Hunger Pains? SNAP Timing and Emergency Room Visits

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Abstract

SNAP benefits play a vital role in combating food insecurity for millions of families. Yet, research shows that the once-a-month lumpsum disbursement of SNAP benefits leaves meaningful deficiencies in recipient households during the final weeks of their benefit cycle. Given the importance of nutrition for health, these deficiencies suggest that recipient health might also be affected by the benefit cycle. Further, the day that households receive benefits changes behaviors and routines (notably by increased shopping), which may crowd out healthcare utilization. This project uses quasi-random assignment of SNAP receipt dates that are linked to administrative data on ER visits to examine whether ER utilization is affected on receipt date, and on days close to the end of the benefit cycle (when nutritional deficiencies may peak). We find no overall increase in ER usage at the end of the benefit month, except among individuals 55 and over. Within this older population, the share of ER visits that comes from individuals that received benefits more than 21 days ago is 1.67% larger than would be expected. Notably, this effect is much larger when the end of the benefit cycle coincides with the end of the calendar month. This suggests that within this older group, increased food insecurity leads to increased ER utilization. On the day of SNAP benefit receipt, we find that the share of ER visitors that received benefits on that day is 3.1% lower than would be expected. This effect is present across all age groups, although the magnitude is smallest for young children.

Keywords: SNAP Benefits, Health Outcomes, Consumption Cycles

JEL Codes: I21, I31, I38

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I. Introduction

There is an extensive literature documenting the association between food insecurity and health outcomes.[1] This association exists not only for conditions associated with nutrition, like anemia or diabetes (Eicher-Miller, et. al. 2009; Seligman, et.al., 2012), but also for conditions like asthma, mental health, and hypertension (Kirkpatrick, et.al., 2010; Seligman, Laraia and Kushel, 2009). Further, food insecurity is a barrier to health care utilization (Kushel, et.al., 2006, Berkowitz, et. al., 2018) and recipients of food benefits generally have lower levels of health care expenditures (Berkowitz, et. al., 2017).

There are several possible mechanisms that might explain an effect of food insecurity on health outcomes. First, food insecurity may be associated with non-adherence to costly medications (Bengle, et. al., 2010; Berkowitz, Seligman and Choudhry, 2014; Knight, et. al., 2016) or delay of needed medical care (Kushel, et. al., 2006). This has been previously identified as a problem among older adults that use SNAP (Srinivasan and Pooler, 2018). Second, times of food insecurity are associated with higher stress levels that could have negative spillovers into health (Bradley, et. al., 2018; Fiese, et. al., 2016). Finally, food insecurity could negatively affect mental health and exacerbate undesirable behaviors (de Mores, et. al., 2016; King, 2018; Gassman-Pines and Bellows, 2016).

The Supplemental Nutrition Assistance Program (SNAP) is the largest safety net program designed to alleviate hunger. It currently provides benefits to over 40 million individuals. There is a substantial literature that evaluates how effective the program is at alleviating food insecurity.[2] Additionally, a growing literature documents that benefit receiving households' consumption and purchasing behavior changes across the SNAP benefit month (Hastings and Washington, 2010; Castellari, et. al., 2017; Wilde and Ranney, 2000; Hamrick and Andrews, 2016). Perhaps most notably, Shapiro (2005) documents a 10-15% decline in caloric consumption between the first and last week of the benefit month. Relatedly, the likelihood an individual on SNAP is classified as food insecure is substantially higher at the end of their respective benefit month (Gregory and Smith, 2018). Taken together, these findings suggest that the benefit cycle might correlate with cycles of health outcomes. More specifically, as individuals move further from benefit receipt in

[1] See Gundersen and Ziliak (2015) for a review of the recent literature.
[2] See Gundersen, Kreider and Pepper (2011) for a summary of this literature.

their respective month, their health might deteriorate. There is also the possibility that changes in their behaviors might lead to increased health care utilization. There is also reason to suspect that possible effects of food insecurity vary by age across the SNAP benefits cycle. For example, the very young and the older populations might be more vulnerable to illness exacerbated by food insecurity. Further, research shows that older populations are more vulnerable to cost-related non-adherence for prescription medications (Breisacher, Gurwitz and Soumerai, 2007) and that school-aged children use school meals to help smooth consumption (Kuhn, 2018).

In contrast to the mechanism described above, household behavior immediately upon receipt may be altered in ways that are associated with negative health outcomes. That is, the day of food stamp receipt might be associated with behavioral responses that are unrelated to food insecurity. For instance, Phillips, Christenfeld, and Ryan (1999) report an increase in mortality across nearly all types of death in the first week of the month, which coincides with many transfer payments as well as income receipts. Evans and Moore (2011 and 2012) investigate this association more completely and trace the mortality cycle directly to the arrival of income and general economic activity, with the most pronounced effects among liquidity-constrained populations. One possible explanation is that income/benefit receipt is associated with increased drug or alcohol use. Indeed, Dobkin and Puller (2007) show the receipt of disability benefits is associated with increases in drug-related hospitalizations and mortality. Carr and Packham (2019) suggest another possible mechanism: increased domestic conflict within families on benefit receipt date. Thus, if SNAP benefit receipt is associated with increased drug or alcohol use or domestic conflict, then we might expect an increase in ER utilization on those dates. In contrast to these findings, Cotti, Gordanier and Ozturk (2016) look specifically at the monthly timing of SNAP benefits and find a reduction in alcohol-related fatal accidents on the day of benefit receipt, possibly through altered household behaviors those days. Additionally, and importantly, several papers (e.g., Hastings and Washington, 2010; Castellari, et. al., 2017; etc.) have shown a notable increase in grocery shopping on SNAP receipt days, which might alter household schedules and lead them to delay other household-related activities, including seeking medical care.

In this paper, we investigate the timing of SNAP benefits and emergency room (ER) visits. We use administrative data on all SNAP recipients under the age of 65 who are also on Medicaid in South Carolina. For a given day, we calculate several measures of interest. First, we measure the share of ER visitors within this population that visited the ER more than three weeks after their most recent SNAP benefit distribution (e.g., in a more food insecure position), which we call the long-wait share, and compare this to the share of the total SNAP population that we expect are actually more than three weeks into their respective SNAP benefit cycle based on the actual SNAP distribution schedule. We find that, on average, the long-wait share in the ER is no higher than the long-wait share in the population. However, among SNAP recipients over the age of 55, the long-wait share is 1.67% higher and the average number of days since receipt of benefits is also slightly higher. When we restrict the analysis to recipients whose long-wait periods of their benefits cycles correspond with days near the end of the calendar month, we find that the effect is much larger. When we break our long-wait analysis down to specific conditions that have been studied regarding food insecurity in the previous literature, we find no comprehensive effects on these specific conditions. However, we do see positive and significant increases in ER visits for both asthma and incidents of anxiety or depression when the long waits coincide with the end of the calendar month.

Using a similar approach, we also compute the share of ER patients observed within this population that received their SNAP benefits each benefit distribution day and compare it to the share of the SNAP population that received benefits that same day. We find that the share that received their benefits on the day they visited the ER is 3.1% lower than we would expect by random chance. A supplemental analysis using data from the American Time Use Survey finds supportive evidence that day of benefit receipt is associated with less time receiving health care. When we break our day-of-receipt results out by different conditions, we find a consistent negative effect associated with the day of receipt. The effect is negative and statistically significant for 20 of the 25 most common conditions. However, we do not find any evidence of an effect for certain conditions like pregnancy-related complications, which we would not expect to be impacted by time use allocation decisions. These results are consistent with a large literature that documents ER use for non-emergency or primary care services. That is to say, certain care may be delayed on the benefit receipt date.

These results have several public policy implications. First, the cyclical nature of ER visits suggests there is a public policy interest in helping households smooth consumption. This could be accomplished by increasing benefits or by possibly splitting benefits into multiple distribution dates. Although, the latter could exacerbate food insecurity if households face large transportation costs that make multiple shopping trips costly or if splitting benefits prevents households from taking advantage of bulk shopping. Related, our results suggest that the timing of benefits within the month might also be important. If households receive other benefits or income early in the month, distribution of SNAP benefits later in the month may have positive effects. Second, these results highlight that, at least for the older SNAP recipients, there are serious health manifestations over the benefit cycle month, especially when this coincides with the calendar month. Efforts to fight hunger might focus on this subgroup as the consequences of food insecurity are more severe. Lastly, the results highlight the salience of non-urgent use of the ER, which, given the high cost of care in emergency settings, is an important area to understand.

This paper is organized as follows: the section that follows describes the related literature and the contribution of this paper, Section III covers important background information and discusses the data, Section IV discusses the empirical methodology, Section V presents the main results regarding food scarcity, Section VI presents the results related to the day of receipt, while Section VII concludes.

