link between financial circumstances and health, it would also be important to examine the consequences of poor financial circumstances that are more permanent and to investigate longer-run responses. Second, it would be instructive to explore further the mechanisms behind the estimated effect, building on the preliminary evidence presented in this study. Third, and related to this, using additional health data to examine the extent to which the effect is driven by changes in more objective health measures or changes in health perceptions would also be a fruitful subject for further research.

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Tables

Table 1. Descriptive Statistics for the Groups of Individuals Used in the Analysis

	SNAP recipients				Non-SNAP recipients	
	Early states		Staggering states		Early states	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Outcome variable						
Fair or poor physical health	0.399	0.490	0.415	0.493	0.144	0.351
Regressor of interest						
End	0.303	0.460	0.305	0.461	0.298	0.457
Individual characteristics						
Age in years	43.107	16.620	44.720	17.150	46.382	17.210
Black	0.269	0.443	0.360	0.480	0.108	0.310
Male	0.287	0.452	0.302	0.459	0.467	0.499
Employed	0.368	0.482	0.392	0.488	0.682	0.466
Retired	0.113	0.316	0.131	0.338	0.154	0.361
Disabled	0.257	0.437	0.243	0.429	0.031	0.174
Less than high school	0.319	0.466	0.332	0.471	0.138	0.345
High school	0.363	0.481	0.381	0.486	0.252	0.434
Some college	0.181	0.385	0.166	0.373	0.182	0.386
College	0.119	0.324	0.111	0.315	0.304	0.460
Advanced degree	0.018	0.134	0.009	0.095	0.123	0.329
Underweight	0.021	0.144	0.018	0.133	0.016	0.127
Normalweight	0.300	0.459	0.262	0.440	0.375	0.484
Overweight	0.305	0.461	0.306	0.461	0.360	0.480
Obese	0.374	0.484	0.414	0.493	0.249	0.433
Household characteristics						
Spouse/partner present in household	0.282	0.450	0.292	0.455	0.551	0.497
Low-income household	0.883	0.322	0.888	0.316	0.251	0.433
No. of adults in household	1.711	0.912	1.696	0.848	1.883	0.775
No. of children in household	1.356	1.394	1.345	1.420	0.891	1.113
Metropolitan area	0.739	0.439	0.814	0.389	0.814	0.389
Observations	1,322		997		18,592	

Notes: Authors' calculations based on 2006–2008 ATUS data supplemented by CPS data. The outcome variable fair or poor physical health equals one if the individual reports fair or poor physical health and zero if the individual reports excellent, very good, or good physical health. The dummy end is one if the individual is interviewed in the last ten days of the month and zero otherwise. The dummy low-income household equals one if the individual lives in a household with a monthly gross income equal to or below 185 percent of the poverty line and zero otherwise. The weight dummies based on the classification of the World Health Organization (2000) take on the value one if the following conditions hold and zero otherwise: Underweight: BMI$<$18.5; normalweight: 18.5$\leq$BMI$<$25; overweight: 25$\leq$BMI$<$30; obese: BMI$\geq$30. Age in years takes on the value 80 for individuals aged 80 through 84 and the value 85 for individuals aged 85 and above. In all regression models controlling for age, we additionally include age squared as a covariate. The dummies black, male, disabled, metropolitan area, and the five education dummies were measured at the last CPS interview. All other listed variables were measured at the ATUS interview.

