SNAP Benefits and Crime: Evidence from Changing Disbursement Schedules

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Abstract

In this paper, we study the effects of the timing of nutritional aid disbursement on crime, using two main sources of variation: (i) a policy change in Illinois that substantially increased the number of SNAP distribution days, and (ii) an existing Indiana policy that issues SNAP benefits by last name. We find that staggering SNAP benefits leads to large reductions in crime and theft at grocery stores by 17.5 percent and 20.9 percent, respectively. Findings also show that theft decreases in the second and third weeks following receipt, but increases in the last week of the benefit cycle due to resource constraints.

JEL Classification: I38, I18, J18, K42

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†Department of Economics, Farmer School of Business, Miami University, 800 E. High St., Oxford, OH 45056, apackham@miamioh.edu. We thank the Indiana Department of Correction for providing convictions data. We also thank Katherine Meckel, Anita Mukherjee, Dani Sandler, Margaret McKeehan, Daeho Kim, Ben Hansen, Andrew Barr, Daniel Grossman, participants at the 2016 Meetings of the Southern Economic Association, 2017 Midwestern Economic Association Meetings, Western Economics Association International and Association for Public Policy Analysis and Management and seminar attendees at Purdue University, Miami University, Ohio State University (Consumer Sciences), University of Louisville and University of Illinois for useful feedback.

1 Introduction

While it is well-documented that income shocks due to monthly government *cash* transfers increase street crime and illicit drug and alcohol use, much less is known about how *in-kind* transfer programs affect criminal behavior (Dobkin and Puller, 2007; Evans and Moore, 2011; Foley, 2011; Wright et al., 2014). One such program, the Supplemental Nutrition Assistance Program (SNAP), provides food-purchasing assistance for nearly 45 million low-income Americans each year. Recipients are issued debit-like cards to which funds are electronically loaded once each month to be redeemed for foods at supermarkets or other authorized retailers. In most states, benefits are made available to a particular recipient on the same day each month, although different groups of recipients have different issuance days (a practice called “staggering").

The objective of this paper is to estimate the effects of SNAP receipt on crime, focusing on policies that change the timing of benefit distribution. First, we examine the effects of staggered SNAP benefit issuance using Chicago reported crime data before and after a policy change that increased the number of distribution days. Second, we use individual-level conviction records from Indiana, where staggered benefit distribution days are determined by first letter of last name, to measure how criminal behavior responds to the monthly disbursement of aid. Third, we analyze the effects of a policy change in Indiana that shifted benefit issuance later in the month but did not increase the number of distribution days.

Two main economic arguments support the notion that monthly SNAP payments affect crime. The first is based on the idea that large, lump sum payments to beneficiaries constitute income shocks, which can increase consumption of complements to crime, such as leisure, or illicit drugs and alcohol. Previous work has found that cash transfers, such as Supplemental Security Income, can lead to increases in drug abuse, and, similarly, in-kind transfers, such as SNAP and Section 8 housing vouchers, can affect alcohol purchases, drunk driving, and violent crime (Dobkin and Puller, 2007; Castellari et al., 2017; Cotti et al., 2015; Carr and Koppa, 2017). These studies suggest that recipients view in-kind benefits as fungible, and receiving benefits may be akin to increasing overall household resources. Accordingly, distributing SNAP benefits later in the month has the potential to shift crimes away from the first of the month to later dates. Given that a primary justification for implementing in-kind transfers is to target aid and reduce perceived fungibility, determining whether in-kind transfers avoid some of the adverse consequences of cash transfers is of utmost importance.

The second argument posits that, unless recipients are fully smoothing their consumption of benefits, they may face the need to reduce food intake at the end of the month due to financial stress and may engage in criminal behavior to obtain resources and/or food in response. While standard economic models of behavior imply that SNAP recipients ration benefits throughout the month to avoid shortages at the end of the benefits cycle, many studies have shown that recipients often run out of food in just 2-3 weeks, which suggests an inability to consumption smooth effectively (Wilde and Ranney, 2000; Shapiro, 2005; Castner and Henke, 2011; Hamrick and Andrews, 2016; Bruich, 2014; Hastings and Washington, 2010; Goldin et al., 2016). Moreover, in many states, there is an extended period of time within each month where no recipients receive disbursements, limiting the amount of resources in low-income communities. These lean times may lead to greater levels of criminal involvement (for both recipients and non-recipients alike) related to procuring resources.[1] Therefore, by providing beneficiaries with aid later in the month, there is potential to reduce the amount of crimes committed due to resource constraints. These policies have other potential neighborhood-based advantages in that they may reduce incentives for individuals to commit crimes together or assist communities in consumption smoothing across households, as friends and neighbors likely receive benefits on different days.

To study the causal effect of SNAP benefit issuance timing on crime, we exploit a policy change

[1]Specifically, crimes related to procuring resources may include theft, burglary, and other financially motivated crimes, as well as domestic violence, in which bargaining and economic signaling models predict that partners or spouses use violence to obtain household resources. In our subsequent analysis, we focus most of our attention on the former, since thefts are likely to be the most directly affected crimes related to resource scarcity.

in Illinois that drastically changed the monthly SNAP distribution cycle. In February 2010, Illinois switched from issuing most benefits on the first of the month to more substantial distribution later in the month. We focus on this change for three reasons. First, the policy change is considerable, affecting nearly 1.12 million individuals.[2] Second, the city of Chicago maintains relatively high crime rates, which gives us a unique opportunity to speak to how low-cost policies can affect cities in which deterring criminal behavior may be of main concern. Third, because Chicago is both large and heterogeneous in terms of socioeconomic status, it provides us an ideal forum in which to study differential effects for high-poverty areas.

Using day-level administrative data from Illinois, we find that SNAP redemptions closely track state issuance dates. Increasing the number of SNAP distribution days leads to a sharp decrease in the number of redemptions on the 1st of the month; after the policy change, the percent of total Illinois SNAP redemptions on the first and second of the month drops from 6 percent and 12 percent to about 3 percent and 6 percent, respectively. The observable change in usage patterns due to the policy change suggests there is some scope for such a policy to affect timing and levels of criminal behavior. To study the extent to which increasing the number of SNAP benefit dates affects crime, we use administrative crime-level data for Chicago from 2007-2013 to analyze effects on overall crime and theft, and additionally analyze when and where these crimes occur. We find, in particular, that crimes and thefts at grocery stores decrease by 17.5 and 20.9 percent, respectively, as a result of benefit staggering. Moreover, we study differential effects of the policy change across Census Tracts and find larger effects in high SNAP enrollment areas and areas with higher concentrations of SNAP retailers.

Furthermore, to study the effect of SNAP receipt on criminal behavior, we use detailed individual-level conviction data from Indiana to disentangle benefits timing and monthly cyclicality of crime. SNAP issuance in Indiana has the distinct feature that benefit days are based on first letter of

[2]This number is calculated based on the fact that 70 percent of the 1.6 million SNAP recipients in Illinois were directly affected by this policy (House Joint Resolution 43, 2013; Food and Nutrition Services, 2011).

last name. This attribute allows us to measure intent-to-treat estimates for crimes committed in the weeks of the "benefit month" following disbursement. We find that crime falls by 4.3 percent in the third week after SNAP issuance, but increases in the last week of the benefit cycle, when resources are likely to be most scarce. These effects are largely driven by end-of-the-month increases in theft by females. Finally, we find that shifting SNAP benefits later in the month (without increasing the number of SNAP issuance days) leads to a decrease in theft by 23.3 percent, on average.

This paper is the first to shed light on how SNAP receipt affects criminal behavior and incentives by analyzing how crime levels are impacted by changing payment schedules, and how types of crime differentially respond to nutritional assistance timing.[3] In doing so, we make three main contributions to the existing literature. First, we measure the magnitude of the monthly cyclicality in crime and theft in Chicago and determine how much this cycle varies according to SNAP distribution. Second, we fill an existing gap in the literature by estimating the effects of *changes* to SNAP distribution on crime. As a result, we address how in-kind income shocks and consumption smoothing affect criminal involvement and build upon Foley (2011) by examining the effects of SNAP distribution schedules on the timing, type, and locations of crimes committed. Our third contribution to the existing literature is the use of conviction-level data to speak to how much staggered SNAP issuance can affect criminal behavior right before benefit receipt. By exploiting the fact that SNAP benefits in Indiana are distributed each month based on the first letter of last name, we disentangle calendar month cyclicality from benefit effects and are able to separate our findings by age groups, gender, race, and ethnicity.

Our analysis proceeds as follows. We first present background information on SNAP issuance policies in Illinois and Indiana. Next, we describe our data and empirical approach. Then, using data containing detailed, crime-level reports, we estimate effects of a SNAP distribution policy

[3]In related work, Yang (2017) recently showed that SNAP and welfare eligibility reduce 1 year recidivism rates for drug offenders, and, in a recent working paper, Barr and Smith find that the availability of the Food Stamp Program in the 1960s and 70s in early childhood led to fewer violent crimes in adulthood as a result of the increase in household purchasing power.

change on overall crime and theft as well as crime and thefts at grocery stores and estimate how monthly SNAP issuance affects the timing of criminal behavior. Finally, we provide a discussion on potential mechanisms that may be driving these results and consider the overall policy implications of staggered SNAP distribution.

2 Background on SNAP Issuance Policies

Despite the fact that SNAP is an entitlement program administered and funded by the United States Department of Agriculture, benefits are issued by states, and states have the authority to tailor rules for eligibility and implementation. This authority extends to the organization and timing of benefits, and as a result, there is significant variation in state SNAP disbursement schedules. Seven states currently distribute all benefits on one day of the month.[4] However, a majority of states stagger issuance throughout the month, wherein different households receive monthly benefits on different days of the month. For example, in a state that staggers, some recipients may receive benefits on the 3rd, while others may receive their SNAP benefits on the 10th of each month.

There are several reasons why states may choose to stagger benefits. First, staggering could reduce administrative or overhead costs for state agencies. By issuing benefits on multiple days each month, government employees do not have to handle as many cases at the beginning of the month, which could lead to fewer errors and better fraud detection. Second, spreading disbursement dates throughout the month could benefit consumers by reducing crowding at grocery stores and ensuring that retailers don't impose large price hikes at the beginning of the month, which could reduce the quantity and/or quality of food a family could buy with benefits. Third, by smoothing shopping spikes throughout the month, staggered disbursement policies may enable retailers to stock more healthy and perishable food items more consistently and manage staffing more effectively.

In this analysis, we focus on Illinois and Indiana to study how SNAP receipt timing affects

[4]States that distribute benefits on the first of the month include Alaska, Nevada, North Dakota, Rhode Island, and Vermont. New Hampshire distributes all benefits on the 5th of each month and South Dakota does so on the 10th.

crime. Prior to 2010, the Illinois Department of Health and Human Services distributed 66 percent of SNAP benefits on the first day of the month. As a result, areas with a high concentration of SNAP recipients experienced crowded grocery stores on the first, which made it difficult for store-owners to properly stock perishable goods and staff stores accordingly (House Joint Resolution 43, 2013).[5] On February 16, 2010, Illinois changed its issuance policy, adding many cases to the 4th, 7th and 10th day of each month.[6] This change in issuance allows us to analyze within-state variation in SNAP policies to determine how SNAP distribution dates later in the month can assist families in smoothing benefit consumption.

Similarly, Indiana altered its SNAP benefits issuance schedule on February 1, 2014. We study the effects of this policy change, and in doing so, also exploit a remarkable feature of Indiana's issuance policy.[7] Since Indiana issues benefits based on the first letter of the recipient's last name, we use this variation to avoid bias due to other factors that may be correlated with both SNAP receipt and criminal activity.