II. Literature Review

This work builds upon the literature that is related to the timing of benefits, food insecurity, and the timing of health-related events. There are a number of papers that consider the monthly cycle of food budgets and ER visits for conditions related to diabetes management. Diabetes management requires a combination of medication and diet control. If individuals face a tradeoff between medication and diet, then they may be more likely to experience hypoglycemia if their diet is insufficient or hyperglycemia if they skip medicine to pay for food (Gucciardi, et. al. 2014). Seligman, et. al. (2014) find that hypoglycemia admission is 27% higher in the last week of the month compared to the first week among the low-income population, with no such difference among the high-income population. Basu, Berkowitz, and Seligman (2017) find a similar relationship and compute the costs associated with the monthly cycle of hypoglycemia. Most relevant to our work, there is a series of excellent papers linking SNAP timing and ER visits. The approach taken in these papers is to look at individuals in the ER and ask their likelihood of being at the ER for a particular condition as a function of the benefit cycle. In the first in this series, Heflin, Hodges and Meuser (2017) link the actual receipt of SNAP to ER visits for one condition in particular: hypoglycemia. They find that contrary to the suggestive evidence from previous studies, conditional on being in the ER, a patient is no more likely to be there for hypoglycemia later in the food-stamp month, although the size of the benefit does matter. In the second, Heflin, et. al (2018) look at SNAP timing and childhood asthma. Again, they find no effect from the timing of the benefit, but they do find that a large benefit reduces the likelihood of a visit. In a similar paper, Arteaga, Heflin and Hodges (2018) look at SNAP timing and pregnancy-related ER visits. Interestingly, in this work they also find an interaction between the timing of benefits within the calendar month and the SNAP cycle. Finally, Ojinnaka and Heflin (2018) look at SNAP timing and hypertension visits. They find no relationship between when in the month benefits are distributed and visits, but again the size of the benefit mattered. Relatedly, there is also a literature that documents the prevalence of hunger and food security (in general) amongst the population that visits the ER (Kersey, et. al., 1999; Biros, Hoffman and Resch, 2005).

We extend these literatures by investigating overall ER utilization regardless of condition. We then extend our main analysis to also measure effects across several specific conditions. Similar to the 2017 and 2018 Heflin et. al. studies, which investigate hypoglycemia and childhood asthma, we find no increase when we study all-condition ER utilization late in the benefit month for the SNAP population on Medicaid as a whole, but we do observe some increase among the oldest recipients. We also find, consistent with Arteaga, et. al. (2018), that the timing of benefits within the calendar month might play an important role on ER utilization.

More broadly, this research contributes to a growing literature that studies the timing of SNAP benefits and its effects on different behaviors that also have a public interest, other than those health conditions that are specifically linked to nutrition. For example, a pair of papers have found evidence that benefit cycles are related to cycles in crime. Foley (2011) and Carr and Packham (2018) find that financially motivated crime rises later in the SNAP benefit month. Cotti, et. al. (2016) find fewer alcohol-related fatal accidents on SNAP receipt dates. Recent work by Gassman-Pines and Bellows (2016, 2018) and Cotti, Gordanier and Ozturk (2018) find evidence that student behavior and performance on end-of-the-year exams is affected by the amount of time that has elapsed since the household received SNAP benefits. We extend this by showing that individuals either delay visits to the ER upon receipt or perhaps engage in substitute behavior making an ER visit less likely upon receipt date.

Lastly, this paper is related to the literature on non-urgent ER usage. There exists a substantial medical literature on non-urgent ER usage and its associations with demographic and socioeconomic factors (Carret, Fassa, & Domingues, 2009). In general, non-urgent usage is associated with a number of factors including poverty, gender and an absence of chronic conditions (Carret, Fassa and Kawachi, 2007; Afilalo, et. al., 2004). Perhaps unsurprisingly, non-urgent usage is more of a problem in the morning and early afternoon (Pereira, et.al., 2001). Within economics, there is a substantial interest in the effect of insurance status on ER usage. While insurance increases access to primary care alternatives and allows better management of conditions, preventing potential ER visits (Miller, 2012; Ayyagari, Shane and Wheby, 2017), it also reduces out-of-pocket expenditures for ER visits, which could cause increased ER utilization (Anderson, Dobkin, and Gross, 2014; Taubman, et. al., 2014). Some literature has also considered the difference between private and public insurance on the ability to obtain a primary care provider and its effect on ER usage (Lines, et. al., 2019).

III. Background and Data

As part of the 1996 Welfare Reform Act, states must issue food stamp benefits through the Electronic Benefit Transfer (EBT) system. SNAP recipients are issued an electronic card and benefits are automatically deposited once a month on a particular date during the month (including weekends). In addition to some control over eligibility requirements and generosity, states are left to determine the distribution schedule for participants. While each recipient only receives benefits on a single day in a month, it is not necessarily the case that every household in the state receives benefits on the same day of the month. Rather, states may choose to spread the distribution of benefits to recipients throughout the month. From the start of our data until October of 2012, South Carolina distributed benefits each day between the 1st and the 10th of the month based upon the last digit of the recipient household's case ID. The last digit of the case ID is randomly assigned by the South Carolina Department of Social Services (DSS), and the distribution of dates in our data is close to uniform (see Table 1). That said, we cannot explicitly draw any conclusions about the randomness of the IDs in South Carolina from the IDs present in the ER utilization data as it could be that the date in the month of treatment has an effect on the propensity to be in the ER data. However, in separate work, Cotti, Gordanier and Ozturk (2018) demonstrate that the distribution of case IDs in South Carolina is uniform across the total population of households treated during the same time period studied here. Hence, we see the expected balance on observables one would anticipate from random assignment. Beginning October 1st, 2012 all new

SNAP cases[3] were subject to the new distribution schedule. Under the new schedule, a household receives their benefits on the date of the month that corresponds to the last digit of their case number if that digit is even. If it is odd, then they receive benefits 10 days after the last digit of their case number (for example, if the last digit is 1, then benefits arrive on the 11th). Since recipients are "grandfathered" into the new schedule, we do not know precisely the share of all SNAP recipients with each receipt date after October 1st of 2012. As such, our primary analysis begins in 2000 and ends in September of 2012.[4]

To measure the impact of periods of food insecurity on individuals' health outcomes, we exploit administratively linked data provided by South Carolina Medicaid and South Carolina DSS. In constructing the data, the office of Revenue and Fiscal Affairs took the administrative data on emergency room and urgent care visits for all the individuals that are on Medicaid at least 9 months in that calendar year. They then merged these records with SNAP records. We were then provided the combined data, which allows us to know, for each ER visit, if the Medicaid recipient was on SNAP at the time of the visit. Additionally, if the patient was in a SNAP receiving household, we know the randomly assigned monthly SNAP receipt date. Hence, in addition to SNAP status, we also compute a variable that tells us the number of days since the last benefit receipt when a person appears in an ER, which ranges from 0 to 30 days.[5] Thus, in our analysis we will only be looking at ER records of individuals in months in which they are on both SNAP and Medicaid, which we will refer to as the population of study.[6] It should also be noted that the population of study is not the same as the population of all SNAP recipients as some SNAP recipients will not be on Medicaid. That said, there is extensive overlap between the populations. Wheaton, Lynch, and Johnson (2016) report the overlap between benefit programs for each state for the year 2013. In South Carolina, 62.5% of SNAP recipients were also covered by Medicaid. However, there were some enrollment differences across groups. Specifically, while virtually all

[3] Any household new to SNAP or any household that had to re-enroll in the program would be considered a new SNAP case, even if they were previously on SNAP.
[4] We are able to perform our analysis in the time period after the transition, if we restrict ourselves to those with even SNAP ids. The results from this time period are similar, although the magnitudes of the estimated effects are slightly larger.
[5] Sometimes households receive emergency SNAP benefits on days that are not their typical receipt date. We, unfortunately, do not have data on these distributions. In those cases, we will be incorrectly assuming they have been treated on their regular distribution date. These instances are uncommon, but will lead to some attenuation bias in our results.
[6] If a family is generally a SNAP recipient, but for administrative reasons has a gap in their benefits, then they will be excluded from our analysis in those "gap" months.

SNAP recipient children were also eligible for Medicaid (99.9%) and 72 % of adults that are parents were Medicaid eligible, among the nonparent adults only around 25% of SNAP recipients were Medicaid eligible. Therefore, estimates that focus on older population groups in our sample are likely coming from a poorer and sicker population than all SNAP recipients in that age group.[7]

The SC Medicaid data is an event-level data set that includes a rich set of information on the patients' demographic characteristics, the reason for Medicaid qualification, about the conditions for which the patient was admitted and discharged, and information on health care providers such as their location. For each observation we also observe International Statistical Classification of Diseases and Related Health Problems codes (commonly known as the ICD codes), which identify primary and secondary diagnoses. Overall, in its raw form, we have data on over 7.1 million unique visits to emergency room facilities from the evaluation time period. Descriptive statistics on basic demographics and the distribution of case IDs are presented in Table 1.