Table 2. Balance Checks

	SNAP recipients						Non-SNAP recipients		
	Early states			Staggering states			Early states		
	Beginning of the month	End of the month	p-value	Beginning of the month	End of the month	p-value	Beginning of the month	End of the month	p-value
Individual characteristics									
Age	43.445	42.329	0.262	45.238	43.539	0.150	46.528	46.037	0.075
Black	0.273	0.259	0.620	0.351	0.382	0.349	0.108	0.109	0.783
Male	0.294	0.269	0.357	0.303	0.299	0.907	0.465	0.472	0.393
Employed	0.357	0.392	0.235	0.387	0.405	0.595	0.683	0.680	0.746
Retired	0.113	0.112	0.970	0.149	0.092	0.015	0.156	0.150	0.282
Disabled	0.261	0.249	0.668	0.231	0.270	0.188	0.031	0.032	0.721
Less than high school	0.322	0.312	0.700	0.323	0.352	0.375	0.138	0.139	0.788
High school	0.370	0.347	0.412	0.388	0.365	0.491	0.249	0.259	0.133
Some college	0.175	0.195	0.393	0.173	0.151	0.395	0.183	0.182	0.948
College	0.113	0.132	0.320	0.105	0.125	0.364	0.308	0.297	0.135
Advanced degree	0.020	0.015	0.567	0.010	0.007	0.589	0.123	0.123	0.921
Underweight	0.024	0.015	0.301	0.020	0.013	0.442	0.016	0.017	0.727
Normalweight	0.302	0.297	0.853	0.255	0.276	0.490	0.370	0.384	0.073
Overweight	0.296	0.324	0.314	0.316	0.283	0.297	0.362	0.354	0.306
Obese	0.378	0.364	0.635	0.408	0.428	0.570	0.251	0.245	0.332
Household characteristics									
Spouse/partner present in household	0.282	0.282	0.985	0.294	0.286	0.794	0.550	0.552	0.813
Low-income household	0.879	0.890	0.575	0.879	0.908	0.181	0.248	0.257	0.209
No. of adults in household	1.698	1.741	0.436	1.687	1.717	0.605	1.883	1.884	0.912
No. of children in household	1.325	1.429	0.211	1.303	1.441	0.159	0.885	0.907	0.215
Metropolitan area	0.745	0.726	0.466	0.820	0.803	0.526	0.814	0.814	0.894
Test for H_0: all differences in means are jointly equal to zero			0.853			0.475			0.652
Observations	921	401		693	304		13,049	5,543	

Notes: Authors' calculations based on 2006–2008 ATUS data supplemented by CPS data. The table reports the means for the listed variables by interview period of the month. All individuals interviewed in the last ten days of the calendar month belong to the group 'end of the month'. All other individuals belong to the group 'beginning of the month'. The p-values for each variable are from t-tests for H_0: *no difference in means between the beginning-of-month and end-of-month group*. The test for H_0: *all differences in means jointly equal to zero* tests for each of the three groups of individuals separately whether the differences in means between the beginning-of-month and end-of-month group for all the listed variables are jointly equal to zero. This test is an F-test based on a regression of the end of-month dummy on all listed variables that tests whether the coefficients on all the included regressors are jointly equal to zero. The dummies normalweight and college are omitted due to multicollinearity. For variable definitions, see the notes for Table 1.

Table 3. Estimates for the Effect of Resource Scarcity on Self-Assessed Physical Health

	Probability of Reporting Fair or Poor Self-Assessed Physical Health					
	Early states approach		Difference-in-differences approach			
Control group			Staggering states SNAP recipients		Early states non-SNAP recipients	
	(1)	(2)	(3)	(4)	(5)	(6)
End	0.053	0.072***	−0.006	−0.004	−0.003	−0.002
	(0.032)	(0.023)	(0.020)	(0.026)	(0.007)	(0.006)
SNAP_early	–	–	−0.034	−0.033	0.238***	0.033**
			(0.025)	(0.022)	(0.018)	(0.013)
SNAP_early × end	–	–	0.059	0.076**	0.056	0.067**
			(0.038)	(0.034)	(0.035)	(0.025)
Individual controls		✓		✓		✓
Household controls		✓		✓		✓
Time controls		✓		✓		✓
State controls		✓				✓
R^2	0.003	0.342	0.002	0.296	0.030	0.241
Observations	1,322	1,322	2,319	2,319	19,914	19,914