In particular, we are able to use conviction-level data to analyze how monthly income shocks affect criminal behavior. Table A1 provides the Indiana schedule of SNAP issuance days throughout the month based on the first letter of the last name for both before and after the policy change

[5]The Illinois Retail Merchants Association, when asked about another potential future policy change, expressed support for the 2010 decision, stating that, "bottlenecking all SNAP beneficiaries to the first 10 days of the month would produce problems with staffing, food ordering, packed stores for 10 days, empty stores for 20, empty store shelves and a lack of access to fresh fruits and vegetables for low income residents." (House Joint Resolution 43, 2013)

[6]SNAP benefits are made available on the 1st, 3rd, 4th, 7th, 8th, 10th, 11th, 14th, 17th, 19th, 21st, and 23rd of every month, based on a combination of the type of case and the case name (House Joint Resolution 43, 2013).

[7]The Indiana Family and Social Services Administration states that the change came about as a way to lessen the burden on grocery stores and other food sellers, as well as improve the shopping experience for SNAP clients (Indiana Family and Social Services Administration, 2013).

in 2014.[8] Prior to 2014, Indiana issued benefits on days spanning the 1st-10th of the month; after 2014, they issued benefits every other day from the 5th-23rd. This policy shift varies from the change in Illinois, which increased the *number* of primary SNAP distribution dates. Indiana did not change the number of SNAP issuance days, but rather spread out benefits and made them available later in the month. Approximately the same number of recipients received benefits on each disbursement day before and after the change. We use this policy change and the last name-based benefit issuance scheme to isolate as-good-as-random variation in the timing of receipt in our empirical models.

3 Data

We use crime data from two administrative datasets. The main advantage of these datasets is that both crime-level panels span several years and contain detailed information for a large number of crimes, including the type of crime committed. To more thoroughly study consumer response to SNAP policies, we supplement these data with information on daily SNAP redemptions and SNAP-authorized store locations. Below we provide a detailed description of the data used in our analysis.

3.1 Chicago Crime Data

For our main analysis, we use Chicago crime-level data from the City of Chicago's online data portal for 2007-2013.[9] For each crime, the dataset contains information on the type of offense, the date and time the crime occurred, the location type (e.g. "grocery" or "apartment"), the block-level address, geographic coordinates, and indicators for whether there was an arrest made. We then group crimes into categories by their listed types and/or locations. The detailed descriptions of

[8] We will henceforth refer to these separate groups as "letter groups." Each group is comprised of 2-4 letters that receive their benefits on the same day, with the exception of "S."

[9] Available for download at https://data.cityofchicago.org/Public-Safety/Crimes-2001-to-present/ijzp-q8t2.

crimes in these data are a critical feature that we exploit to specifically analyze theft at grocery stores. Using geographic coordinates, we match crimes to their respective Census Tract locations to create a date-by-Census Tract panel of counts of each crime type. This allows us to use Census Tract fixed effects to control for neighborhood characteristics that may influence criminal behavior and to consider heterogeneity across various types of communities.

To count the number of retailers in each Census Tract in 2010 (the year the policy changed), we geocode addresses from the USDA Food and Nutrition Services list of SNAP-authorized retailers. We also integrate a measure of SNAP enrollment from the American Community Survey (2010 5-year estimates). Both of these measures allow us to examine heterogeneity by neighborhoods, and compare results across Census Tracts with high and low SNAP enrollment rates and SNAP retailer concentration.

Table A2 Panel A contains summary statistics for these crime data. On average a Census Tract in Chicago has 1.260 crimes per day, of which 0.262 are thefts. When we focus on crime and theft at grocery stores, the means drop to 0.014 and 0.009, respectively. Across the city of Chicago, this implies a daily city-wide mean of 11.452 and 7.362 crimes and thefts at grocery stores, respectively, which corresponds to approximately 4,180 crimes and 2,687 thefts at grocery stores each year.

3.2 Illinois SNAP Redemptions Data

To track the consumer response to the changes in SNAP distribution in Illinois, we use SNAP redemptions data from the Illinois Department of Human Services. These data contain information on the daily SNAP redemptions (total dollar amount of benefits redeemed) from January 1, 2008, to December 31, 2014. During this time period, Illinois beneficiaries redeemed $7,480,298 on average, per day. We include these data to capture how beneficiaries alter purchasing behavior when SNAP disbursement schedules change.

3.3 Indiana Convictions Data

For the Indiana analysis, we use individual-level administrative conviction records from the Indiana Department of Correction that contain information on the first letter of the last name, date the crime was committed, date of birth, race, ethnicity, gender, county of conviction, and charged offense for all convictions in 2014-2016. Although the data span several years, we omit all crimes committed prior to 2012 to minimize the potential for selection bias for cases that take longer than two years to adjudicate. One important attribute of these data is that they contain offense dates matched to the offender's first letter of last name, which allows us to study variations in crime by letter across days of the month.[10]

One of the limitations of these data is that although they contain information on the convicted individual's last name, we do not know which individuals received SNAP benefits prior to their conviction. Therefore, estimates on the effects of SNAP receipt on crime using these data will represent intent-to-treat effects and will understate the true effects of SNAP disbursement.

Table A2 Panel B shows summary statistics for the Indiana convictions data. The average crimes committed per day in Indiana (resulting in conviction) for each last name letter is 0.844, with the largest share of crimes due to drug crimes (mean=0.228). Thefts in Indiana average 0.098 per day per last name letter, or 930 per year statewide.

4 Methods

This section details our estimation techniques for measuring the effects of SNAP issuance schedules on criminal activity.

[10]With the exception of the date the offense was committed, these data are available online through the IDOC Offender Search Tool at http://www.in.gov/apps/indcorrection/ofs/ors.

4.1 Within-State Policy Change

We exploit the sharp change in the Illinois SNAP distribution schedule on February 16, 2010, which increased the number of distribution days, to identify the effects of staggered SNAP distribution on crime. This strategy is motivated by the idea that characteristics related to outcomes of interest vary smoothly across this treatment threshold; therefore, any discontinuity in criminal outcomes can be reasonably attributed to the change in SNAP issuance.

The main model is an interrupted time series model, which is equivalent to a regression discontinuity (RD) model in that we will look for a break in the trend in crimes at the time of the policy change. To this end, we create figures plotting means and linear fits of the data on either side of the cutoff to illustrate the magnitude of the break, and we control for polynomials of the days from the cutoff like a running variable. We estimate the following Census Tract-level model using OLS where y_{it} is the count of crimes (of various types) on date t in Census Tract i:

$$y_{it} = \beta_0 + \beta_1 * SNAP\ staggered_t + f(days\ from\ cutoff_t) + \pi_w + \gamma_m + \psi_y + \lambda_i + u_{it} \quad (1)$$

where β_1 is the coefficient of interest (the effect of staggered SNAP distribution), $SNAPstaggered_t$ is an indicator variable equal to one for days after the policy change, π_w is day-of-week fixed effects, γ_m is day-of-month fixed effects, ψ_y is year fixed effects, and λ_i is Census Tract fixed effects. To account for the substantial variation in weather in Chicago, and its effect on crime, we also control for daily weather patterns (temperature, precipitation and wind). We control for the days from cutoff (running variable) in multiple ways and allow it to vary on either side of the cutoff. Standard errors are clustered on the Census Tract-level. Because the distribution schedule changed again in July 2013, we do not use any observations after June 2013, and, for symmetry, do not use any data from before January 2007. While our preferred specifications limit the sample to observations that fall within the MSE-optimal bandwidths, as suggested by Calonico et al. (2016), our results are not sensitive to this choice. Results from a range of bandwidths yield similar results, and will be discussed in Section 5.

Our identifying assumption is that characteristics related to crime vary smoothly across the time of treatment, namely February 2010. Specifically, since the policy change occurred in the middle of the month, the interruption to benefit issuance scheduling likely also affected individuals during the first 15 days of the month. Therefore, we consider the full month to be treated in the following analyses, and normalize our running variable to be equal to zero on February 1, 2010.[11] The fact that SNAP recipients cannot manipulate disbursement timing alleviates potential selection concerns. That said, with any discontinuity-based identification, it is important to consider whether there may be additional policy changes or general disruptions related to outcomes of interest that coincide with the policy change of interest. During 2010 no other major policy changes in Illinois corresponded with the change in SNAP distribution to the best of our knowledge. Finally, we note that we present figures showing large discontinuities in criminal behavior across the treatment threshold and perform a number of robustness checks to provide additional support for the identification assumption.

We estimate the effects of the Illinois policy change on the types of crimes, days of the month and geographies that are most likely to respond to the change. Because half of all families receiving SNAP exhaust their SNAP benefits in two weeks (Castner and Henke, 2011), recipients may face a scarcity of resources during the remainder of the month. In response to this scarcity, they may turn to crime to meet nutritional needs. Crimes aimed at obtaining resources broadly (and food specifically) are more likely to respond to this mechanism, so we consider the effects on crime of any type, theft, crime at grocery stores, and theft at grocery stores.[12] We also compare the effects on the post-policy change range of disbursement dates (the 2nd to the 23rd of each month) to the old primary disbursement date (the 1st) and the remainder of the month during which there is never

[11]We have also considered a model which drops February 2010 entirely. Estimates indicate a decrease in crime and theft by 3.9 and 11.2 percent, respectively, which is statistically similar to Column 1 of our main results table at the 99% level.

[12]Although there are reasons to believe that battery, assault and drug crimes may also respond, we find no evidence that any of these types of crimes respond to the policy.

SNAP disbursement (the 24th to the 31st), and present visual evidence of the day-by-day distribution of monthly crime levels before and after the policy change. Geographically, we compare neighborhoods in Chicago with high and low SNAP enrollment, and high and low concentrations of SNAP retailers (both relative to the median across the city in 2010).

Finally, we consider the extent to which baseline specification choices drive the results of this analysis. We begin by estimating nonlinear functions of the days from cutoff, then estimate a count model to confirm that our choice of OLS does not drive our results. We additionally show results from models using triangular kernel weighting and provide evidence that the main findings are consistent for a range of bandwidths.

4.2 Variation by Last Name

Our second estimation strategy compares the monthly criminal patterns of groups of individuals with different SNAP disbursement dates. To do so, we exploit a noteworthy feature of Indiana SNAP issuance policies – specifically that distribution dates are based on the first letters of SNAP recipients' last names – to identify how benefit receipt affects criminal behavior.

Indiana also changed its disbursement schedule during our period of study, moving all "letter groups" to different days later in the month. This allows us to capitalize on variation within calendar days *and* within letter groups in our identification. We build a letter-by-date panel from 2012-2016 containing the counts of various types of crime, and for each date we calculate the "days since disbursement" ($days\ since_{lt}$) for each letter according to the disbursement schedule.[13]

Given that crime levels fluctuate within calendar months, and benefits may be exhausted in less than four weeks, it may be the case that SNAP distribution affects criminal behavior differently across weeks in the benefit month. We first estimate an equation of the following form:

$$y_{lt} = \beta_0 + \beta_1 * week2_{lt} + \beta_2 * week3_{lt} + \beta_3 * week4_{lt} + \gamma_l + \pi_t + u_{lt} \quad (2)$$

[13]The policy change means that for a given day of the calendar month, each letter group has two different values for $days\ since_{lt}$.

where y_{lt} is the number of crimes committed by individuals whose last names starts with letter l (of the alphabet) on day t, $week2_{lt}$ is an indicator variable equal to one if it has been at least 7, but less than 14 days since potential SNAP receipt for letter l, based on the Indiana SNAP issuance schedule, $week3_{lt}$ is an indicator variable equal to one if it has been at least 14, but less than 21 days since potential SNAP receipt, and $week4_{lt}$ is an indicator variable equal to one if it has been at least 21 days since potential SNAP receipt. Additionally, we include letter fixed effects, γ_l, to account for systematic differences in criminal behavior across first letter of last name and time fixed effects, π_t, which include month, year, day-of-month, and day-of-week fixed effects to control for crime variation across months and years. We cluster our estimates on the first letter of last name.[14]

We estimate effects relative to the first week of benefit distribution for two reasons. First, if SNAP benefits induce an income shock that is consistent with inciting criminal behavior, we will be able to measure how much crime decreases in the weeks following that initial shock. Second, if recipients do run out of benefits within 2-3 weeks, it is important to estimate the effects of crime at the end of the benefit month when resources are most scarce.