[Table 1]

IV. Methodology

For our main analysis, we ask the following question: Does either the date of benefit receipt or the number of days since benefit receipt affect ER use? To address these question, we utilize the distribution of the number of days since SNAP receipt for our population of study (SNAP recipients on Medicaid) who actually visit the ER *on a particular day*, compared to the distribution of days since receipt for all SNAP recipients on that exact same year-month-day in the SNAP population.[8] Since SNAP distribution dates are randomly assigned, the distribution in the entire SNAP population is the same as the distribution in our population of study. We use three primary measures of the distribution: 1) the average number of days since receipt among ER patients, 2)

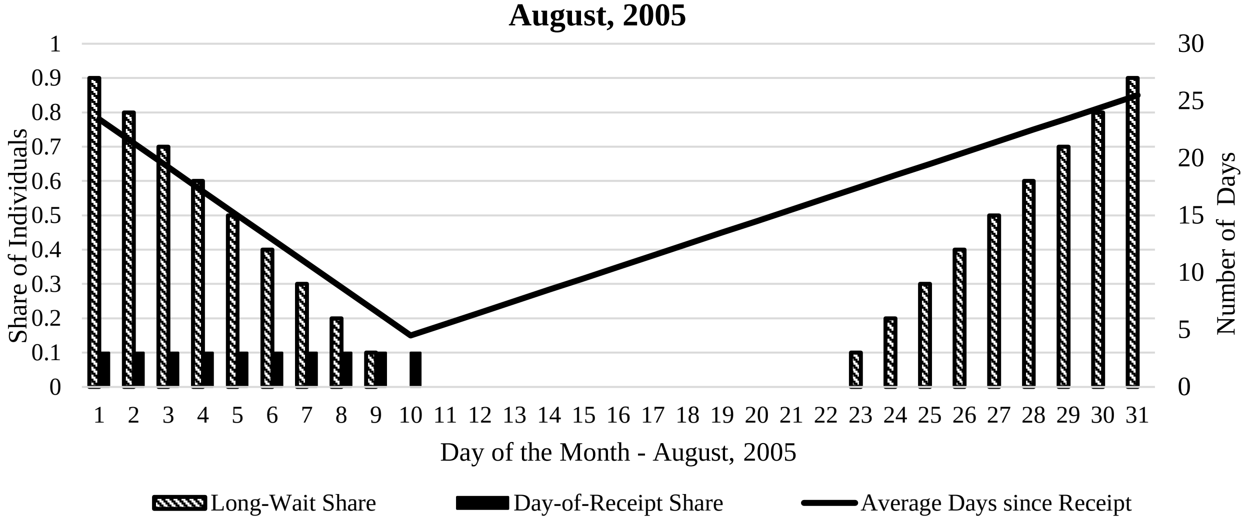
[7] It is important to note that the imperfect match between the observed Medicaid-SNAP population and the entire SNAP population doesn't impact our identification, because the random assignment of SNAP receipt day is not impacted by being on Medicaid or not. Hence, the share of the Medicaid-SNAP and Non-Medicaid-SNAP populations who receive food stamps on any particular SNAP distribution day would be 10% in both cases.

[8] We also perform a similar analysis using an individual's probability to visit the ER, using a 20% subsample of the individual level ER visit data. In order to allow for regression analysis, we expanded the dataset to include rows for each day in the entire calendar month in which each SNAP recipient visited the ER, hence providing us all the days in that month in which each individual wasn't observed at the ER as well (e.g., non-ER visit days). This provided us with a large set of individual-level panel data, with over 20 million observations, which allowed us to conduct a series of fixed effects logit regressions with control variables (e.g., race, age, etc.) to evaluate the robustness of our estimates. Results were very similar and are presented in Appendix Table 2.

the share of ER patients that received SNAP benefits more than three weeks prior (long-wait share)[9], and 3) the share of ER patients that received SNAP benefits on the date of the visit (day-of-receipt share). We denote this as ER_{jt}, where j is the measure computed (long-wait share, day-of-receipt share, average days-since receipt) and t is the day.

Next, we compute these measures for the entire SNAP population (not just the individuals in the ER on a given day) by using the known distribution schedule and the fact that case IDs are assigned randomly. Again, since these are assigned randomly, this is the same distribution as our population of study. We denote this expected share in the entire SNAP population as Pop_{jt}, where j indexes the measure and t is the day. The exact values this measure takes are similar from month-to-month, however, there are slight changes depending on whether the month prior had 28, 29, 30 or 31 days in it. For example, Figure 1 below depicts the values these take for the population of interest over the month of August, for the year 2005 (following a 31-day month under the old distribution schedule).

Figure 1: Sample Benefit Month Statistics
August, 2005



Note: Share of Individuals with longer than three weeks since receipt (Long-Wait Share), share of individuals who are receiving their benefits (day-of-receipt share) and average days since receipt for all SNAP recepients on a given day of August 2005 is represented. Scale for the shares (captured by bars) is on the first y-axis. Scale for the average of days since receipt (captured by the solid line) is given on the secondary axis.

[9] Results are robust to other definitions of what constitutes a long-wait, e.g. more than 25 days, as shown in Appendix Table 1.

Then, we form the variable $Diff_{jt}$, as the difference in percentage terms of these measures between the population of study that appears in the ER and the entire population of study on a given day as follows,

$$Diff_{jt} = \frac{ER_{jt} - Pop_{jt}}{Pop_{jt}}$$

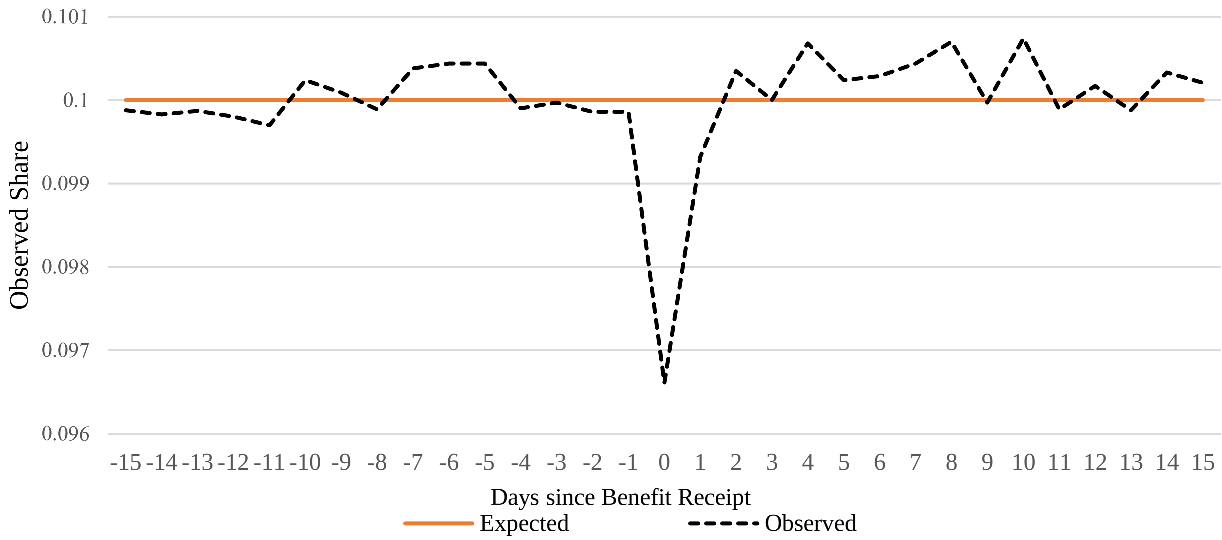
where, ER_{jt} is the value of measure *j* for the ER visitors in the population of study on day *t* and Pop_{jt} is the value of the measure for the entire population of study on day *t*.

Since the long-wait share among the ER visitors and the SNAP population will always be zero from the 10th-21st of each month and the share receiving benefits on that day will only be non-zero 10 days each month, the analysis will only use the days where Pop_{jt} is non-zero. Our main analysis will then test whether $Diff_{jt}$ is non-zero. When looking at age groups (or conditions) we perform the same analysis, but compute ER_{jt} as the value of measure *j* for the ER population in that age group (or with that condition) on day *t*.

It is worth noting that the presence of a monthly cycle in the number of SNAP recipients in the ER is not a problem for identification. For example, if there are more SNAP ER visitors on the first of the month, it is not a problem for this analysis, because we are computing the share of SNAP recipients on a given calendar date with a *particular treatment date*. Anything that causes a change in the number of ER visits among SNAP recipients will not on its own change the share with a particular case ID. As such, our results can be interpreted as the effect from the benefit cycle, independent of any monthly cycle that affects all recipients equally, although the size of the effect may vary within the monthly cycle.