Notes: Standard errors clustered at the state level are in parentheses. The estimations are based on 2006–2008 ATUS data supplemented by CPS data. All models are estimated via OLS. The outcome variable is a dummy variable that equals one for individual i if i reports fair or poor physical health and zero otherwise. The dummy end equals one for individual i if i was interviewed in the last ten days of the calendar month and zero otherwise. SNAP_early is one for individual i if i is a SNAP recipient from the *early states* and zero otherwise. The set of individual controls consists of the variables listed under individual characteristics in Table 1. The dummies college and normalweight are omitted due to multicollinearity, and age squared is additionally added. The set of household controls consists of the variables listed under household characteristics in Table 1. The time controls are a full set of year×month dummies and a dummy that equals one for individual i if i's interview took place on the weekend and zero otherwise. The state controls are dummies for each state. For the SNAP recipients from the *early states* interviewed at the beginning of the month, the probability of reporting fair or poor physical health is 0.383.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Table 4. Estimates for the Effect of Resource Scarcity on Reported Sleeplessness

Control group	Early states approach		Difference-in-differences approach			
			Staggering states SNAP recipients		Early states non-SNAP recipients	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Outcome: Dummy equal to 1 if an individual reports any sleeplessness						
End	0.034^{**}	0.040^{**}	-0.008	-0.011	-0.003	-0.003
	(0.017)	(0.018)	(0.013)	(0.013)	(0.005)	(0.005)
SNAP_early	–	–	-0.010	-0.013	0.010	-0.013
			(0.015)	(0.015)	(0.008)	(0.009)
SNAP_early × end	–	–	0.042^{*}	0.044^{**}	0.037^{*}	0.039^{**}
			(0.023)	(0.022)	(0.020)	(0.019)
R^2	0.004	0.088	0.002	0.032	0.001	0.013
Panel B. Outcome: Number of minutes of reported sleeplessness						
End	5.704^{**}	5.863^{**}	-0.045	-0.150	-0.301	-0.347
	(2.367)	(2.279)	(1.724)	(1.647)	(0.492)	(0.497)
SNAP_early	–	–	-1.132	-1.272	0.729	-2.144^{*}
			(1.465)	(1.550)	(0.775)	(1.148)
SNAP_early × end	–	–	5.748^{*}	5.883^{**}	6.004^{**}	6.186^{**}
			(3.084)	(2.996)	(2.729)	(2.689)
R^2	0.006	0.071	0.004	0.034	0.001	0.017
Individual controls		✓		✓		✓
Household controls		✓		✓		✓
Time controls		✓		✓		✓
State controls		✓				✓
Observations	1,322	1,322	2,319	2,319	19,914	19,914

Notes: Standard errors clustered at the state level are in parentheses. The estimations are based on 2006–2008 ATUS data supplemented by CPS data. All models are estimated via OLS. The dummy end equals one for individual i if i was interviewed in the last ten days of the calendar month and zero otherwise. SNAP_early is one for individual i if i is a SNAP recipient from the *early states* and zero otherwise. For a description of the control variables, see the notes for Table 3. For the SNAP recipients from the *early states* interviewed at the beginning of the month, the probability of reporting any sleeplessness is 0.061 and the average number of minutes of reported sleeplessness is 4.643.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Table 5. Robustness Checks Using Alternative End-of-Month Definitions

Control group	Early states approach		Difference-in-differences approach			
			Staggering states SNAP recipients		Early states non-SNAP recipients	
	(1)	(2)	(3)	(4)	(5)	(6)
Probability of Reporting Fair or Poor Self-Assessed Physical Health						
SNAP_early	–	–	−0.021	−0.038*	0.041***	0.032**
			(0.021)	(0.022)	(0.014)	(0.012)
Last 7 days of month						
End7	0.071*	–	0.024	–	−0.004	–
	(0.036)		(0.033)		(0.006)	
SNAP_early × end7	–	–	0.050	–	0.063*	–
			(0.047)		(0.033)	
Last 13 days of month						
End13	–	0.053***	–	−0.013	–	−0.003
		(0.017)		(0.024)		(0.005)
SNAP_early × end13	–	–	–	0.068**	–	0.056***
				(0.030)		(0.019)
R^2	0.341	0.340	0.296	0.295	0.240	0.241
Observations	1,322	1,322	2,319	2,319	19,914	19,914
Probability of Reporting any Sleeplessness						
SNAP_early	–	–	−0.010	−0.016	−0.011	−0.018*
			(0.015)	(0.015)	(0.010)	(0.010)
Last 7 days of month						
End7	0.043*	–	−0.008	–	−0.003	–
	(0.023)		(0.013)		(0.005)	
SNAP_early × end7	–	–	0.046*	–	0.044*	–
			(0.027)		(0.024)	
Last 13 days of month						
End13	–	0.041**	–	−0.005	–	−0.005
		(0.019)		(0.012)		(0.005)
SNAP_early × end13	–	–	–	0.041*	–	0.042**
				(0.022)		(0.019)
R^2	0.087	0.089	0.032	0.033	0.013	0.013
Observations	1,322	1,322	2,319	2,319	19,914	19,914