Alternatively, we can model crime as a function of the distance from the disbursement date. To estimate the extent to which crime levels respond to SNAP receipt nonlinearly, we estimate the following flexible model:

$$y_{lt} = \beta_0 + \beta_1 * days\ since_{lt} + \beta_2 * days\ since_{lt}^2 + \gamma_l + \pi_t + u_{lt} \tag{3}$$

[14]We acknowledge that last name letter may have systematic differences across race and/or ethnicity. We note that when replicating Table 3, additionally controlling for race, ethnicity, and gender, all estimates are statistically similar to the main results at the 99% level. These results suggest that it is unlikely that groups of individuals with the same last name letter change their criminal behavior in an identical and systematic manner over time, orthogonal to SNAP staggering policy changes. Therefore, we assert that the differences in issuance timing by last name represent as-good-as-random variation.

where $days\,since_{lt}$ measures the number of days since an individual could have been issued SNAP benefits, based on last name, γ_l are letter fixed effects and π_t are time fixed effects, including year, month, day-of-month and day-of-week fixed effects. Analyses allow errors to be correlated within last name letter over time when constructing standard-error estimates.

For comparison, we also present estimates from a regression discontinuity model, similar to our Illinois analysis, exploiting the February 2014 policy change in Indiana using a day-level specification that corresponds to Equation 1. In the Indiana policy change, the number of days of SNAP issuance and the density of recipients per day did not change, but the distribution days changed from the 1st-10th of the month to the 5th-23rd of the month, which allows us to measure how shifting, rather than staggering, SNAP benefits affects crime.

Lastly, we note that since we do not have information on SNAP receipt, all estimates will measure intent-to-treat effects. Therefore, any estimates based on the above methods will understate the true effects of in-kind transfers on crime.

5 Results

5.1 Within-State Policy Change Results

5.1.1 Main Results

First, to analyze the extent to which staggering SNAP benefits reduces crime, we present graphical evidence in Figures 1 and A1 for the MSE-optimal bandwidth and full bandwidth, respectively. Each figure plots residualized monthly means of daily, Census Tract-level counts.[15] The months to the left of the vertical line are before the policy change, indicating that the distribution of benefits occurred primarily on the 1st of the month. The months to the right of the vertical line are after the policy change when SNAP benefit issuance was more spread out from the 1st to the 23rd. We also

[15]Monthly cyclicity in crime is particularly pronounced in Chicago given its cold winters. Appendix Figure A2 replicates these figures for crime at grocery stores and theft at grocery stores without differencing out weather and Census Tract fixed effects, and the conclusions are similar.

display linear fits and 95% confidence intervals for the Census Tract-by-day counts of the crimes (after removing weather effects and Census Tract fixed effects).

Overall, we estimate large and statistically significant reductions in overall crime and theft (top rows). Moreover, crime and theft occurring at grocery stores (bottom rows) both exhibit large drop-offs after the policy change, and the effect on theft at grocery stores is particularly striking.

Table 1 presents estimates from the same comparisons shown in Figures 1 and A1 based on the OLS model described in Equation 1. The results include both average effects for the full bandwidth and MSE-optimal bandwidths (Columns 1 and 2, respectively) as well as results by day-of-month ranges for all four crime outcomes (Columns 3-5). We also report the pre-period means for each time span by crime type. Standard errors are clustered on the Census Tract-level, although results are robust to clustering on the days from the cutoff.[16,17]

These empirical results in Columns 1 and 2 largely reinforce the conclusions that can be drawn from the figures - staggering SNAP benefits leads to a decrease in overall crime by 3.9-13.1 percent and theft by 10.5-11.4 percent, driven by reductions in crime at grocery stores and theft at grocery stores by 17.5 percent and 20.9 percent, respectively.[18] These effects correspond to approximately

[16]Clustering on the days from the cutoff would be the analog of clustering on the running variable in a regression discontinuity model. We note that our approach of clustering on Census Tract leads to more conservative estimates.

[17]These results hold even when we do not account for time fixed effects. See Figure A2 for a replication of Figure A1 with non-residualized means.

[18]We also find similar results for theft at retail stores, residences, and street theft (reduction of 15.0 percent, 12.5 percent, and 8.8 percent, respectively). However, we estimate statistically insignificant effects for ATM and bank thefts. These results imply that staggered SNAP policies are likely targeting resource scarcity more so than financial insecurity. Estimates on retail store thefts, street thefts, and thefts at residences, combined with our results on grocery store thefts, indicate that staggering SNAP benefits led to 16 fewer thefts per day citywide, accounting for up to 70 percent of the total crime reduction and 85 percent of the reduction in thefts.

835 fewer crimes at grocery stores and 687 fewer thefts at grocery stores per year in the city of Chicago and imply that issuing benefits later in the month can help families better consumption smooth and avoid resource scarcity during the end of the month.

5.1.2 Timing Results

Our results generally indicate that crimes go down after staggering SNAP benefit issuance dates. However, it is unclear what is driving this effect. To examine potential mechanisms, we consider the days and locations most likely to be most affected by the policy change. If recipients are resource-constrained and commit crimes at the end of the month in response to an inability to smooth consumption, we might expect to see crime levels in the latter part of the month experience larger drops compared to days earlier in the month. On the other hand, if recipients now receive fewer resources on the first, we may expect to see reductions in crime earlier in the month. In this section, we consider evidence on the differential effects of the Illinois policy change across the days of the month.

To estimate the effects of benefit staggering on the timing of criminal behavior, we identify three distinct ranges of days within each month in which we may expect to see differential effects of the Illinois policy change: the 1st of the month, the 2nd to 23rd, and the 24th to the end. Prior to the policy change, over 60 percent of SNAP benefits were given out on the first of the month, but after the change they were spread over the 1st to 23rd, implying a large reduction in the benefits given out on the 1st, and an increase in those given out on days ranging from the 2nd to the 23rd. No SNAP recipient ever received benefits from the 24th to the end of the month.

Importantly, if consumers are able to fully smooth consumption throughout the month, we would not expect a change in issuance timing to affect behavior. To show how consumers respond to this change, we present SNAP redemptions data in Figure 2.[19] Prior to the policy change, nearly

[19]Figure A3 additionally shows the month-level means and linear fits for SNAP redemptions analogous to Figure A1. While SNAP redemptions increase over time, there is no distinct discontinuity in redemptions after February 2010, indicating that the policy change was not simultaneously

6 percent of all SNAP benefit redemptions occurred on the first of the month and 12 percent on the second, with approximately 2-3 percent redeemed each day 2-3 weeks after receipt, and less than 2 percent redeemed each day in the last week of the month. After Illinois began to stagger benefits, however, the percent of SNAP benefits redeemed on the first of the month fell to only 3 percent and remained more consistent throughout the month. Therefore, Figure 2 indicates that consumers do alter shopping behavior when benefit distribution days change. It is reasonable to believe that recipients also change consumption behavior and other behaviors, like criminal involvement, when they experience an income shock later in the month.

Table 1 Columns 3-5 present estimates based on the OLS model in Equation 1 restricting the sample to the day groups discussed above (1st of the month, 2nd to 23rd, 24th to 31st). Estimates in Column 3 indicate that on the first of the month, theft, crime at grocery stores, and theft at grocery stores do not change as a result of staggered SNAP benefits. Estimates for overall crime levels are negative and statistically significant. This may be because staggered SNAP distribution influences other types of criminal behavior, such as alcohol or drug crimes, not captured in the grocery theft or grocery crime estimates, and therefore has the ability to diminish large first-of-the-month income shocks.[20,21]

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paired with a large increase in total benefits.

[20]Another potential explanation is that, after the policy change, the first of the month becomes the end of the benefit month for many households. Therefore, it's possible that any first-of-the-month effects from other sources of income are mitigated by the availability of nutritional assistance. We explore this possibility in the following section.

[21]The existing literature on cash transfers and first-of-the-month shocks seem to indicate that this may indeed be the case. For example, evidence from cash transfer programs, like Temporary Assistance for Needy Families (TANF) and Supplemental Security Income (SSI), indicate that recipients are much more likely to engage in drug usage after receipt; in particular, beneficiaries are 2.5 percent more likely to die of drug-induced mortality and 15-18 percent more likely to be hospitalized from drug-related illness right after benefit issuance (Evans and Moore (2011);

Columns 4 and 5 of Table 1 present findings for days 2-23 and days 24-31, respectively. All of the estimates in Column 4 are negative and statistically significant, implying that the policy change caused a reduction in all reported types of crime. In particular, thefts in the city of Chicago decreased by 14.7 percent. However, we also estimate large changes in thefts and crimes at grocery stores. The magnitudes of these effects suggest that staggered SNAP distribution led to a 33.6 percent reduction in grocery store theft and approximately a 25.6 percent decrease for grocery store crimes in days 2-23. Taken together, these results suggest that staggering SNAP benefits has the potential to reduce crimes associated with resource constraints in the first three weeks of the month, when families begin to exhaust their benefits. However, estimates in Column 5 are statistically insignificant. These findings indicate that staggering SNAP benefits does not change recipient behavior in the never-treated range (days 24-31), which implies that although staggered SNAP policies can lower overall crime levels, especially in days 2-23, recipients may still feel resource constrained at the very end of the calendar month, before receiving other income transfers.

To further explore the dynamics of the effects over the month, we plot the mean Census Tract-level crimes (after differencing out year and month fixed effects) by day of month in Figure 3.[22] The solid line is a polynomial fit of these means for the months after the policy change (when SNAP benefits were staggered from the 1st to 23rd). The dashed line corresponds to the time before the policy change, when SNAP was mostly disbursed on the 1st of the month. The area between the two vertical lines contains the range of days over which many more SNAP disbursements were given out after the policy change.

With the exception of a decrease on the first of the month, overall crime and thefts, which are shown in the top rows, do not appear to exhibit any systematic changes due to the policy. Conversely, both crime and theft at grocery stores are higher after the policy change from the 2nd to the 10th, and then much lower for the remainder of the month (except for the very end). We also find large "first-of-the-month" effects, which appear to be somewhat mitigated by the change

Dobkin and Puller (2007)).