Before we present our main results, we first graphically show the benefit cycle and ER visits. Because South Carolina distributes SNAP benefits ten days each month, for any given day of the benefit month, the share of SNAP households with a given number of days in their SNAP benefits cycle should equal 10%. So, for a visual comparison, we compute the share of our population of study actually observed at the ER at each of the possible benefit durations for each of the ten benefit cycles a household could be on (e.g.; day 0 through day 30). Then we average the shares observed across the ten different distribution schedules for each of the standardized number of days since receipt (0 days through 30 days). For example, day 0 in the benefit month is computed as the average of the share of people receiving benefits on the 1st of the month among the ER visitors on the 1st of the month, the share receiving benefits on the 2nd of the month among the ER visitors on the 2nd of the month, etc. While 8 days post-receipt is computed as the average share of people receiving benefits on the 1st of the month among the ER visitors on the 9th of the month, the share receiving benefits on the 2nd of the month among the ER visitors on the 10th of the month, etc. Since the distribution across dates is random across the ten distribution days, if SNAP receipt and the SNAP benefits cycle do not impact ER visit propensity then there should be no notable difference in the observed ER share for each day and the share we should observe based on the known SC distribution schedule. Specifically, we should observe on average 0.10 each day.

Figure 2: Emergency Department Use over the Benefit Month for all Recipients



Note: This figure shows the observed share of individuals with a given receipt day by their position in the benefit cycle normalized around their receipt day (day 0), averaged for all receipients over the whole sample period.

As can be seen in Figure 2, the monthly benefit cycle depicted appears to be relatively flat around 0.10 on all days during the SNAP benefits cycle, with the striking exception of a large drop on day 0, which corresponds to the day of actual SNAP receipt for each respective person. In particular, the difference between the observed share and the expected share (0.10) on the day of receipt is approximately 5 times larger than the difference on any other day.[10]

To further analyze and better understand the effect of food stamp timing on ER usage, we group our analysis into two sections: one where we look at measures related to periods of greater food insecurity and ER usage and another at the effect of day of receipt on ER usage.

[10] We create the same figure for each of our age groups separately in Appendix Figure 1.

V. Results of Food Insecurity and ER Utilization

In Panel A of Table 2 we report the results of our main analysis on the effect of periods of greater food insecurity (measured by long-wait share and days since receipt) on ER utilization. We first show the expected share in the population of study for both long-waits and days since receipt and the share in the population of study that appears in the ER on that date. We then show the results of statistically testing whether $Diff_{jt}$ is in fact zero.

[Table 2]

For both the long-wait share and the days since receipt, the expected values (0.4866 and 14.747, respectively) and the observed values (0.4861 and 14.760) are practically identical. We do estimate that the average number of days since receipt is statistically different in the observed group (0.1% larger than expected), but this is a small economic difference. Hence, for the overall SNAP population studied there is virtually no evidence of the benefits cycle impacting ER visits.

As mentioned in the introduction, there are a number of reasons why the effect of food insecurity might vary by age. First, the very young and the older population might be more vulnerable to illness brought on by food insecurity. Second, parents might try to shield the effects of food insecurity from their children (for example, by skipping meals), and school-aged children might use school meals to help smooth consumption (Kuhn, 2018). Finally, research has shown that the older population is more vulnerable to cost-related nonadherence for prescription medications (Breisacher, Gurwitz and Soumerai, 2007). As a result, in Panel B of Table 2 we present the analogous estimates broken out by age group. We observe the effect from long-waits is near zero and insignificant overall and for all age groups, with the exception of those over the age of 55, who experience a 1.67% increase in the long-wait share. Similarly, we observe an increase in the average time since receipt in both of the older age groups, albeit smaller than the long wait effects. These results are consistent with the idea that the health of older individuals may be more sensitive to increased food insecurity, which other research has shown to be sensitive to the SNAP benefit cycle for specific conditions.

Next we look at how the measured long wait effects may vary based on when a SNAP recipient is in a long wait during the calendar month. In particular, as most income and income-related transfers occur on or near the beginning of each calendar month, there is an important and general “income availability” cycle that impacts low-income households and is correlated with the calendar month cycle. Further, research by Seligman, et. al. (2014) on hypoglycemia and Arteaga, Heflin, and Hodges (2018) on pregnancy-related conditions, do find higher ER admissions at the end of the calendar month for low-income populations, with the latter paper focusing on SNAP recipients explicitly. When overlaying the South Carolina SNAP distribution schedule (which stretches into the middle of the calendar month) on top of the broad income/transfer monthly cycle, which begins at the beginning of the calendar month, we are presented with two distinct groups of SNAP recipients. Specifically, those whose SNAP payments are largely aligned with other potential sources of income or transfers (e.g., disability payments, TANF, etc.) and those whose SNAP payments are received later in the calendar month. This creates an important difference as to when a SNAP recipient finds themselves in the period of long wait after their SNAP distribution. This is illustrated in Figure 1, as a notable share of the SNAP population will be in this food scarce position at the beginning of the calendar month (when other sources of income are more prevalent), while others are in this position at the end of the calendar month (when other sources of income are more scarce). Hence, SNAP recipients who are near the end of their SNAP benefit cycle at the end of the calendar month are likely in a different (more severe) food insecurity position than those at the beginning of the month, because they are farther from the distribution of other income or benefits like TANF or disability payments. If food insecurity created by the SNAP benefit cycle is driving the results presented in Table 2 for the 55-64 age group, we would expect higher effects for those who are in a long wait at the end of the calendar month. In Table 3 we report the results of our analysis of long-wait shares only for the long-waits that occur at the end of the calendar month.

[Table 3]

When we look at these long-wait spells that occur at the end of the month, we do indeed find a small increase in ER utilization of about 0.5% across all ages. When we look at the effect by age groups, the older groups are again affected more substantially, with the effect now present even for the middle-aged adults. Individuals aged 35-54 are about 1% more likely to be in the ER than expected, while the share of ER visitors that are in long waits amongst the 55-64 group is 2.5% higher than expected. This result is consistent with the fact that SNAP populations smooth poorly, and suggests that a form of “forced” smoothing created by the uneven distribution of income-like sources may aid in smoothing.

In Table 4 we expand our analysis to look at our results in the context of some specific conditions. First, we look at conditions that have been studied in the context of SNAP timing, specifically, *hypoglycemia* (Heflin, Hodges and Mueser, 2016), *hypertension* (Ojinnaka and Heflin, 2018), *asthma* (Heflin, et. al., 2019) and conditions related to *pregnancy* (Arteaga, Heflin and Hodges, 2018).[11] We also explore other conditions that are shown to lead to ER admission for non-adherence to medications, such as *heart failure* (Roebuck et al, 2011) and *mental disorders* (Heaton, Tundia and Luder, 2013 – ICD9 295* 296* 297* 298* and 299*).[12] We further consider *anxiety* and *depression* (300.0* and 311) as they are highly correlated with food insecurity (Leung et al, 2015; Whitaker et al, 2006)

[Table 4]

As shown in Table 4 and Appendix Table 3, we find no effect overall on any of these conditions. This is largely consistent with the series of papers on SNAP timing and ER visits for specific conditions referenced earlier and with the results presented in Panel A of Table 2 on ER visits in general. However, when this investigation is restricted to the end-of-the-month long waits (analogous to Table 3), we see an increased share of asthma visits and an increased share of anxiety and depression visits from those in long waits. Again, this is suggestive that while the overall effect of being at the end of your SNAP benefit cycle is zero, when these events occur at the end of the calendar month as well, there may be important effects on the population.

VI. Results on Day of Receipt and ER Utilization

In this section we seek to study how day of SNAP receipt might affect ER usage. In Table 5, we begin with an analysis analogous to that presented in Table 2, where we first report the observed proportion of individuals in the ER on their receipt days and the expected proportion. We then test whether this differs overall and for each subgroup.

[Table 5]

[11] Following Heflin et al (2018) we used all relevant ICD-9 diagnosis codes (493*) to indicate ER care for asthma. For hypoglycemia as in Heflin Hodges and Mueser (2016) we used the protocol established and validated by Ginde et al.(2008) For pregnancy related conditions we used ICD-9 codes Howard (2009) established (630-679) plus V220, V221, V230, V270, V271, V272, V273, V274, V275, V276, V277, V279 following Arteaga, Heflin and Hodges (2018).

[12] The results of this analysis using the 25 most common codes can be found in Appendix Table 3.

Consistent with what is suggested by Figure 2, we see that the effect associated with day of receipt is immediate, negative, and statistically significant (p-value<0.01), suggesting over a 3.1% decline in the relative share that would be expected. In Panel B we see that relationship across different age groups is qualitatively similar, although the magnitude of the difference is increasing monotonically with age. More specifically, we observe that the effect is relatively flat among adults, while the estimate for children under five is less than half the magnitude of the effect on the population that is over 55 and is statistically smaller than that of adults. One possible explanation for this result is that SNAP receipt affects time use patterns that dissuade individuals from using the ER on that date. In particular, individuals may choose to delay non-urgent care that they would have otherwise visited the ER for treatment.