Notes: Standard errors clustered at the state level are in parentheses. The estimations are based on 2006–2008 ATUS data supplemented by CPS data. All models are estimated via OLS. The outcome variable is a dummy variable that equals one for individual i if i reports fair or poor physical health and zero otherwise. The dummy end7 (end13) equals one for individual i if i was interviewed in the last seven (13) days of the calendar month and zero otherwise. SNAP_early is one for individual i if i is a SNAP recipient from the *early states* and zero otherwise. All regressions include the same control variables as the full specifications in Table 3.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Table 6. Robustness Checks for Self-Rated Physical Health (Alternative Early States Definition and Week Dummies)

	Probability of Reporting Fair or Poor Self-Assessed Physical Health					
	Early states approach		Difference-in-differences approach			
Control group			Staggering states SNAP recipients		Early states non-SNAP recipients	
	(1)	(2)	(3)	(4)	(5)	(6)
SNAP_early	–	–	−0.018	−0.043	0.040***	0.022
			(0.021)	(0.034)	(0.013)	(0.019)
End	0.069***	–	0.009	–	0.000	–
	(0.023)		(0.027)		(0.006)	
SNAP_early × end	–	–	0.059*	–	0.062**	–
			(0.035)		(0.025)	
Week-of-month dummies						
Week2	–	0.021	–	0.034	–	0.006
		(0.034)		(0.036)		(0.006)
Week3	–	0.035	–	−0.010	–	0.001
		(0.038)		(0.033)		(0.006)
Week4	–	0.091***	–	0.002	–	0.000
		(0.024)		(0.029)		(0.008)
SNAP_early × week2	–	–	–	−0.010	–	0.012
				(0.046)		(0.032)
SNAP_early × week3	–	–	–	0.040	–	0.030
				(0.049)		(0.037)
SNAP_early × week4	–	–	–	0.088**	–	0.076***
				(0.037)		(0.027)
Alternative early states definition	✓		✓		✓	
R^2	0.341	0.342	0.295	0.296	0.237	0.241
Observations	1,181	1,322	2,319	2,319	17,638	19,914

Notes: Standard errors clustered at the state level are in parentheses. The estimations are based on 2006–2008 ATUS data supplemented by CPS data. All models are estimated via OLS. The outcome variable is a dummy variable that equals one for individual i if i reports fair or poor physical health and zero otherwise. The dummy end equals one for individual i if i was interviewed in the last ten days of the calendar month and zero otherwise. SNAP_early is one for individual i if i is a SNAP recipient from the *early states* and zero otherwise. The dummies week2, week3, week4 are equal to one for individual i if i's interview took place in week two, three, and four, respectively, of the calendar month and zero otherwise. Week4 includes all remaining days after the third week of the month. All regressions include the same control variables as the full specifications in Table 3. The alternative *early states* definition defines all states as *early states* that have a SNAP issuance period which starts on the first day of the month and lasts at most ten days. All other states are defined as the *staggering states*.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Table 7. Robustness Checks for Sleeplessness (Alternative Early States Definition and Week Dummies)