[22]These plots can be compared to Figure 2 in Foley (2011).

in disbursement.[23]

5.1.3 Geographic Results

If SNAP distribution affects the available resources for SNAP recipients and/or communities where a large proportion of SNAP recipients live or shop, then crime rates will be more responsive to the policy change in areas of high SNAP usage. Moreover, if individuals have a propensity to commit crimes in groups based on a shared influx (or lack) of resources, smoothing disbursement may help to reduce overall crime. We explore these possibilities by first considering geographic subgroups according to two metrics of SNAP usage in Chicago: the proportion of residents enrolled in the SNAP program and the number of certified SNAP retailers. We define high (low) SNAP enrollment as having more (less) than the median percentage of SNAP enrollees in a Census Tract, and define high (low) SNAP retailer concentration as having more (less) than the median number of SNAP retailers in a Census Tract.[24]

Table 2 contains results by these subgroups of Census Tracts. Column 1 replicates the baseline estimates presented in Table 1 Column 1 for reference. Columns 2 and 3 contain the results for low and high SNAP enrollment rates, respectively, which are obtained by estimating Equation 1 for the given subgroup. For both crime and theft in general, we estimate negative and statistically significant reductions across nearly all columns. Effects for crime and theft comparing high and

[23]Due to the large spikes in crime on the first of the month, one concern is that the default reporting date of a crime is the first if the date is otherwise unknown. While this is unlikely, it would not cause concern for identification unless reporting systematically changed on the same date as the policy change. We find no evidence of first-of-the-month effects for crimes occurring at grocery stores.

[24]According to the American Community Survey (ACS), the median percentage of SNAP enrollees by Census Tracts in Chicago in 2010 is 13.6 percent. The median number of SNAP retailers is 2, and the number ranges from 0 to 18. See Figure A4 for a map of SNAP retailers and grocery store crimes in Chicago Census Tracts.

low enrollment and retailers are statistically similar for each neighborhood group, suggesting that staggered SNAP policies have the potential to affect criminal activity city-wide. However, only high enrollment areas experience a statistically significant decline in crime and theft at grocery stores. Specifically, crime at grocery stores declines by approximately 24 percent, while theft at grocery stores declines by 32 percent in these Census Tracts.

Differences between these areas could also reasonably be attributed to the lack of grocery stores.[25] The last two columns in Table 2 address this idea directly. If SNAP recipients are committing theft or other impulsive crimes at grocery stores, they are likely to do so in stores that accept SNAP. Therefore, we may expect the effects to be larger in Census Tracts that have a large number of SNAP retailers. Indeed, estimates in Column 5 provide support for such a story. Crime at grocery stores declines by 24.2 percent in Census Tracts with a high concentration of SNAP retailers; we do not find any evidence of reductions in grocery store theft or crime in neighborhoods with few SNAP retailers. Similarly, staggering SNAP benefits reduces theft at grocery stores by 28.8 percent in Census Tracts with a high concentration of SNAP retailers.

5.2 Variation by Last Name Results

5.2.1 Main Results

In the section above, we show that staggering SNAP benefits has the potential to reduce crimes across the month; however, we cannot speak to when these crimes occur relative to a particular individual's receipt date. To disentangle the effects of benefit issuance from monthly crime cycles, we first present trends in crimes committed over the benefit month and calendar month. Here, "benefit month" is defined as the month-long time span between disbursements for a given individual. That is, the "first" of the month corresponds to the first day on which SNAP benefits are available (their disbursement date). We compare crimes committed to the number of days since

[25] While we have considered using a subgroup of only food deserts, as defined by the USDA, estimates are imprecise and therefore less meaningful for this analysis.

a convicted individual would have received SNAP benefits, based on the first letter of their last name.[26] Figure A5 displays the average number of crimes committed by days since SNAP receipt and the average number of crimes committed by calendar day, controlling for month and year fixed effects. These figures suggest that criminal behavior spikes on the first of the month, but remains fairly stable over the calendar month, decreasing in the third week and increasing in the fourth week. When observing crimes as a function of days since SNAP receipt, however, cyclicality is much less pronounced, as overall crime and theft do not seem to experience such sharp first of the month effects. Interestingly, theft and alcohol crimes increase at the end of the benefit month.

Table 3 Panel A presents estimates that measure how crime fluctuates in the weeks following SNAP distribution. Estimates are relative to the first week after SNAP receipt, as we may expect crime to be either highest (if SNAP benefits provide enough of an income shock to encourage criminal behavior) or lowest (as resources are the least constrained in the first week of receipt) in this week. In the second week following potential SNAP receipt, there is no statistically significant effect on criminal behavior for any crime type relative to the first week. From 14-21 days after SNAP issuance, overall crime levels fall by about 4.1 percent, although estimates for all other crime types are statistically insignificant. In the fourth week of the benefit month, alcohol crimes increase by 11.7 percent.[27] It is possible that financial stress near the end of the month increases incentives to drink heavily, or, alternatively, that as food becomes more scarce, recipients have a lower threshold for intoxication.[28]

Following Foley (2011) we additionally show these results grouped by three days instead of weeks in Figure A7 and Table A3. When grouping effects into more bins, estimates for overall

[26]For example, if John Smith committed a crime on the 27th in 2014, he would have potentially had SNAP benefits issued to him on the 19th, 8 days previously. Although the crime would be recorded as 27 days into the calendar month, we additionally classify the crime as being committed 8 days into the benefit month.

[27]Alcohol crimes include public intoxication and driving while intoxicated.

[28]For a graphical depiction of these results, see Figure A6.

crime levels and drug crimes are statistically insignificant for all day groups. However, we find that theft and alcohol crimes increase in days 27-31 of the benefit month, or 4 weeks after SNAP receipt.

These findings suggest that, unlike other in-kind or cash transfers that are distributed at the beginning of the month, staggered SNAP benefits do not incentivize criminal behavior at the beginning of the benefit month relative to other times of the month. This could be due to the fact that SNAP benefits are relatively small in-kind transfers (about $127 per person per month) or, as a recent study has found, that individuals do not view SNAP benefits as fungible (Hastings and Shapiro, 2017).

Since Figure A5 and results in Panel A of Table 3 indicate that SNAP distribution dates and criminal behavior are related nonlinearly, Table 3 Panel B shows effects of SNAP issuance on crime quadratically controlling for days since receiving SNAP. While crime levels decrease at the beginning of the benefit month, they exhibit a positive and increasing relationship at the end of the month, approximately after 28 days. Contrary to other studies on cash transfers, we find no effects of SNAP receipt on drug crimes. As in the week-by-week results in Panel A, crime levels hit their lowest point when we expect beneficiaries to exhaust benefits, and average crime levels increase at the end of the benefit month when resources are most scarce. Findings from Panels A and B suggests that recipients stay home and commit less crimes during the second and third weeks of the benefit month, relative to the first week, and increase criminal involvement right before receipt. One potential explanation is that beneficiaries experience an income shock in the first week, which lends recipients the ability to go out with friends and/or purchase complements of crime. However, during the second and third weeks, there are no available funds for leisure, and recipients stay home. By the end of the benefit month, recipients have run out of food or other resources, and commit more crimes as a way to alleviate this scarcity. To elucidate the complex nature of this relationship, we explore subgroups of individuals in the next section.

5.2.2 Subgroup Analysis

It may be the case that individuals of various age, race, ethnicity and gender are affected by SNAP policies differently, likely due to differential participation rates in the program.[29] To explore the extent to which criminal behavior between these subgroups varies, we estimate effects of staggered SNAP benefit timing on convicted crimes and show these results in Tables A5 (race, ethnicity, and gender subgroups) and A6 (age subgroups).

About 3 percent of the sample of Indiana offenders is Hispanic, 28 percent is black, 68 percent is white and 15 percent is female. In Table A5, Panel A shows the effects of staggering SNAP benefits on crimes committed by white persons; as expected, estimates are similar to the main results for Indiana and indicate a decrease of overall crime and theft in the third week after receipt. Panels B and C display effects for African Americans and Hispanics, respectively, and nearly all estimates are small and statistically insignificant. Panel D presents estimates for females. Importantly, estimates indicate that theft increases by 14.2 percent in the fourth week of the month after receiving SNAP benefits. This suggests that females are more likely to steal food or other resources after exhausting their benefits.

Given that females are especially affected by such policies, we expand on this analysis by examining the effects of SNAP disbursement changes on crimes by females for three day groups in Table 4 to get a better sense of how the timing of criminal behavior is affected during the fourth week of the benefit month. Findings indicate that theft increases by 26.5 percent 24-26 days after receipt and 21.6 percent 27-31 days after SNAP receipt. Overall, these effects correspond to 551 more thefts (resulting in conviction) in the 3rd and 4th weeks following benefit receipt by females in the State of Indiana over a four-year period.[30] Combined with findings from Table A6, which in-

[29]We also estimate effects of SNAP staggering in Indiana counties with below and above average rates of SNAP usage and display these results in Table A4. Estimates indicate similar patterns for each crime type. It may be the case that county-level data are insufficiently granular to capture potential spillover effects that SNAP benefits have on communities as a whole.

[30]This calculation is based on the fact that there were 1,146 total thefts committed by females

dicate that effects on theft are driven by individuals above the age of 40, our results imply a striking conclusion: at the end of the month, older women commit theft as a way to provide resources for their families. This narrative is especially troubling when considering potential spillover effects to children. For example, if single mothers commit more crimes as a result of resource scarcity, making them more likely to lose government financial assistance or even face incarceration, it could impose large costs on their families as well.

When separating effects by age group, shown in Table A6, we note that effects on alcohol crimes are driven by the youngest age group, 18-24 year olds.[31] Since this group is the most likely to abuse alcohol, and estimates correspond to approximately 36 crimes per year, this result is perhaps less troubling from a social welfare perspective.

5.2.3 Indiana's Policy Change

We also replicate the policy change analysis from Section 5.1.1 using data from Indiana. In January 2014, the State of Indiana altered the SNAP issuance policy dates from the first ten days of the month to a more spread out distribution schedule, starting on the 5th and ending on the 23rd. To phase in this change, in the month of January only, SNAP clients received half of their benefits on the 2013 date and half on their new date. By February 2014, the new schedule took full effect. See Table A1 for the SNAP issuance schedules.

We use this within-state variation to analyze how shifting benefit issuance towards the middle of the month affects criminal behavior. To do so, we provide corresponding figures to show how crime levels responded to the change in policy just after February 1, 2014. Figures A8 and A9 present average monthly crime levels over time, controlling for daily weather patterns. We note that shifting the SNAP benefit schedule seems to have a less immediate impact than expanding the

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between 2012-2015.

[31]Results indicate that alcohol crimes increase by 33 percent 21-30 days after SNAP distribution, however, given the relatively low baseline, this corresponds to only 36.1 more crimes per year. This is based on a daily mean of 0.099 alcohol crimes committed by 18-24 year olds in Indiana.

number of benefit days.

Table A7 contains the analogous point estimates (from estimating a state-wide version of Equation 1), as well as separate estimates for the 1st-5th of the month, which were treated prior to the policy change but not after, days 6-10, which were treated in both periods, days 11-23, which were only treated after the policy change and days 24-31, which were never treated. Notably, Indiana enacted sentencing reform in June 2014, which affected the classification of crimes committed within the state.[32] Due to this change, we drop any observations outside of a 120-day window to eliminate the possibility of this reform overstating any estimates of the SNAP issuance change.[33]

We estimate that shifting SNAP benefit distribution to later in the month reduces theft by 23.3 percent, on average, although other crime levels do not respond to this policy change. These effects are driven by large and statistically significant decreases in thefts on the first five days of the calendar month, i.e. 2-4 weeks after benefit receipt. Estimates for days 6-10, 11-23 and 24-31 are statistically insignificant for all crime types, with the exception of the overall crime level, which

[32]Specifically, the new law: “Provides that: (1) after June 30, 2014, and before July 1, 2015, a person convicted of a Level 6 felony may not be committed to the department of correction if the person’s earliest possible release date is less than 91 days from the date of sentencing, unless the commitment is due to the person violating a condition of probation, parole, or community corrections and the violation is not technical; and (2) after June 30, 2015, a person convicted of a Level 6 felony may not be committed to the department of correction if the person’s earliest possible release date is less than 366 days from the date of sentencing, unless the commitment is due to the person violating a condition of probation, parole, or community corrections by committing a new criminal offense" (General Assembly of the State of Indiana, 2015).