Specific Conditions and the Day-of-Receipt Effect

To try to shed some light on this possible mechanism, we select specific conditions that might be associated with non-urgent care. In previous literature describing the association of non-urgent ER use, Carret, et. al. (2009) say "the principal diagnoses found in persons that visited the ER inappropriately varied considerably from study to study." That said, they do point to some work suggesting respiratory problems, abdominal and chest pain, and eye and ear problems are non-urgent (Afilalo, et.al., 2004; Sempere-Selva, et. al., 2001).[13] Table 6 reports the percent deviation of observed from expected for the share of individuals who are on their receipt days for conditions in these categories, specifically respiratory infections (ICD9 codes 46* including sinusitis, pharyngitis, common cold etc.), urinary tract infections (599.0), ear infections (382*), chest pain (786.50), abdominal pain (789.00). We also include pregnancy-related complications (630-679, plus V220, V221, V230, V270, V271, V272, V273, V274, V275, V276, V277, V279), and fractures (800*-869*) as a check since these likely are not delayed.

[Table 6]

[13] NYU Emergency Department Visit Classification algorithm (NYU ED Algorithm) is commonly used in the literature to capture severity of non-emergency status of the condition. However, this measure is based on hospital mortality and hospital admissions associated with the condition for the visit. In our context the issue is more about ability to delay care for the individual and engage in other behavior. For example, a broken bone can be debilitating, but one may be able to delay care for an ear ache or cough or back pain for a few days. Nonetheless, we also created a non-emergency indicator using the NYU ED Algorithm (following Gandhi and Sabik (2014) method) and reported the non-emergency index for the top 25 conditions to capture general non-emergency use of Emergency Departments (this is not available for injuries and there are also unclassified conditions). An alternative method is to use Evaluation and Management (E&M) codes (Jeffery et al, 2016), which we did not have access to in our Medicaid data.

In general, we observe typically negative and statistically significant effects for these conditions, but there are some notable exceptions. First, as expected, pregnancy-related complications seem to be unrelated to the day of receipt. Visits for fractures are negative, but statistically insignificant. For both of these conditions, it is arguably less likely an individual would delay care, so we would not expect large differences if time use is the driving factor. On the other hand, admissions for upper respiratory, urinary tract and ear infections, and chest and abdominal pain (all non-urgent conditions for which people commonly visit ERs according to previous work) are significantly lower than expected on receipt date. We also report *Day of Receipt* effects for the top 25 most common conditions in our data; reported in Appendix Table 4. In this table deviations from expected SNAP share are most statistically significant for minor injuries (contusions) and some pain conditions (headaches, but not migraines).

Time Use Analysis

To try to establish some external validity behind the primary *Day of Receipt* result and the potential time use story, we perform a supplemental analysis using data from the American Time Use Survey (ATUS). ATUS has extensive information on the amount of time people spend on number of activities including seeking and utilizing medical care. It also includes information on the date of the activity, economic characteristics of the participants' household (such as SNAP participation), and the state of the respondent. Hence, we can link the ATUS's time use measures to SNAP treatment dates from all 50 US States for individuals living in households receiving SNAP benefits. That said, the ATUS does have a couple of notable limitations. First, while the data is available from 2003 – 2017, information about whether or not an ATUS participant's household is participating in the food stamp program is only available for six years (2006-2008, 2014-2016). As a result, there are less than 6,000 observations in the ATUS available from food stamp receiving households. Second, while we can tell if these households were participating in the food stamp program during the time of the survey and we know the date of the interview as well as the state they live in, we do not know their specific receipt date. Hence, we must use the probability that a recipient would receive benefits on each of the possible receipt days given their state of residence as our measure of SNAP treatment. Thus, in this supplemental analysis our treatment variables are measures of the likelihood that survey individuals receiving food stamps were treated on the date their time use was captured, which ranges from 0 to 1.

Formally, we estimate the following general fixed effects model of the effect of receiving SNAP benefits on daily time use habits:

$$Y_{ist} = \beta_0 + SNAP_{st}\beta_M + X_{ist}\beta_X + \tau_t + \gamma_s + m_m + \varepsilon_{ist} \quad (1)$$

where Y_{ist} is minutes of time used on an activity (i.e.; utilizing medical care services), for individual *i* in state *s* at time *t*. $SNAP_{st}$ is the propensity that a particular individual in state s is treated on a given day. X_{ist} is a vector of household- and individual-level demographic characteristics, which includes individual or families of indicator variables for household size, household income, age, marital status, race, employment status, education status, and presence of minor children (under 18 years old). State-specific fixed effects, denoted by γ_s, absorb time-invariant differences in time-use patterns across states. Metropolitan-specific fixed effects, denoted by m_m, absorb time-invariant differences in time-use patterns between urban and rural areas. τ_t is a vector of time fixed effects which account for year, month, day of the week, and "pay day" (defined as the 1st or 15th of each month) trends in time use that are common nationally. β_0 is a constant coefficient and ε_{ist} is the error term; standard errors are clustered by state.

We begin by estimating the effect on time spent grocery shopping. There exists a great deal of research that demonstrates a large increase in grocery shopping behavior on the day of food stamp benefits receipt. Hence, this investigation allows us to test the power of our ATUS food stamp sample and also verify that the results of this analysis are consistent and intuitive. If we were to find no effect on time spent grocery shopping, then it would call into question the power of our treatment variable in this section. However, a large increase of time use on grocery shopping behavior would, at a minimum, suggest that the model can capture well established time use patterns for the SNAP population that correspond to SNAP benefit receipt, and lend further credence to this approach.

[Table 7]

The estimate in Column (1) of Table 7 demonstrates a notable increase in time grocery shopping on SNAP receipt days. Estimates indicate that food stamp recipients increase their time allocation to grocery shopping by 16.9 minutes (235% relative to a mean of 5.292 minutes on the average day in the sample) on days in which food stamps are received. Next, we switch to our main outcome of interest in this supplemental analysis: time use for medical care services. Results, shown in Column (2) of Table 7, demonstrate a notable decrease in time engaged in using medical care services on SNAP receipt days. Estimates indicate that food stamp recipients reduce their time allocation to medical care services by 9.4 minutes (178% relative to a mean of 5.3 minutes on the average day in the sample) on days in which food stamps are received.

The results presented in Table 5 and Figure 2 also demonstrate a notable decline in ER utilization on SNAP receipt days in South Carolina. The ATUS investigation presented here demonstrates that we observe similar phenomenon in the ATUS time use data for medical care services defined more broadly, which suggests that a) SNAP families indeed respond to food stamp receipt by reducing time engaged in utilizing medical care services, likely in favor of grocery shopping, and b) that this effect is not isolated to South Carolina, but is likely a national phenomenon. Given the strong association between benefit receipt date and ER utilization in the South Carolina data and the corresponding evidence in the ATUS that this response is at least in part a time use response, it suggests that some of the ER visits are non-urgent in nature.

VII. Discussion, Conclusions, and Policy Implications

In this paper we look at the relationship between the monthly SNAP benefit receipt cycle and ER visits. We find that, for individuals over the age of 55, there is an increase in ER utilization at the end of their benefits cycle. This suggests severe food insecurity may be impacting their health in important ways. Yet, ER utilization does not go up for younger adults at the end of their benefits cycle. As such older individuals, which already have worse underlying health, may be more susceptible to the health effects of increased hunger. Alternatively, because they are often on other medications, it may be that they are foregoing those medications late in the SNAP benefit month as a result of financial constraints. Overall, this suggests that spreading SNAP distributions throughout the month (i.e., having multiple disbursements) might help with consumption smoothing and improve the health outcomes of older recipients.

Second, we find that, relative to what would be expected, recipients are less likely to visit the ER on the day of their receipt. This day-of-receipt effect seems to be related to patients delaying treatment for non-urgent conditions. There are no reductions in ER visits for urgent conditions such as pregnancy and fractures. Further, ER visits for conditions thought to be related to stress are all significantly lower on the day of receipt. The size of the day-of-receipt effect for non-urgent conditions is also significantly smaller for children than adults. To the extent that our results are due to individuals delaying care on their receipt date, especially if this is because they are busier that day, the disproportionately small effect among children might not be worrisome. Additionally, parents might take efforts to shield children from food insecurity even if it exacerbates their own insecurity. There is also evidence that school meals help smooth consumption among school-aged children (Kuhn, 2018), and we find supportive evidence of this using ATUS data.

Putting the heterogeneous effects we observe together, it seems that the decline in ER visits on the day of SNAP benefit receipt is somewhat due to a reallocation of activities, in particular a shift towards grocery shopping. This finding, however, leads to notable concerns about health access, health expenditures, and health outcomes. First, that there are impacts on ER visits for non-urgent conditions suggests that a segment of the Medicaid population uses the ER as a form of primary care. This alone is troubling for many reasons. For instance, information about how to access primary care might be lacking and/or office-based physicians might not be accepting Medicaid patients. Next, from a health expenditures standpoint, ER services are an extremely expensive option for care. So, the indication that a segment of the Medicaid population is using ER services for non-urgent care suggests the presence of an important cost inefficiency. Further, from a health outcomes perspective, utilizing the ER for primary care services would suggest a lack of patient-doctor continuity, which can lead to poorer health outcomes for patients. Hence, there are several policy-related implications of this study's findings that are worth serious consideration and further investigation.