	Probability of Reporting any Sleeplessness					
	Early states approach		Difference-in-differences approach			
Control group			Staggering states SNAP recipients		Early states non-SNAP recipients	
	(1)	(2)	(3)	(4)	(5)	(6)
SNAP_early	–	–	−0.020	−0.058**	−0.013	−0.040**
			(0.015)	(0.023)	(0.010)	(0.015)
End	0.035*	–	−0.002	–	−0.005	–
	(0.020)		(0.012)		(0.005)	
SNAP_early × end	–	–	0.030	–	0.036*	–
			(0.024)		(0.021)	
Week-of-month dummies						
Week2	–	−0.025	–	−0.040**	–	−0.005
		(0.017)		(0.018)		(0.004)
Week3	–	0.035	–	−0.030	–	0.007*
		(0.022)		(0.024)		(0.004)
Week4	–	0.062***	–	−0.032*	–	−0.008*
		(0.022)		(0.017)		(0.005)
SNAP_early × week2	–	–	–	0.068**	–	0.034*
				(0.026)		(0.020)
SNAP_early × week3	–	–	–	0.069**	–	0.046**
				(0.032)		(0.021)
SNAP_early × week4	–	–	–	0.089***	–	0.068***
				(0.029)		(0.025)
Alternative early states definition	✓		✓		✓	
R^2	0.100	0.090	0.033	0.035	0.012	0.013
Observations	1,183	1,322	2,323	2,319	17,656	19,914

Notes: Standard errors clustered at the state level are in parentheses. The estimations are based on 2006–2008 ATUS data supplemented by CPS data. All models are estimated via OLS. The outcome variable is a dummy variable that equals one for individual i if i reports fair or poor physical health and zero otherwise. The dummy end equals one for individual i if i was interviewed in the last ten days of the calendar month and zero otherwise. SNAP_early is one for individual i if i is a SNAP recipient from the *early states* and zero otherwise. The dummies week2, week3, week4 are equal to one for individual i if i's interview took place in week two, three, and four, respectively, of the calendar month and zero otherwise. Week4 includes all remaining days after the third week of the month. All regressions include the same control variables as the full specifications in Table 3. The alternative *early states* definition defines all states as *early states* that have a SNAP issuance period which starts on the first day of the month and lasts at most ten days. All other states are defined as the *staggering states*.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Table 8. Placebo Tests

Comparison	Staggering states		Non-SNAP recipients	
	SNAP recipients – non-SNAP recipients		Early states – staggering States	
	(1)	(2)	(3)	(4)
Probability of Reporting Poor or Fair Self-Rated Health				
End	−0.009	−0.010	−0.009	−0.009
	(0.007)	(0.006)	(0.007)	(0.006)
SNAP	0.260***	0.069***	–	–
	(0.019)	(0.018)		
SNAP × end	0.003	−0.010	–	–
	(0.017)	(0.024)		
Early	–	–	−0.012	−0.001
			(0.012)	(0.005)
Early × end	–	–	0.006	0.007
			(0.010)	(0.008)
R^2	0.032	0.237	0.000	0.204
Observations	14,040	14,040	31,635	31,635
Probability of Reporting any Sleeplessness				
End	−0.005	−0.006	−0.005	−0.005
	(0.012)	(0.003)	(0.003)	(0.003)
SNAP	0.022*	0.002	–	–
	(0.012)	(0.11)		
SNAP × end	−0.004	−0.005	–	–
	(0.013)	(0.014)		
Early	–	–	−0.001	0.002
			(0.005)	(0.004)
Early × end	–	–	0.002	0.003
			(0.006)	(0.006)
R^2	0.001	0.015	0.000	0.010
Observations	14,051	14,051	31,662	31,662
Individual controls		✓		✓
Household controls		✓		✓
Time controls		✓		✓
State controls		✓		

Notes: Standard errors clustered at the state level are in parentheses. The estimations are based on 2006–2008 ATUS data supplemented by CPS data. All models are estimated via OLS. The outcome variable is a dummy variable that equals one for individual i if i reports fair or poor physical health and zero otherwise. The dummy end equals one for individual i if i was interviewed in the last ten days of the calendar month and zero otherwise. The dummy SNAP is one for individual i if i is a SNAP recipient and zero otherwise. The dummy early is one for individual i if i is from the *early states* and zero otherwise. For a description of the control variables, see the notes for Table 3.