[33]Estimating the MSE-optimal bandwidth for each crime type yields a one-sided bandwidth of 99, 166, 145, and 125 days for crime, theft, drug crimes, and alcohol crimes, respectively. Therefore, this reduced bandwidth is smaller than the MSE-optimal bandwidth for all outcomes except the overall crime level. However, we note that we drop a maximum of 46 day observations, indicating that without sentencing reform, estimates would likely be similar, albeit more precise.

appears to increase at the end of the month, although we note that these effects are not statistically significant when we use the full sample. Given the small optimal bandwidth of 99 days, effects estimated for this 8-day range are based on few observations and are likely to be spurious.[34] These findings reinforce the same conclusion as before: staggered SNAP policies can help families to better consumption smooth and lower crimes associated with resource scarcity.

5.3 Robustness Checks

5.3.1 Model Specification

In this section, we present a set of sensitivity checks to provide additional support for our main identification assumptions. We first turn to the discontinuity-based specification. A standard concern in such models is that the results are a product of over- or underfitting the data or a product of bandwidth selection. To combat these concerns, we explore various alternative specifications in this section and show that our average estimates are robust to these other specifications.

First, we allow the function of the days from the date of the policy change (the running variable) to vary in order. Column 1 in Table 5 replicates the main (baseline average effect) results. Columns 2 and 3 contain the results when we allow for our running variable to vary quadratically and cubically on either side of the cutoff, respectively. The quadratic models generally produce results close to the baseline models. Under a cubic fit some of the estimate magnitudes are smaller, but all

[34]Specifically, it is unclear what crime types are driving this large increase in overall crime levels at the end of the month. While we estimate statistically insignificant increases in drug crimes at the end of the month (p-value=0.2), we estimate that shifting SNAP dates later in the month leads to an 177.4 percent increase in arrests for drug dealing during days 24-31 as well as increases in sex offenses. However, we find no effects specifically for drug possession, rape, or sexual battery, nor do we estimate statistically significant effects for robbery, burglary, or weapon crimes. Therefore, such policies have the potential to shift some drug crimes and violent crimes towards the end of the month, although most crime types are unaffected.

are still statistically significant and are similar to baseline estimates.

Additionally, we estimate a Poisson model due to the discrete nature of crime data. These results are shown in Table 5 Column 4. Because some tracts never have a theft or a crime occurring at a grocery store (perhaps because they have no grocery stores) a number of observations are dropped in this model for those categories. Again, the estimates are very close to the main results.

Second, we explore how sensitive the estimates are to kernel selection. In keeping with the current methodology in regression discontinuity models, we follow Calonico et al. (2016) to determine the mean square error optimal bandwidth for the RD estimator throughout the paper and estimate the model with a triangular kernel, instead of a uniform kernel, in Column 5.[35] All of the point estimates are stable when compared to the main results and statistically significant. We also use the triangular kernel to estimate the average effects on the full bandwidth in Column 6, and we find consistent results. All coefficients are negative and statistically significant, although some vary slightly in magnitude.

To further test bandwidth sensitivity, we replicate the models under a range of bandwidths. We test bandwidths from 2 months on either side to the full bandwidth (39 months) specification in increments of one month at a time. Figure A10 reports the coefficients and standard errors from models using each of these alternative bandwidths. For all outcomes, the estimated coefficient on the policy change is negative and consistent across the different bandwidths.[36]

Additionally, we conduct permutation inference using placebo estimates from pre-period crime data to provide evidence that the discontinuity observed in Chicago is a result of the SNAP policy change in the spirit of Abadie et al. (2010). To do so, we randomly select a date from 2007-2010,

[35]Although the newest version of the STATA rdrobust package does allow for the consideration of covariates in the bandwidth selection, we cannot use year and day-of-month fixed effects in this step. Because some of the fixed effects are zero in smaller bandwidths, it is unable to select one when we include them. All other covariates are included in bandwidth selection.

[36]Estimates from bandwidths ranging from 4-39 months are statistically significant at the 5% level.

and assign it as a treatment cutoff date, without replacement.[37] We then generate distributions of t-statistics based on these RD estimates, using the preferred specification in Equation 1 and MSE-optimal bandwidths associated with Table 1, to determine what percent of the simulated estimates from 1,000 random draws are less than the estimate reported in Table 1. The distributions of placebo estimates for crime, theft, grocery store crimes and grocery store thefts are shown in Figure A11. Based on these placebo distributions, 14.5 and 0 percent of t-statistics are less than the reported estimates for any crime and theft in absolute value, respectively, while 0.4 percent and 0.9 percent of placebo t-statistics are smaller in absolute value than the reported estimates for grocery store crimes and thefts, respectively, which provides additional support for the idea that the policy change is driving the reported results.

Finally, we provide additional support that the variation in Indiana SNAP issuance is comparable across groups. Table A8 displays the average crimes committed by each SNAP letter group and the available demographic characteristics. When estimating a joint comparison test, the number of convictions by letter group are statistically indistinguishable (F-stat=2.54). These statistics suggest that the letter groups are quite similar, although our use of first letter of last name fixed effects does not require this to be the case.[38]

5.3.2 Alternative Explanations

Given that monthly fluctuations in Chicago crime are driven by weather patterns, we include controls for weather variables, which include average daily high and low temperatures, snowfall, wind

[37]When randomly selecting a treatment date, we drop observations that would be included within the optimal bandwidth according to our true treatment date.

[38]We note that race and ethnicity does vary by group; however, when including demographic controls into our main analysis, all estimates are statistically similar at the 99% level, which suggests that these factors are not driving our results.

speed and precipitation, in all RD specifications.[39,40] If weather patterns changed at the same time as the implementation of the new SNAP issuance schedule, we would be concerned that our estimates overstate the true impact of changes in household behavior on crime. As shown in Figure A12, all of these weather variables are smooth across the treatment threshold. In Figure A13, we also show that our results are not being driven by sharp changes in labor market conditions using data from the Bureau of Labor Statistics.

Another important consideration is that increasing the number of SNAP issuance dates raises the probability that every month some proportion of total recipients receive benefits on the weekend. Therefore, if recipients consume different amounts or types of goods when they experience an income shock on the weekend, it may be the case that our estimates are simply accounting for weekday versus weekend consumption patterns. This may be problematic, if, for instance, recipients purchase more complements to crime (like alcohol or drugs) when receiving benefits on the weekend, or if, on the contrary, individuals are more likely to stay home and out of trouble.[41]

To explore the extent to which individuals receiving SNAP benefits on the weekend commit crime, we replicate our main results in Table A9, but additionally control for an indicator variable equal to one for any benefit issuance dates that fall on a Friday or Saturday. Although weekend benefit receipt is associated with more crimes and thefts overall, crime and thefts at grocery stores seem unaffected by whether or not individuals receive benefits on the weekend. Estimates are statistically indistinguishable from those in Table 1, and indicate that weekend benefit issuance

[39] Daily weather data for Chicago are from the Global Historical Climatology Network and are based on temperature, precipitation and average wind speeds from the Chicago O'Hare International Airport weather station.

[40] Estimates without these controls are similar to results in Table 1, and indicate that staggering SNAP benefits reduced crime and theft at grocery stores and that these declines are driven by the 2-23 day range.

[41] For support of each of these stories, see Castellari et al. (2017) for evidence of the former, and Cotti et al. (2015) for evidence of the latter.

does not play a major role in affecting a recipient's ability to consumption smooth during the month.[42]

Finally, these estimates may overstate the extent to which staggering benefits reduces crime if it changes the likelihood of getting caught for a grocery store crime or theft. Specifically, if the policy change shifts crowds to other SNAP disbursement dates, more crimes may go undetected. Our estimates imply that reporting bias due to grocery store crowding is unlikely in this context, as we do not see a large increase in SNAP redemptions on the 12 issuance dates as a percent of total sales before and after the policy change.[43] Although the reduction in shopping on the first of the month is substantial, the increase on other days small - around 1 percent more in spending each day.[44,45] Lastly, we note that since overall incidences of theft decreases after the policy change, our

[42]We additionally provide similar results, controlling for weekend paydays (i.e. an indicator variable equal to one if the 1st or 15th of the month falls on a Friday or Saturday) in Table A10 to explore how other potential income shocks could affect crime. We use these dates due to the fact that over 36 percent of American businesses (and 72.9 percent of businesses with over 1,000 employees) have a biweekly pay schedule (Burgess, 2014). Effects remain largely unchanged.

[43]Additionally, we may expect that suppliers are able to anticipate demand and displace crowding through higher prices on SNAP receipt days. Recent evidence suggests that Illinois grocers did not change prices as a result of SNAP benefit staggering, indicating that SNAP beneficiaries likely crowd out other customers on receipt days (Goldin et al., 2016).

[44]Moreover, if large stores experience crowds every day of the month, they may be less likely to respond to changes in SNAP policy. See Table A11 for an analysis of the effects of staggering benefits in Census Tracts with supermarkets. Estimates are similar to the main results and indicate an overall reduction in grocery store crime and theft driven by reductions from the 2nd-23rd.

[45]Another alternative explanation is that when the number of SNAP issuance days increases, stores respond by stocking less fresh or perishable (i.e. more "valuable") items near the beginning of the month due to the drop in potential customers, which incentivizes less crime. However, when analyzing effects for Census Tracts with supermarkets (Table A11), which sell fresh food more

findings point to changes other than grocery store staffing and reporting.[46]

6 Discussion

In this paper we document a stark effect of dispersing distribution of SNAP benefits over a larger span of days each month – a reduction in the number of overall crimes and thefts, with much larger effects for crimes and thefts that occur in grocery stores. To measure this effect, we examine the responses to a large policy change in the city of Chicago. Prior to this change, over two-thirds of SNAP benefits were given out on the 1st of the month, and after, benefits were spread over the 1st to the 23rd. We test for discontinuous changes at the time of this policy, and find that crime and thefts at grocery stores fall by approximately 18-21 percent after the policy change, corresponding to 2.5 fewer grocery store crimes across the city per day. Our results show that reductions in criminal behavior at grocery stores spillover to other crimes as well; we estimate that staggering SNAP benefits led to approximately 43 fewer crimes in Chicago, driven by an reduction of 26 fewer thefts per day, or nearly 9,500 thefts per year. We find no evidence to support the idea that changes in crime detection are responsible for the drop in reported crimes.

Given the fact that incidence of grocery crimes not only falls on the first of the month, but remains lower throughout the month after the policy change, it is likely that when participants are better able to smooth food consumption, it leads to both less economic activity at the beginning of the month and also less financial desperation at the end of the month. Moreover, increasing the number of SNAP distribution days reduces the chance that groups of individuals in low-income communities all receive benefits at the same time. Therefore, staggering SNAP benefits has the potential to eliminate or reduce the presence of negative peer effects within communities caused by simultaneous income shocks. Such distribution schedules also have the potential to aid in community-level consumption smoothing, reducing the need for residents to commit crimes to

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consistently, we do not find evidence for such an effect.

[46]Importantly, we estimate similar reductions in street theft and theft at retail stores and residences, suggesting that the reporting of theft was not affected by the policy change.

obtain basic resources. Given the evidence that staggered cash transfers from programs like TANF can reduce crime by 21 percent (Hsu, 2016), our estimates fit into a broader literature on how changing the timing of other government transfers can affect total social welfare.