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Table 1: Descriptive Statistics

Average Age	20.98
Shares by Age Group:	
Ages < 5	23.77
Ages 5-17	26.06
Ages 18-34	26.8
Ages 35-54	18.41
Ages 55-64	4.96
Black	0.51
White	0.35
Female	0.65
Shares by Distribution Days	
1	10.05
2	10.15
3	9.96
4	10.13
5	10.08
6	9.89
7	10.03
8	9.94
9	9.9
10	9.86

Table 2: Emergency Room Use over the SNAP Benefit Month

	Long Wait	**Days Since Receipt**
Panel A: All Ages		
Expected Share or Days	0.4866	14.747
Observed Share or Days	0.4861	14.760
$\frac{(Observed - Expected)}{Expected}$	-0.00003	0.0012***
	(0.0012)	(0.0003)

Panel B: By Age Group	**Long Wait**	**Days Since Receipt**
Ages < 5	-0.0008	0.0002
	(0.0023)	(0.0007)
Ages 5-17	-0.0007	0.0012*
	(0.0023)	(0.0006)
Ages 18-34	-0.0034	0.0008
	(0.0022)	(0.0006)
Ages 35-54	0.0031	0.0021***
	(0.0027)	(0.0008)
Ages 55-64	0.0167***	0.0044***
	(0.0058)	(0.0015)
Number of observations	2421	4249

Notes: Percent deviation from the expected is reported for each measure by age group. Long wait is defined as an indicator for the event day being more than 21 days since the day of last SNAP receipt. Days since receipt is a continuous measure. Standard errors are reported in parenthesis. * and *** indicate significance at 10% and 1% levels, respectively.

Table 3: Emergency Department Utilization at the End of the SNAP Benefit Month: *End of the Calendar Month Long Wait* by Age Groups

	End of the Month Long Wait
All	0.0048***
	(0.0017)
Ages < 5	0.0049
	(0.0032)
Ages 5-17	0.0031
	(0.0033)
Ages 18-34	-0.0002
	(0.0033)
Ages 35-54	0.0101***
	(0.0038)
Ages 55-64	0.0245***
	(0.0086)
Number of observations	1174

Notes: Percent deviation from the expected is reported for each measure. *Long Waits* at the end of the month are individuals with days since receipts over 21 days on the days>21 for the calendar month. Standard errors are reported in parenthesis. *** indicates significance 1% level.

Table 4: Emergency Department Utilization at the End of the SNAP Benefit Month for Commonly Studied Conditions: Any *Long Wait* and *End of the Calendar Month-Long Wait*

	Long Wait		**End of the Month Long Wait**	
	All	**Ages 55-64**	**All**	**Ages 55-64**
Any Condition	-0.00003	0.0167***	0.0048***	0.02446***
	(0.0012)	(0.0058)	(0.0017)	(0.0086)
Hypertension	-0.0272	0.0098	-0.0248	0.0769
	(0.0209)	0.0401	(0.0303)	(0.0627)
	N=2197	*N=1216*	*N=1064*	*N=570*
Asthma	0.0039	0.0596	0.0349***	0.0888
	(0.0079)	(0.0455)	(0.0114)	(0.0657)
	N=2421	*N=1105*	*N=1174*	*N=544*
Heart Failure	-0.0083	0.0107	-0.0536	0.0024
	(0.0279)	(0.0419)	(0.0366)	(0.0640)
	N=1823	*N=1075*	*N=866*	*N=509*
Hypoglycemia	0.0135	-0.0912	-0.0313	-0.1466
	(0.0623)	(0.1205)	(0.0805)	(0.1603)
	N=517	*N=119*	*N=241*	*N=53*
Mental Illness	0.0218	0.0609	-0.0023	0.0949
	(0.0175)	(0.0531)	(0.0239)	(0.0806)
	N=2345	*N=751*	*N=1135*	*N=367*
Anxiety and Depression	0.0141	0.0389	0.0342*	0.1004*
	(0.0143)	(0.0492)	(0.0206)	(0.0554)
	N=2403	*N=875*	*N=1165*	*N=646*
Pregnancy Related Complications	-0.0105*	-	0.0097	-
	(0.0061)	-	(0.0089)	-
	N=2421	-	*N=1174*	-

Notes: Baseline Long wait measure (days since last receipt>21) is used for the *Long Wait* indicator. *End of Month Long Wait* is defined as an indicator for long waits with days>21 of the calendar month. Percent deviation from the expected is reported for each measure. Standard errors are given in parenthesis. * and *** indicate significance at 10% and 1% levels, respectively. *N* for each condition is the number of long wait days for which that particular condition is observed.

Table 5: Emergency Room Use on the Day of SNAP Receipt, by Age Groups

	Day of Receipt
Panel A – All Ages	
Expected Share	0.1000
Observed Share	0.0969
$\frac{(Observed - Expected)}{Expected}$	-0.0314***
	(0.0032)
Panel B – By Age Group	
Ages < 5	-0.0195***
	(0.0065)
Ages 5-17	-0.0295***
	(0.0059)
Ages 18-34	-0.0382***
	(0.0060)
Ages 35-54	-0.0384***
	(0.0074)
Age 55+	-0.0453***
	(0.0142)
Number of observations	1385

Notes: Percent deviation of the observed share from the expected share is reported for each age group. Standard errors are reported in parenthesis. *** indicates significance at 1% level.

Table 6: Emergency Department Utilization on the Day of SNAP Receipt for Select Conditions

Any Condition	-0.0314***
	(0.0032)
Acute Upper Respiratory Infections	-0.0189*
	(0.0097)
	N=1385
Urinary Tract Infections	-0.0444*
	(0.0229)
	N=1385
Ear Infections	-0.0331**
	(0.0152)
	N=1385
Chest Pain	-0.0924***
	(0.0331)
	N=1375
Abdominal Pain	-0.0314
	(0.0228)
	N=1385
Fractures	-0.0157
	(0.0123)
	N=1385
	(0.0307)
Pregnancy Related Complications	0.0011
	(0.0168)
	N=1385

Notes: Percent deviation of the observed share from the expected share of ER patients on their day of receipt is reported for each condition. *N* for each cell indicates number of days in which a specific condition is ever recorded on any of the distribution days. Standard errors are reported in parenthesis. * and *** indicate significance at 10% and 1% levels, respectively.

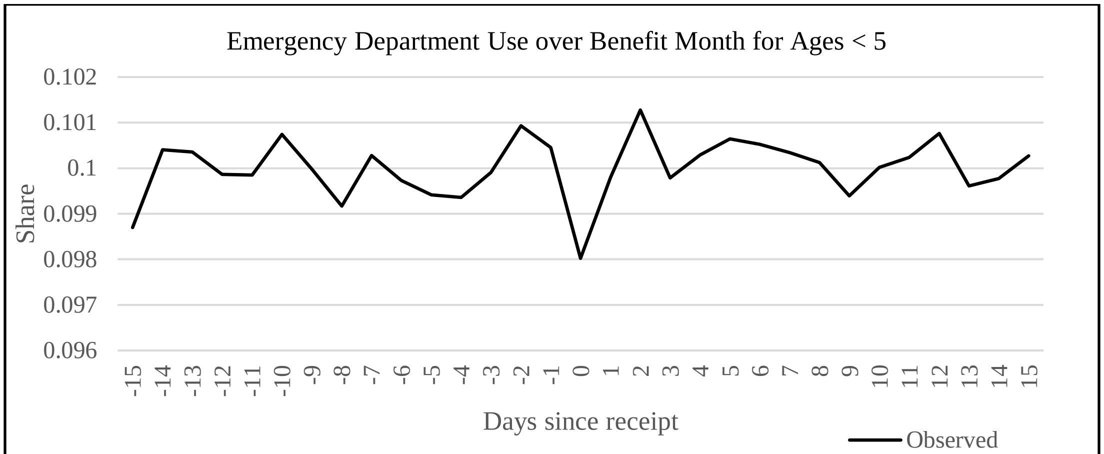
Table 7: Time Use and Day of SNAP Receipt

	Time Grocery Shopping (minutes)	Time Using Medical Care Services (minutes)
Probability of SNAP Receipt	16.88***	-9.40**
	(5.28)	(4.46)
Average Minutes/Day (all days)	7.18	5.27
Number of observations	5868	5868