*** Significant at the 1 percent level.

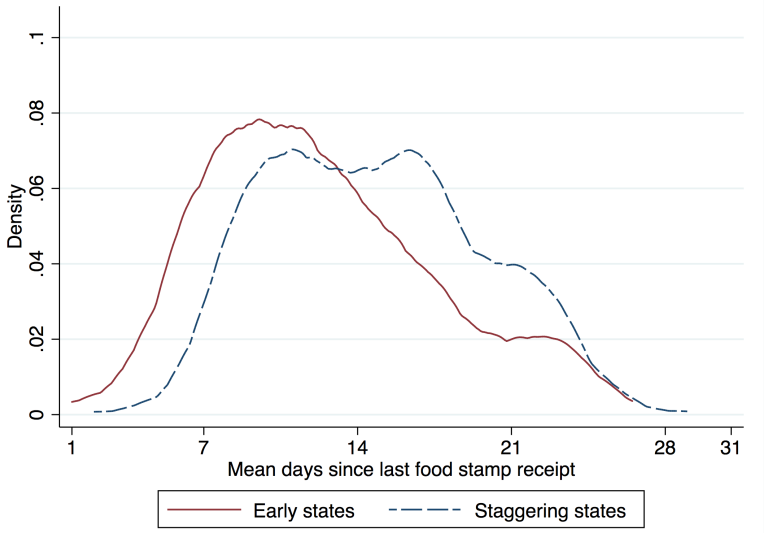
** Significant at the 5 percent level.

* Significant at the 10 percent level.

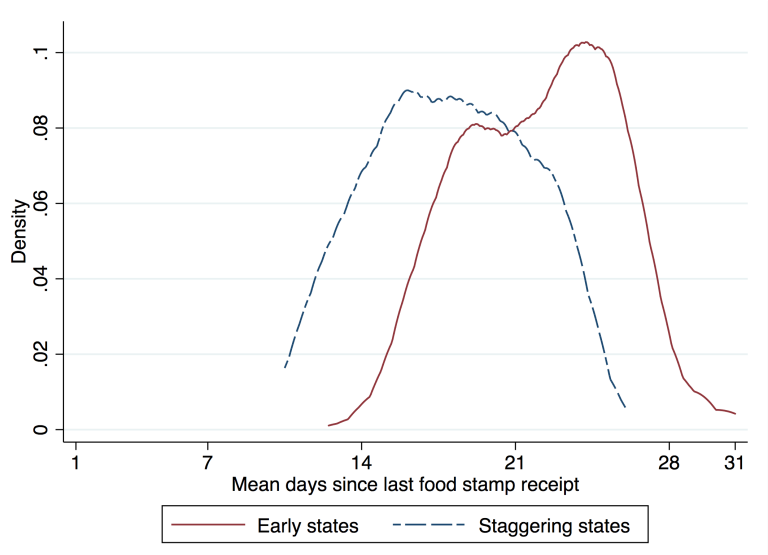
Figures

Figure 1. Distribution of the Mean Number of Days since the last SNAP voucher receipt

Panel A. Beginning of the Month



Panel B. End of the Month



Notes: The bandwidth is selected according to Silverman's rule of thumb. All individuals interviewed in the last ten days of the calendar month belong to the group 'end of the month'. All other individuals belong to the group 'beginning of the month'. See Footnote 14 for how we compute the mean days since the last SNAP voucher receipt for a given individual.

Appendix

Appendix Table 1. Supplemental Nutrition Assistance Program (SNAP) Issuance Dates

State	Monthly issuance day(s)
Early states group	
Alaska	1
Arkansas	4, 5, 8, 9, 10, 11, 12, 13
California	1–10
Colorado	1–10
Connecticut	1–3
District of Columbia	1–10
Hawaii	1, 3, 5[a]
Idaho	1–5
Indiana	1–10
Iowa	1–10
Kansas	1–10
Kentucky	1–10
Michigan	1–9
Minnesota	4–13
Montana	2–6
Nebraska	1–5
Nevada	1
New Jersey	1–5
New York	1–9[b]
North Carolina	3–12
North Dakota	1
Ohio	1–10
Oklahoma	1
Oregon	1–9
Rhode Island	1
South Carolina	1–10
Tennessee	1–10
Vermont	1
Virginia	1
Washington	1–10
West Virginia	1–9
Wyoming	1–4

Notes: The table continues on the next page.