We also analyze how the benefit month and calendar month vary and find that criminal activity is highest in the first and fourth weeks after SNAP issuance, with a decrease of 4.1 percent in the third week after disbursement. We document evidence of a quadratic relationship between SNAP benefits and criminal behavior, where crime increases immediately after SNAP receipt and again at the end of the benefit month. While we find effects of SNAP disbursement on overall crime level, we do not see effects for drug crimes. Conversely, we find that alcohol-related crime peaks just before benefit issuance, and that theft also peaks at this time. The results for theft are driven by females and older individuals. Moreover, we find that shifting SNAP benefits later in the month reduces crime and theft, on average, and these reductions are concentrated 2-4 weeks after receipt, when households begin to exhaust benefits. Altogether, our findings suggest that low-income families are most affected by benefit timing policies, and that small changes to benefit timing could have positive spillover effects for non-SNAP recipients.

These findings are important for understanding the choices that families in poverty face in response to the timing of government transfers. Our results suggest that families may seek illicit income during the parts of the month during which they experience relative scarcity, echoing findings that many families run out of SNAP benefits well before the end of the month (Castner and Henke, 2011). Our results support and refine the conclusions in Foley (2011) establishing that financially motivated crimes aimed specifically at obtaining food respond to such policy changes.

Taken with the existing evidence on consumption patterns of SNAP recipients and the other social and personal benefits of spreading out the distribution of government transfers, our findings have substantial policy implications. First and foremost, staggering SNAP benefits over the course of the month decreases crime and theft, particularly at grocery stores. In the case of Chicago, it reduced the number of annual grocery store crimes by over 800 and annual grocery store thefts by over 680. While the number of prevented crimes may seem low, such policies have the potential to yield large benefits compared to the cost of staggered rollout. Since benefits are distributed electronically, the total costs of staggering are often small; in 2013, Illinois estimated a cost of $294,010 of changing issuance dates, with a large majority of spending (73.9 percent) due to informing beneficiaries of the upcoming change. According to estimates of the costs of crime by Heaton (2010), staggering SNAP issuance led to over $1,442,000 in annual benefits for the city of Chicago just in grocery store theft reductions alone.[47] This estimate does not take into consideration spillover effects on other types of thefts or crime in general, which would imply that such policies vastly outweigh the cost of implementation.

Finally, we note that deliberately scheduling the delivery of benefits so that families receive transfers over the course of the month would benefit families and communities more broadly. Careful scheduling of other transfers families receive in conjunction with SNAP (such as wages from work or TANF) could also help to alleviate consumption shocks, as could splitting families' monthly benefits into multiple staggered payments.

[47]This is based on approximately $2,100 in costs per larceny crime and our estimated 21 percent reduction in grocery store thefts.

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Table 1: Effect of Staggering SNAP Benefits on Crime

			Day of Month Range		
	Average Effect	Average Effect	1st of Month	Days 2-23	Days 24-31
Crime					
SNAP Staggered	-0.0531***	-0.1439***	-0.4855***	-0.1646***	0.9530
	(0.0085)	(0.0384)	(0.1399)	(0.0514)	(6.0892)
Pre-Period Mean	1.377	1.101	1.592	1.137	1.011
N	1941114	72802	2454	53170	17178
Theft					
SNAP Staggered	-0.0316***	-0.0267***	0.2546	-0.0379***	0.0081
	(0.0040)	(0.0049)	(0.1862)	(0.0058)	(0.0133)
Pre-Period Mean	0.278	0.255	0.324	0.257	0.245
N	1941114	231494	7362	170144	53988
Crime at Grocery					
SNAP Staggered	-0.0039***	-0.0028**	-0.0011	-0.0041***	0.0001
	(0.0012)	(0.0013)	(0.0160)	(0.0016)	(0.0024)
Pre-Period Mean	0.016	0.016	0.014	0.016	0.015
N	1941114	493254	15542	356648	121064
Theft at Grocery					
SNAP Staggered	-0.0030***	-0.0023**	-0.0011	-0.0037***	0.0015
	(0.0011)	(0.0011)	(0.0283)	(0.0014)	(0.0021)
Pre-Period Mean	0.010	0.011	0.009	0.011	0.010
N	1941114	398366	13088	287936	97342
Bandwidth	Full	Optimal	Optimal	Optimal	Optimal

Notes: Estimates are based on crime data from the city of Chicago. Each coefficient is generated by a separate Census Tract-by-day regression of Equation 1 using the listed crime type as the dependent variable and using data from all days (Columns 1 and 2) or the ranges listed at the top of each column. Daily weather data for Chicago are from the Global Historical Climatology Network and are based on temperature, precipitation and average wind speeds from the Chicago O'Hare International Airport weather station. Each regression includes year, day-of-month, and day-of-week fixed effects. Standard errors are clustered on the Census Tract level and reported in parentheses. We also report the mean of each outcome for the period before the policy change (January 1, 2007, to February 15, 2010).

*, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table 2: Neighborhood Subgroups

	Average Effect	SNAP Enrollment Low	SNAP Enrollment High	SNAP Retailers Low	SNAP Retailers High
Crime					
SNAP Staggered	-0.1439***	-0.0805*	-0.2073***	-0.1295***	-0.1589**
	(0.0384)	(0.0441)	(0.0628)	(0.0410)	(0.0658)
Pre-Period Mean	1.101	0.740	1.463	0.717	1.502
N	72802	36401	36401	37202	35600
Theft					
SNAP Staggered	-0.0267***	-0.0256***	-0.0277***	-0.0209***	-0.0327***
	(0.0049)	(0.0072)	(0.0067)	(0.0060)	(0.0079)
Pre-Period Mean	0.255	0.266	0.245	0.188	0.326
N	231494	115747	115747	118294	113200
Crime at Grocery					
SNAP Staggered	-0.0028**	-0.0018	-0.0038*	0.0001	-0.0058**
	(0.0013)	(0.0015)	(0.0020)	(0.0011)	(0.0023)
Pre-Period Mean	0.016	0.015	0.016	0.008	0.024
N	493254	246627	246627	252054	241200
Theft at Grocery					
SNAP Staggered	-0.0023**	-0.0014	-0.0032*	-0.0001	-0.0046**
	(0.0011)	(0.0012)	(0.0018)	(0.0008)	(0.0020)
Pre-Period Mean	0.011	0.012	0.010	0.005	0.016
N	398366	199183	199183	203566	194800

Notes: Estimates are based on crime data from the city of Chicago. Each coefficient is generated by a separate Census Tract-by-day regression of Equation 1 using the listed crime type as the dependent variable and using data from all Census Tracts (Columns 1 and 2) or the Census Tracts described at the top of each column. Daily weather data for Chicago are from the Global Historical Climatology Network and are based on temperature, precipitation and average wind speeds from the Chicago O'Hare International Airport weather station. Each regression includes year, day-of-month, and day-of-week fixed effects. Standard errors are clustered on the Census Tract level and reported in parentheses. We also report the mean of each outcome for the period before the policy change (January 1, 2007, to February 15, 2010).

*, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table 3: Effect of SNAP Receipt on Crimes Committed After Issuance (Indiana)

	Crime	**Theft**	**Drugs**	**Alcohol**
Panel A. Weeks Since Issuance				
Second Week	-0.019	0.002	-0.003	0.001
	(0.021)	(0.005)	(0.006)	(0.003)
Third Week	-0.035*	-0.005	-0.005	0.000
	(0.017)	(0.004)	(0.005)	(0.003)
Fourth Week	-0.009	0.003	-0.007	0.004**
	(0.018)	(0.003)	(0.007)	(0.002)
Mean	0.844	0.098	0.228	0.034
N	45630	45630	45630	45630
Panel B. Nonlinear Effects				
Days Since SNAP	-0.00746**	-0.00110	-0.00027	-0.00053
	(0.00339)	(0.00064)	(0.00100)	(0.00037)
Days Since SNAP Squared	0.00026**	0.00004*	0.00000	0.00002**
	(0.00011)	(0.00002)	(0.00003)	(0.00001)
Mean	0.844	0.098	0.228	0.034
N	45630	45630	45630	45630

Notes: Estimates are based on conviction-level crime data from the Indiana Department of Correction from 2012-2016. Each regression includes month, year, day-of-month, and day-of-week fixed effects. Robust standard errors are clustered on last name letter and are shown in parenthesis. Panel A displays estimates of SNAP receipt on criminal behavior in the weeks following issuance, relative to the first week of receipt. Panel B shows effects of SNAP issuance on crime quadratically controlling for days since receiving SNAP.

*, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table 4: Effect of SNAP Receipt on Crime Committed by Females (Indiana)

	Crime	**Theft**	**Drugs**	**Alcohol**
Days Since Issuance				
3-5 Days	0.006	0.005	-0.004	0.002
	(0.008)	(0.004)	(0.005)	(0.002)
6-8 Days	0.002	0.002	0.000	-0.002
	(0.007)	(0.002)	(0.005)	(0.001)
9-11 Days	0.003	0.004	-0.013**	0.001
	(0.006)	(0.003)	(0.006)	(0.002)
12-14 Days	0.003	-0.000	0.002	0.002
	(0.008)	(0.002)	(0.005)	(0.001)
15-17 Days	0.008	0.001	0.000	-0.002
	(0.008)	(0.004)	(0.004)	(0.001)
18-20 Days	0.006	0.003	-0.009*	0.001
	(0.010)	(0.003)	(0.004)	(0.001)
21-23 Days	-0.001	0.005	-0.006	-0.002
	(0.009)	(0.004)	(0.004)	(0.002)
24-26 Days	0.014	0.008***	-0.005	0.001
	(0.008)	(0.002)	(0.004)	(0.002)
27-31 Days	0.011	0.006*	-0.002	-0.001
	(0.008)	(0.003)	(0.004)	(0.001)
Mean	0.139	0.025	0.050	0.006
N	45630	45630	45630	45630

Notes: Estimates are based on conviction-level crime data from the Indiana Department of Correction from 2012-2016 for 46,530 letter-day observations. Each regression includes month, year, day-of-month, and day-of-week fixed effects. Robust standard errors are clustered on last name letter and are shown in parenthesis.

*, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

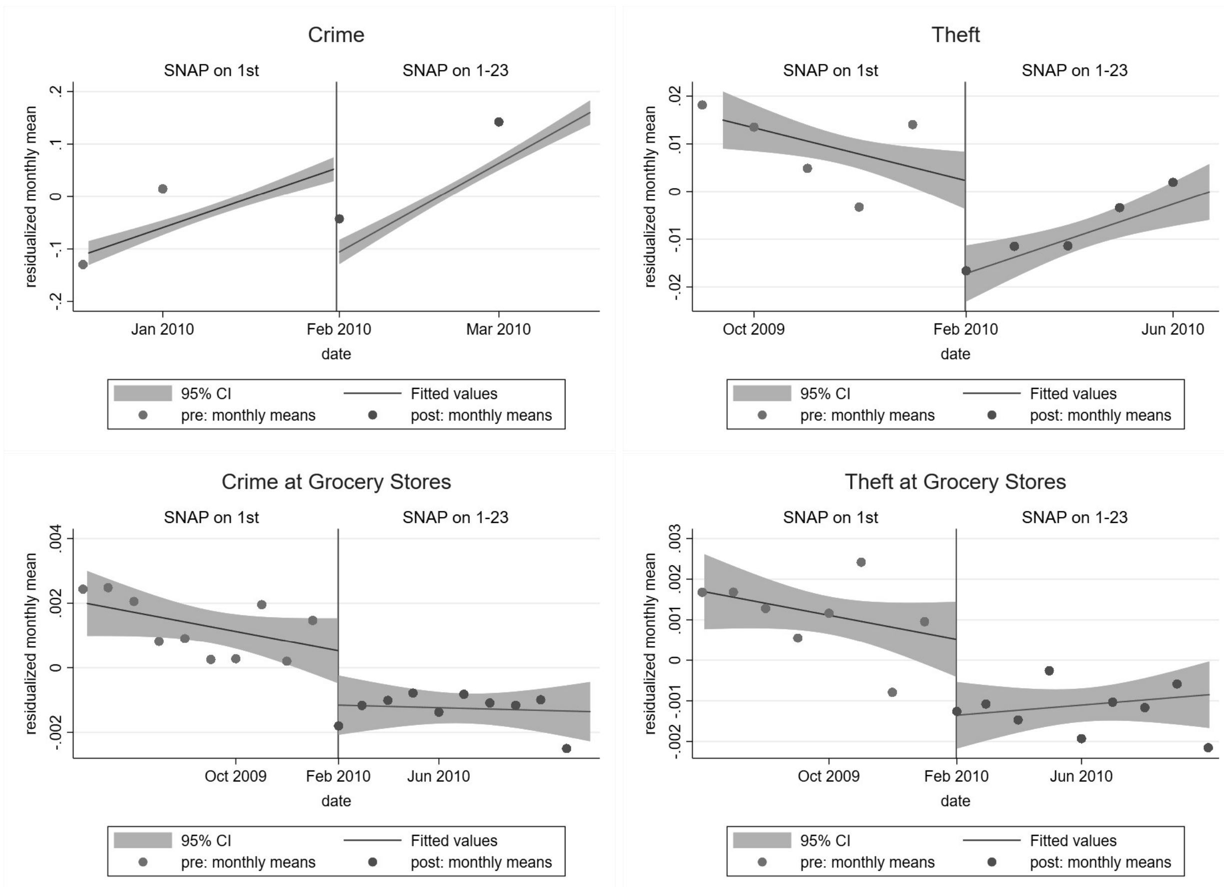
Table 5: Robustness Checks

	Baseline	Quad Fit	Cubic Fit	Poisson	Triangular Kernel MSERD Bandwidth	Triangular Kernel Full Bandwidth
Crime						
SNAP Staggered	-0.0531***	-0.0374***	-0.0242**	-0.0436***	-0.0435***	-0.1079***
	(0.0085)	(0.0092)	(0.0098)	(0.0073)	(0.0048)	(0.0216)
Theft						
SNAP Staggered	-0.0316***	-0.0324***	-0.0300***	-0.1302***	-0.0314***	-0.0205***
	(0.0040)	(0.0043)	(0.0044)	(0.0155)	(0.0019)	(0.0046)
Crime at Grocery						
SNAP Staggered	-0.0039***	-0.0036***	-0.0029**	-0.2722***	-0.0038***	-0.0038***
	(0.0012)	(0.0012)	(0.0013)	(0.0715)	(0.0004)	(0.0009)
Theft at Grocery						
SNAP Staggered	-0.0030***	-0.0029***	-0.0026**	-0.3257***	-0.0030***	-0.0020***
	(0.0011)	(0.0011)	(0.0010)	(0.0938)	(0.0003)	(0.0006)

Notes: Each coefficient is generated by a separate Census Tract-by-day regression of Equation 1 using the listed crime type as the dependent variable. Column 1 replicates the baseline results for comparison. Columns 2 and 3 allow for the days from the cutoff to vary quadratically and cubically (in addition to on either side of the threshold) respectively. Column 4 does not use OLS as previous results have, but instead reports Poisson coefficients. Columns 5 and 6 fit the model using a triangular kernel instead of uniform kernel. Column 5 uses a MSE-driven bandwidth, while Column 6 reports estimates from the full sample. One-sided MSE-optimal bandwidths for crime, theft, crime at grocery stores, and theft at grocery stores when using a triangular kernel are 52, 174, 215, and 346 days, respectively. Crime data are from the city of Chicago.

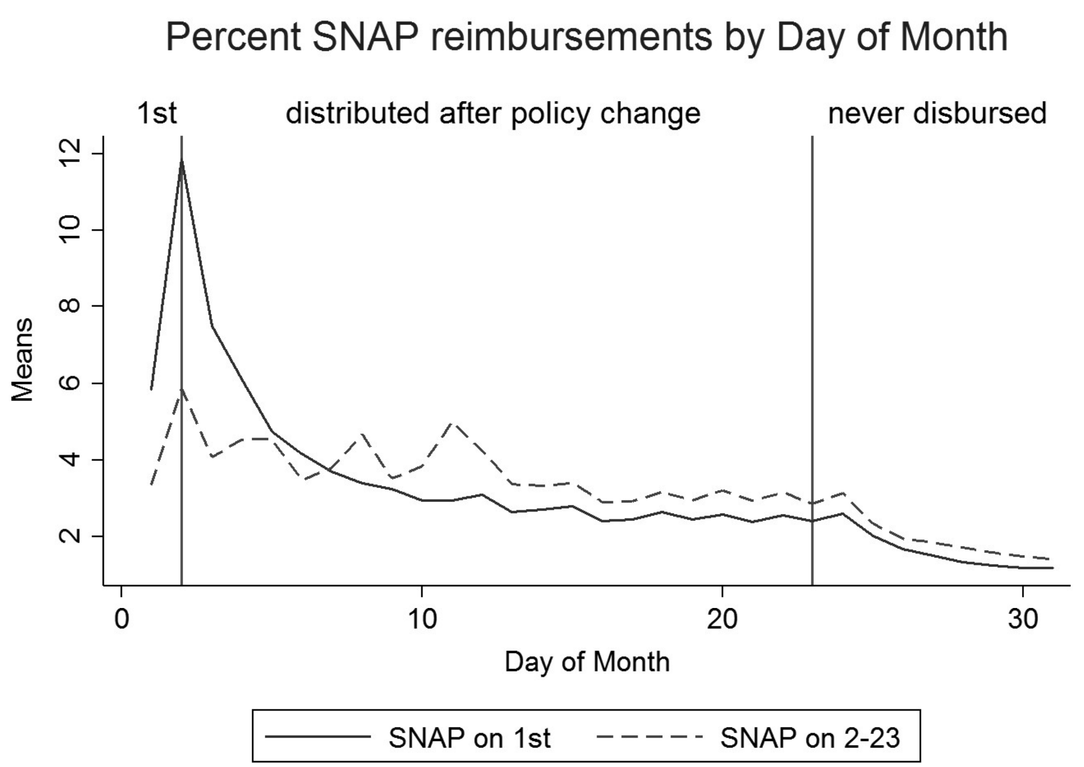
*, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Figure 1: Effect of Illinois SNAP Disbursement Change on Crime (Optimal Bandwidth)



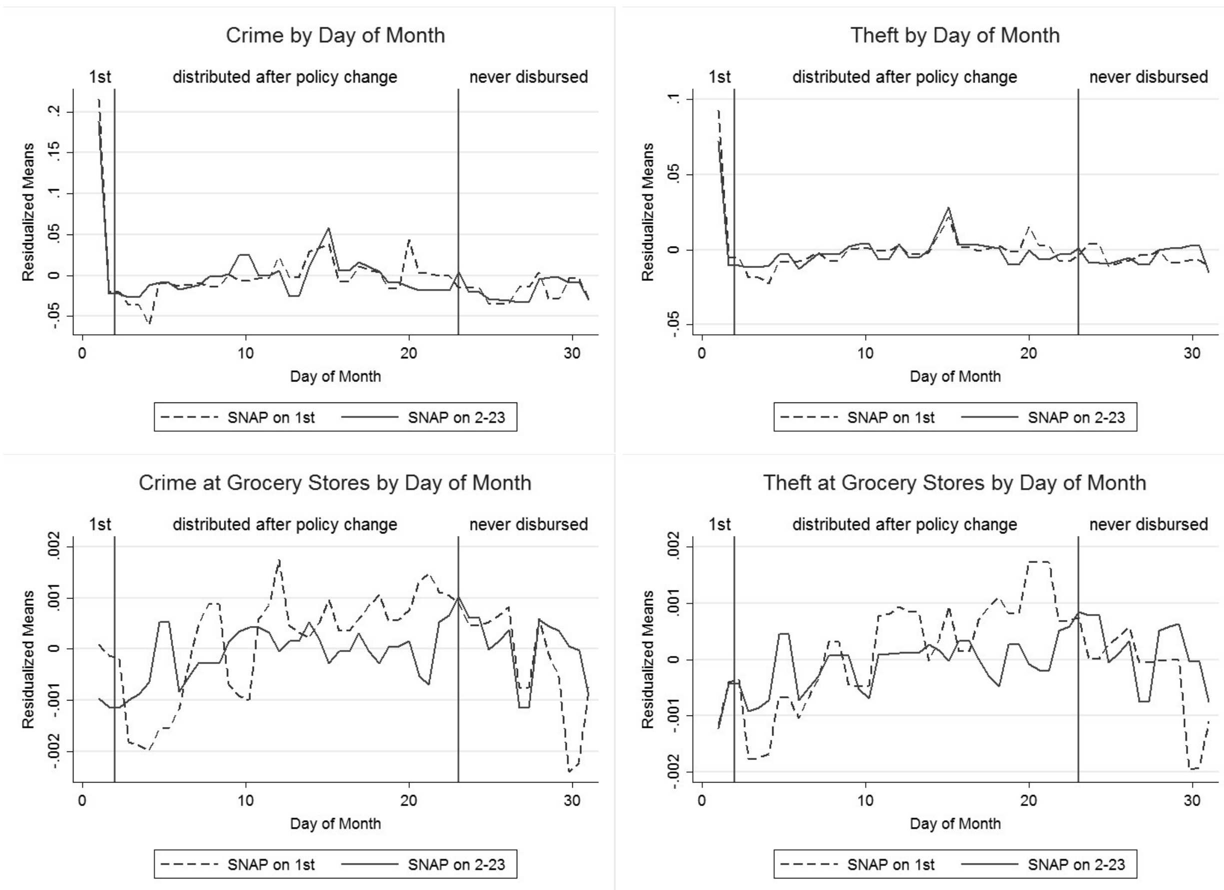
Notes: Each figure plots month-level means of residuals (after differencing out weather effects and Census Tract fixed effects) and linear fits (with 95% confidence intervals) of each of the crimes listed. To the left of the vertical line, SNAP benefits were given out primarily on the 1st of the month, and to the right, they were distributed over the 1st to the 23rd. Crime data are from the city of Chicago. Daily weather data for Chicago are from the Global Historical Climatology Network and are based on temperature, precipitation and average wind speeds from the Chicago O'Hare International Airport weather station.

Figure 2: Effect of Illinois SNAP Disbursement Change on SNAP Redemptions



Notes: Authors' calculation based on daily SNAP redemptions data from the Illinois Department of Health and Human Services. The solid line is calculated for January 2007 - January 2010. The dashed line, indicating the post-period after the policy change, is calculated for February 2010 - May 2013.

Figure 3: Crime by Day of Month



Notes: Each figure displays residualized (for month and year differences in levels) kernel-weighted local polynomial plots of crimes of each denoted type on the Census Tract level across days of the month. The range of days between the vertical lines contains the “new" distribution dates after the policy change. The area to the right (the 24th-31st) includes days on which SNAP benefits were never distributed. Crime data are from the city of Chicago.