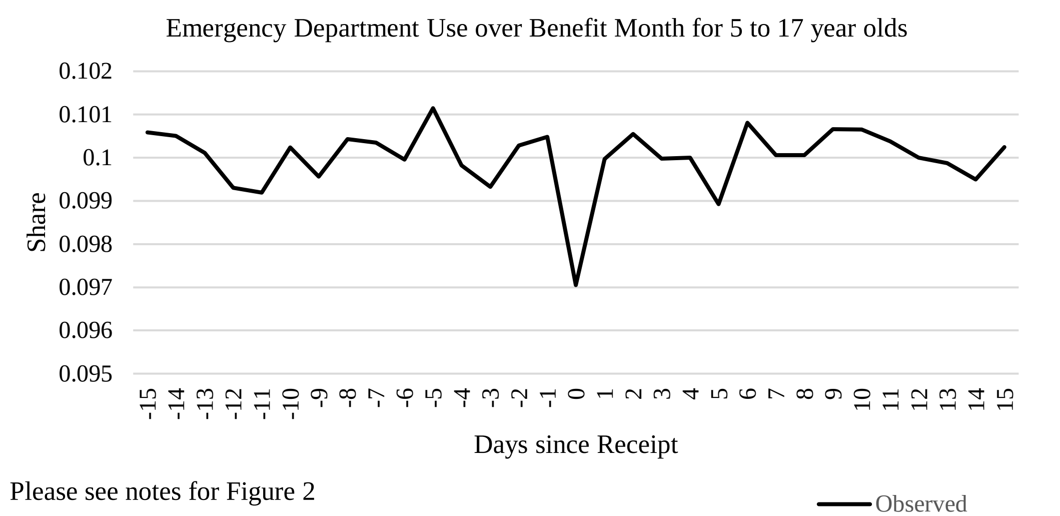
Notes: Sample includes only the SNAP Recipients. Specifications include 1) fixed effects for state, metro, year (2006-2008, 2014-2016), month, day of the week, and payday; 2) household-level controls for size, presence of children, and income; and 3) individual controls for age, race, marital status, education status, and employment status. Standard errors are clustered by state. Robust standard errors in parentheses. ** and *** indicate significance at 1% and 5% levels, respectively.

APPENDIX

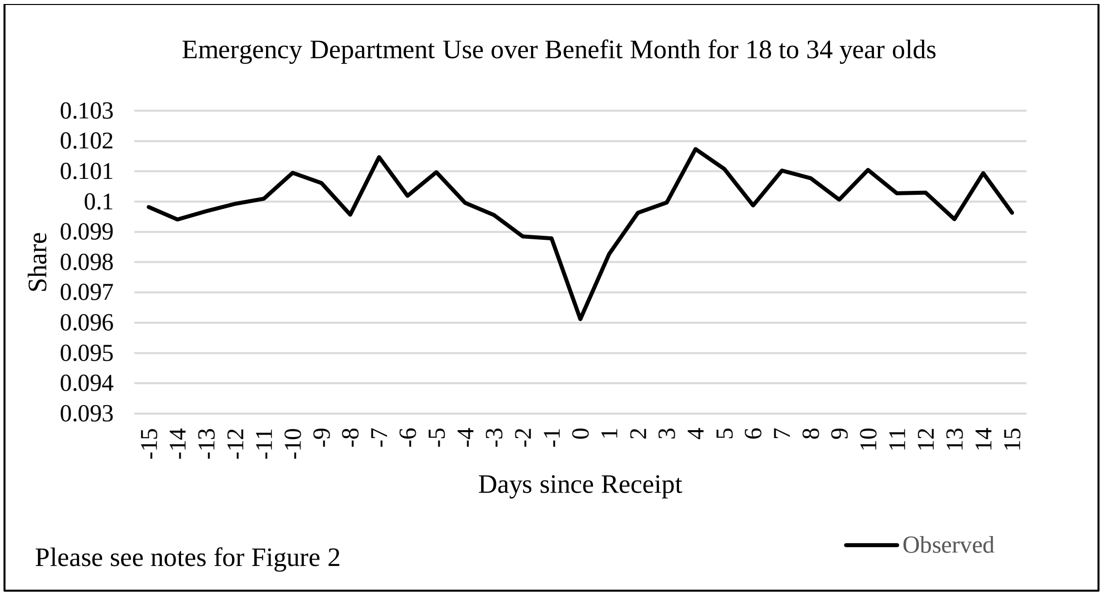
Appendix Figure 1: Emergency Room Utilization over the Benefit Month by Age Groups

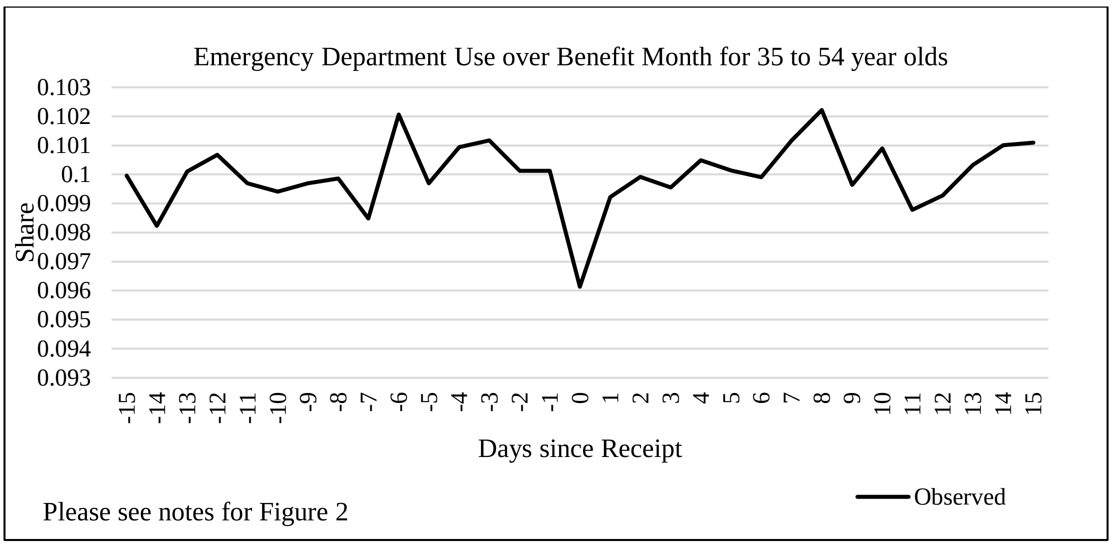


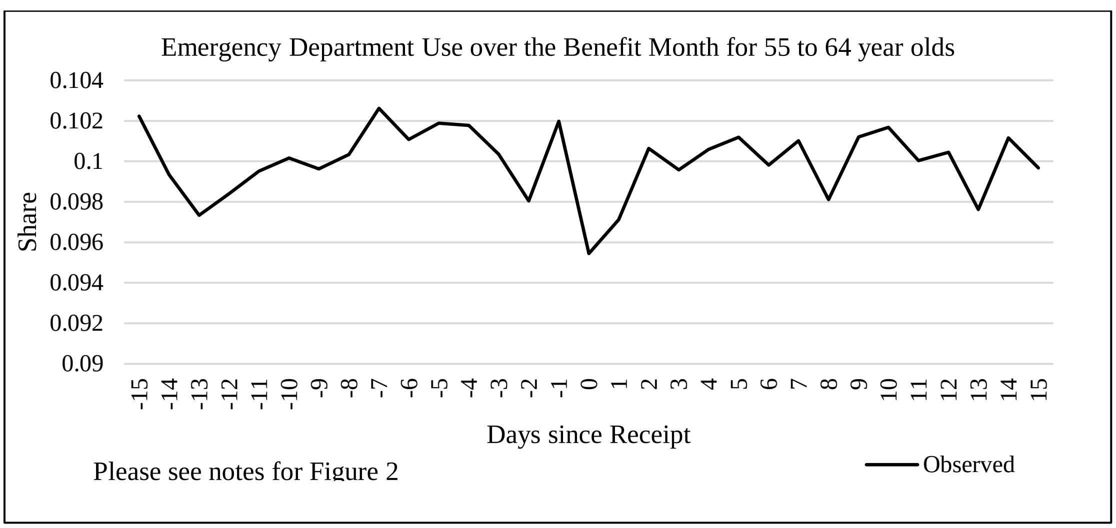
Please see notes for Figure 2



Please see notes for Figure 2


Emergency Department Use over Benefit Month for 18 to 34 year olds
Share
0.103
0.102
0.101
0.1
0.099
0.098
0.097
0.096
0.095
0.094
0.093
-15 -14 -13 -12 -11 -10 -9 -8 -7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
Days since Receipt
Observed
Please see notes for Figure 2


Emergency Department Use over Benefit Month for 35 to 54 year olds
Share
0.103
0.102
0.101
0.1
0.099
0.098
0.097
0.096
0.095
0.094
0.093
-15 -14 -13 -12 -11 -10 -9 -8 -7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
Days since Receipt
Observed
Please see notes for Figure 2


Emergency Department Use over the Benefit Month for 55 to 64 year olds
Share
0.104
0.102
0.1
0.098
0.096
0.094
0.092
0.09
-15 -14 -13 -12 -11 -10 -9 -8 -7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
Days since Receipt
Observed
Please see notes for Figure 2