Appendix Table 1. Continued

State	Monthly issuance day(s)
Staggering states group	
Alabama	4–18
Arizona	1–13
Delaware	5–11
Florida	1–15
Georgia	5–14
Illinois	1, 3, 8, 11, 14, 17, 19, 21, 23[a]
Louisiana	5–14
Maine	10–14
Maryland	6–15
Massachusetts	1–14
Mississippi	5–19
Missouri	1–22
New Hampshire	5
New Mexico	1–20
Pennsylvania	1-17[c]
South Dakota	10
Texas	1–15
Utah	5, 11, 15
Wisconsin	2, 3, 5, 6, 8, 9, 11, 12, 14, 15

Notes: The issuance dates are from Hamrick and Andrews (2016), who obtained the dates from the US Department of Agriculture. All of the dates are the actual issuance days for the years 2006–2008. A state belongs to the *early states* group if its SNAP voucher issuance period starts before the fifth day of each month and lasts at most ten days. A state belongs to the *staggering states* group if it does not belong to the *early states* group. For further details on these definitions, see Section III..

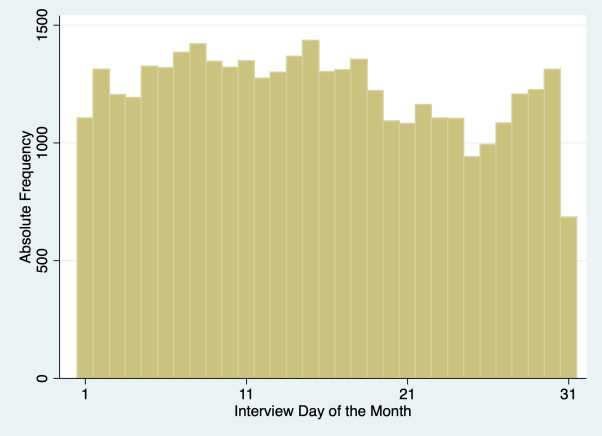
[a] There is uncertainty in the historical records about the exact dates.

[b] Weighted average issuance period for NY upstate and NY City, which have differing issuance days.

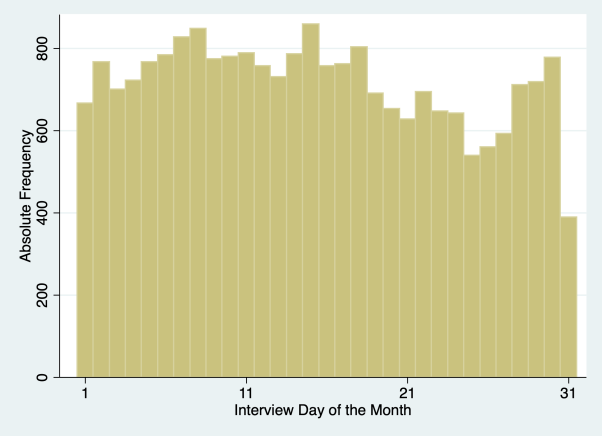
[c] Issuance days depend on the specific month.

Figure 2. Distribution of the Interview Days over the Month

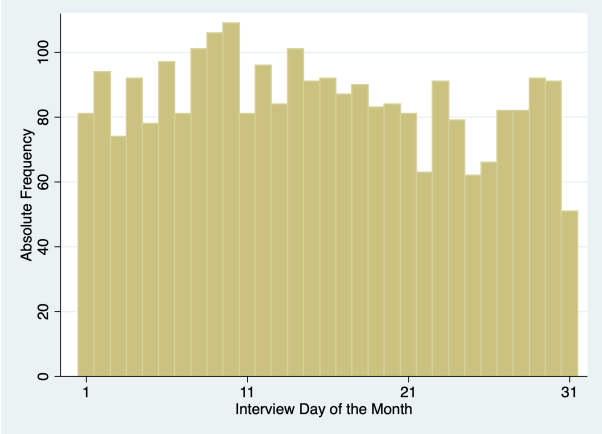
Panel A: Complete Dataset



Panel B: Early States



Panel C: SNAP recipients



Notes: Histograms of the absolute frequencies of interviews over the month, for the complete dataset, *early states* and SNAP recipients