Appendix Table 1: Emergency Room use and SNAP benefit month - Alternative Long Wait Measures

	16 days+	**22 days+ (Baseline)**	**25 days+**	**27 days+**
All	0.00031	-0.00003	-0.00021	-0.00228
	(0.0009)	(0.0012)	(0.0015)	(0.0018)
Ages < 5	-0.00045	-0.00077	-0.00063	-0.00373
	(0.0017)	(0.0023)	(0.0029)	(0.0035)
Ages 5-17	0.00167	-0.00073	0.00144	-0.00177
	(0.0017)	(0.0023)	(0.0029)	(0.0035)
Ages 18-34	-0.00362**	-0.00341	-0.00806***	-0.01233***
	(0.0016)	(0.0022)	(0.0027)	(0.0034)
Ages 35-54	0.00322	0.00311	0.00674**	0.00837**
	(0.0019)	(0.0027)	(0.0033)	(0.0041)
Ages 55-64	0.00969**	0.01672***	0.01397**	0.01645**
	(0.0041)	(0.0058)	(0.0069)	(0.0086)
Number of observations	3413	2421	2000	1724

Notes: Percent deviation from the expected is reported for each measure. Standard errors are reported in parenthesis. **, *** indicate significance at 5% and 1% levels, respectively.

Appendix Table 2: Individual Level Panel Data Analysis Using a 20% Random Sample of the Event Level Data

		Odds Ratio (Std Dev)	
Variable	**Definition**	**All Ages**	**Ages 55-64**
Day of Receipt Indicator	Number of days since receipt =0	0.977***	0.975***
		(0.0074)	(0.0339)
Long Wait Indicator	Number of days since receipt > 15 days	0.997	0.984
		(0.0039)	(0.0179)
	Number of days since receipt > 21 days	1.000	1.013
		(0.0040)	(0.0184)
	Number of days since receipt > 24 days	1.001	1.040**
		(0.0043)	(0.0203)
Days Since Receipt	Number of days since receipt	1.000	1.001
		(0.0002)	(0.0009)
Number of Observations		20,031,418	1,000,521

*Notes:*20% of the sample is randomly chosen for the analysis. Given each observed event we expanded the data for each day of the month to include days when the individual did not go to the ER. Outcome variable in each model is a dummy indicator for having any emergency department use in a given day. Odds ratios are reported separately for all individuals and for the oldest age group (Ages 55-64) for variables Days Since Receipt (a continuous variable) Long Wait (Indicator, alternative definitions based on days since receipt is given on each column), and Day of Receipt (Indicator, days since receipt=0) Standard Errors are given in parenthesis. **and *** indicate significance at 5% and 1% levels, respectively.

Appendix Table 3: ***Long Wait*** **Statistics for the Top 25 ICD9 Codes Observed in the Data - LONG WAIT**

ICD9	Number of claims	%	Description	Long Wait			End of Month Long Wait		
				#	% diff	std	#	% diff	std
4659	163716	5.08	Acute uri NOS	2421	-0.0006	0.0059	1174	0.0083	0.0088
3829	130341	4.04	Otitis media NOS	2421	-0.0002	0.0063	1174	-0.0056	0.0092
462	81836	2.54	Acute pharyngitis	2421	0.0088	0.0072	1174	0.0119	0.0105
78900	65444	2.03	Other symptoms involving abdomen and pelvis	2421	-0.0070	0.0081	1174	-0.0007	0.0118
7999	64588	2	Other unknown and unspecified cause of morbidity and mortality	722	-0.0088	0.0518	344	0.0947	0.0800
5990	63388	1.97	Other disorders of urethra and urinary tract	2421	0.0096	0.0087	1174	0.0128	0.0128
7840	63508	1.97	Headache	2421	0.0173	0.0092	1174	0.0353***	0.0134
5589	50127	1.55	Other and unspecified noninfectious gastroenteritis and colitis	2421	-0.0054	0.0107	1174	0.0005	0.0158
4660	44926	1.39	Acute bronchitis	2401	-0.0235**	0.0113	1166	0.0022	0.0174
7806	41281	1.28	Fever and other physiologic disturbances of temperature regulation	1647	0.0010	0.0121	796	-0.0052	0.0164
49392	40013	1.24	Asthma, unspecified type, with (acute) exacerbation	2288	0.0053	0.0114	1110	0.0362*	0.0166
78703	39197	1.22	Vomiting alone	2413	-0.0126	0.0122	1170	-0.0108	0.0177
7242	35249	1.09	Lumbago	2407	0.0288**	0.0138	1167	0.0363*	0.0199
920	34722	1.08	Contusion face/scalp/nck	2416	-0.0004	0.0122	1170	-0.0061	0.0178
486	33893	1.05	Pneumonia, organism unspecified	2399	0.0261*	0.0135	1166	0.0134	0.0175
490	31706	0.98	Bronchitis NOS	2396	.013824	0.0143	1166	0.0452**	0.0224
78650	31257	0.97	Chestpain	2408	0.0022	0.0132	1170	0.0012	0.0186
78060	30744	0.95	Fever, unspecified	782	0.0085	0.0126	380	0.0139	0.0183
34690	29505	0.92	Migraine, unspecified, without mention of intractable migraine without mention of status migrainosus	2392	0.0144	0.0146	1160	0.0129	0.0209
64893	29777	0.92	Oth curr cond-antepartum	2372	-0.0025	0.0148	1144	0.0047	0.0211
84500	28478	0.88	Sprain of ankle, unspecified site	2407	-.0183258	0.0139	1166	-0.0052	0.0211
49390	26591	0.82	Asthma, unspecified type, unspecified	2398	.015434	0.0142	1164	0.0371*	0.0197
8470	25965	0.81	Sprain of neck	2399	.0103259	0.0150	1163	-0.0089	0.0196
7295	25552	0.79	Pain in limb	2402	-0.0300**	0.0139	1166	-.0294877	0.0191
78652	23769	0.74	Painful respiration	2397	0.0244	0.0153	1159	0.0393*	0.0225

Notes: % refers to share of ICD9 codes in primary diagnosis in all claims. # refers to number of long wait days with each ICD9 code.

Appendix Table 4: *Day of Receipt* Statistics for the Top 25 ICD9 Codes Observed in the Data

ICD9	Description	Day of Receipt			NYU Algorithm		
		#	% diff	std err	Non-Emergent	Unclassified	Injury
4659	Acute uri NOS	1385	-0.0292*	0.0156	0.82		
3829	Otitis media NOS	1385	-0.0326**	0.0157	0.96		
462	Acute pharyngitis	1385	-0.0258	0.0194	0.94		
78900	Other symptoms involving abdomen and pelvis	1385	-0.0339	0.0228	0.67		
7999	Other unknown and unspecified cause of morbidity and mortality	419	0.1887	0.1445	0.50		
5990	Other disorders of urethra and urinary tract	1385	-0.0476**	0.0229	0.76		
7840	Headache	1385	-0.0429*	0.0231	0.87		
5589	Other and unspecified noninfectious gastroenteritis and colitis	1385	-0.0460*	0.0278	0.84		
4660	Acute bronchitis	1,373	-0.0149	0.0319	0.82		
7806	Fever and other physiologic disturbances of temperature regulation	944	0.0042	0.0302	0.00	1.00	
49392	Asthma, unspecified type, with (acute) exacerbation	1308	-0.0241	0.0304	0.02		
78703	Vomiting alone	1380	0.0907**	0.0385	0.82		
7242	Lumbago	1378	-0.0486	0.0343	0.89		
920	Contusion face/scalp/nck	1382	-0.0853***	0.0306	0.00		1.00
486	Pneumonia, organism unspecified	1369	-0.0269	0.0337	0.33		
490	Bronchitis NOS	1366	-0.1040***	0.0349	0.82		
78650	Chestpain	1375	-0.0961***	0.0331	0.32		
78060	Fever, unspecified	447	-0.0859***	0.0294	0.00	1.00	
34690	Migraine, unspecified, without mention of intractable migraine without mention of status migrainosus	1369	0.0177	0.0411	0.87		
64893	Oth curr cond-antepartum	1363	0.0062	0.0411	1.00		
84500	Sprain of ankle, unspecified site	1376	-0.0252	0.0371	0.00		1.00
49390	Asthma, unspecified type, unspecified	1371	-0.0448	0.0378	0.02		
8470	Sprain of neck	1374	0.0647	0.0415	0.00		1.00
7295	Pain in limb	1374	-0.0413	0.0393	0.88		
78652	Painful respiration	1375	-0.0765**	0.0372	0.82		

Notes: See Appendix Table 3 for the frequency and the share of each ICD9 code. *Non-emergent* is calculated as the sum of two NYU ED Utilization Algorithm Clasifications, "Non-Emergent" and "Emergent Primary Care Treatable", following Gandhi and Sabik (2014).