Online Appendix

Table A1: Indiana Monthly Benefit Issuance Schedule

	Disbursement Date	
First Letter of Last Name	Before 2014	After 2014
A or B	1st	5th
C or D	2nd	7th
E, F, or G	3rd	9th
H or I	4th	11th
J, K, or L	5th	13th
M or N	6th	15th
O, P, Q, or R	7th	17th
S	8th	19th
T, U, or V	9th	21st
W, X, Y, or Z	10th	23rd

Notes: Information on Indiana's monthly benefit issuance schedule is from the United States Department of Agriculture Food and Nutrition Service Monthly Issuance Schedule for all states. "Before 2014" denotes Indiana's SNAP disbursement schedule prior to 2014, while "After 2014" denotes the current SNAP schedule, which changed in February 2014 after a statewide policy change. The staggered issuance benefits information with links to state documents can be found at `http://www.fns.usda.gov/snap/snap-monthly-benefit-issuance-schedule`.

Table A2: Summary Statistics

Panel A: Chicago, by Census Tract	Mean	St.Dev.
Crime	1.260	1.572
Theft	0.262	0.605
Crimes at Grocery Stores	0.014	0.126
Theft at Grocery Stores	0.009	0.102
Percent Household on SNAP (2010)	0.171	0.143
Number of SNAP Retailers (2010)	2.979	2.680

Panel B: Indiana, by Last Name Letter	Mean	St.Dev.
Crime	0.844	1.387
Theft	0.098	0.355
Drugs	0.228	0.577
Alcohol	0.034	0.195

Notes: Panel A displays means and standard deviations for 1,941,114 Census Tract-day observations that span 2007-2013. Chicago crime data are from the Chicago online Data portal (`https://data.cityofchicago.org/Public-Safety/Crimes-2001-to-present/ijzp-q8t2`), SNAP enrollment data are from the American Community Survey and SNAP retailer data are from the USDA Food and Nutrition Service. Panel B displays means and standard deviations for crime types committed by day and last name letter in the state of Indiana for 45,646 letter-by-day observations from 2012-2016. Indiana crime data are from the Indiana Department of Correction.

Table A3: Effect of SNAP Receipt on Crime by Days Since Issuance (Indiana)

	Crime	**Theft**	**Drugs**	**Alcohol**
Days Since Issuance				
3-5 Days	-0.000	0.004	0.005	-0.003
	(0.021)	(0.007)	(0.010)	(0.003)
6-8 Days	-0.026	0.005	-0.005	-0.005
	(0.027)	(0.008)	(0.008)	(0.003)
9-11 Days	-0.036	0.007	-0.003	0.003
	(0.030)	(0.008)	(0.010)	(0.003)
12-14 Days	-0.024	-0.010	0.003	0.003
	(0.028)	(0.006)	(0.008)	(0.003)
15-17 Days	-0.021	-0.005	0.008	-0.003
	(0.025)	(0.007)	(0.009)	(0.004)
18-20 Days	-0.037	-0.005	-0.018	-0.000
	(0.031)	(0.006)	(0.011)	(0.003)
21-23 Days	-0.042	0.009	-0.007	-0.005
	(0.028)	(0.007)	(0.010)	(0.003)
24-26 Days	-0.004	0.001	-0.008	0.007*
	(0.030)	(0.005)	(0.011)	(0.003)
27-31 Days	0.033	0.013**	0.004	0.008**
	(0.030)	(0.006)	(0.011)	(0.003)
N	45630	45630	45630	45630

Notes: Estimates are based on conviction-level crime data from the Indiana Department of Correction from 2012-2016. Each regression includes month, year, day-of-month, and day-of-week fixed effects. Robust standard errors are clustered on last name letter and are shown in parenthesis. *, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table A4: Effect of SNAP Receipt on Crime by County (Indiana)

	Crime	**Theft**	**Drugs**	**Alcohol**
Panel A. All counties				
Second Week	-0.020	0.002	-0.003	0.002
	(0.023)	(0.006)	(0.007)	(0.003)
Third Week	-0.043**	-0.006	-0.006	0.001
	(0.019)	(0.005)	(0.006)	(0.004)
Fourth Week	-0.014	0.003	-0.008	0.004**
	(0.021)	(0.004)	(0.008)	(0.002)
Mean	0.969	0.039	0.262	0.039
N	3615300	3615300	3615300	3615300
Panel B. High SNAP counties (SNAP Recipients $>$ IN Mean)				
Second Week	-0.020	0.002	-0.003	0.002
	(0.023)	(0.006)	(0.007)	(0.003)
Third Week	-0.043**	-0.006	-0.006	0.001
	(0.019)	(0.005)	(0.006)	(0.004)
Fourth Week	-0.014	0.003	-0.008	0.004**
	(0.021)	(0.004)	(0.008)	(0.002)
Mean	0.969	0.039	0.262	0.039
N	1793610	1793610	1793610	1793610
Panel C. Low SNAP counties (SNAP Recipients $<$ IN Mean)				
Second Week	-0.020	0.002	-0.003	0.002
	(0.023)	(0.006)	(0.007)	(0.003)
Third Week	-0.043**	-0.006	-0.006	0.001
	(0.019)	(0.005)	(0.006)	(0.004)
Fourth Week	-0.013	0.003	-0.008	0.005**
	(0.021)	(0.004)	(0.008)	(0.002)
Mean	0.969	0.039	0.262	0.039
N	1821690	1821690	1821690	1821690

Notes: Estimates are based on conviction-level crime data from the Indiana Department of Correction from 2012-2016. Each regression includes month, year, day-of-month, day-of-week, and county fixed effects. Robust standard errors are clustered on last name letter and are shown in parenthesis.

*, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table A5: Effect of SNAP Receipt on Crime by Race, Ethnicity, and Gender (Indiana)

	Crime	**Theft**	**Drugs**	**Alcohol**
Panel A. White				
Second Week	-0.006	-0.000	-0.006	0.002
	(0.014)	(0.004)	(0.005)	(0.002)
Third Week	-0.029**	-0.009**	-0.007	0.001
	(0.013)	(0.004)	(0.004)	(0.003)
Fourth Week	-0.007	-0.001	-0.007	0.004**
	(0.015)	(0.004)	(0.006)	(0.002)
Panel B. Black				
Second Week	-0.017*	0.002	0.003	-0.001
	(0.009)	(0.002)	(0.002)	(0.001)
Third Week	-0.010	0.003*	0.001	-0.001
	(0.006)	(0.002)	(0.002)	(0.001)
Fourth Week	-0.008	0.003	-0.000	-0.001
	(0.007)	(0.002)	(0.003)	(0.001)
Panel C. Hispanic				
Second Week	0.002	0.000	-0.000	-0.000
	(0.002)	(0.000)	(0.001)	(0.001)
Third Week	0.002	-0.000	-0.000	-0.000
	(0.001)	(0.000)	(0.001)	(0.001)
Fourth Week	0.002	0.000	-0.000	0.000
	(0.002)	(0.000)	(0.001)	(0.000)
Panel D. Female				
Second Week	0.002	0.001	-0.003	-0.001
	(0.006)	(0.002)	(0.004)	(0.001)
Third Week	0.002	-0.001	-0.001	-0.001
	(0.005)	(0.002)	(0.004)	(0.001)
Fourth Week	0.005	0.004*	-0.002	-0.001
	(0.005)	(0.002)	(0.003)	(0.001)
N	45630	45630	45630	45630

Notes: Estimates are based on conviction-level crime data from the Indiana Department of Correction from 2012-2016. Each regression includes month, year, day-of-month, and day-of-week fixed effects. Robust standard errors are clustered on last name letter and are shown in parenthesis.
*, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table A6: Effect of SNAP Receipt on Crime by Age Group (Indiana)

	Crime	**Theft**	**Drugs**	**Alcohol**
Panel A. Ages 18-24				
Second Week of Month	0.004	0.002	0.002	0.001
	(0.008)	(0.002)	(0.003)	(0.001)
Third Week of Month	-0.009	-0.002	-0.004	0.001
	(0.008)	(0.002)	(0.003)	(0.001)
Fourth Week of Month	0.007	0.004	0.001	0.002***
	(0.007)	(0.002)	(0.002)	(0.001)
Panel B. Ages 25-29				
Second Week of Month	-0.007	-0.002	-0.003	0.000
	(0.006)	(0.002)	(0.004)	(0.001)
Third Week of Month	-0.011*	-0.002	-0.004*	0.000
	(0.006)	(0.003)	(0.002)	(0.001)
Fourth Week of Month	-0.004	-0.002	-0.005	0.001
	(0.007)	(0.002)	(0.003)	(0.001)
Panel C. Ages 30-34				
Second Week of Month	-0.005	0.001	-0.004	-0.001*
	(0.007)	(0.002)	(0.002)	(0.001)
Third Week of Month	-0.012	-0.002	-0.000	-0.001
	(0.009)	(0.002)	(0.004)	(0.001)
Fourth Week of Month	-0.007	-0.002	-0.002	-0.001
	(0.007)	(0.002)	(0.003)	(0.001)
Panel D. Ages 35-39				
Second Week of Month	-0.003	0.001	0.002	0.002
	(0.004)	(0.001)	(0.002)	(0.001)
Third Week of Month	0.005	-0.001	0.002	0.002*
	(0.005)	(0.001)	(0.002)	(0.001)
Fourth Week of Month	-0.004	-0.000	-0.001	0.000
	(0.004)	(0.002)	(0.002)	(0.001)
Panel E. Ages 40 and Over				
Second Week of Month	-0.009	-0.001	-0.000	-0.001
	(0.007)	(0.002)	(0.003)	(0.002)
Third Week of Month	-0.008	0.002	0.001	-0.001
	(0.006)	(0.002)	(0.003)	(0.002)
Fourth Week of Month	-0.003	0.003*	-0.001	0.001
	(0.006)	(0.002)	(0.004)	(0.001)
N	45630	45630	45630	45630

Notes: Estimates are based on conviction-level crime data from the Indiana Department of Correction from 2012-2016. Each regression includes month, year, day-of-month, and day-of-week fixed effects. Robust standard errors are clustered on last name letter and are shown in parenthesis.
*, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table A7: Effect of Shifting SNAP Benefit Dates on Crime (Indiana)

			Day of Month Range			
	Average Effect	Average Effect	Days 1-5	Days 6-10	Days 11-23	Days 24-31
Crime						
SNAP Staggered	-0.1056*	-0.0204	-1.1176***	0.0276	-0.0359	0.7810**
	(0.0516)	(0.0733)	(0.3397)	(0.3614)	(0.1846)	(0.3393)
Pre-Period Mean	1.230	1.226	1.459	1.154	1.246	1.115
N	45630	5122	910	910	2028	1274
Theft						
SNAP Staggered	-0.0568***	-0.0471**	-0.2203*	0.0040	-0.0435	0.1356
	(0.0195)	(0.0212)	(0.1148)	(0.0984)	(0.0478)	(0.1338)
Pre-Period Mean	0.161	0.202	0.255	0.169	0.212	0.180
N	45630	6214	936	1040	2704	1534
Drugs						
SNAP Staggered	-0.0278	0.0341	-0.1416	0.2023	0.0623	0.2155
	(0.0206)	(0.0279)	(0.1754)	(0.1223)	(0.0728)	(0.1666)
Pre-Period Mean	0.343	0.325	0.380	0.308	0.332	0.297
N	45630	6214	936	1040	2704	1534
Alcohol						
SNAP Staggered	-0.0292**	-0.0084	-0.1063	-0.0194	0.0031	-0.0754
	(0.0133)	(0.0180)	(0.0744)	(0.0413)	(0.0306)	(0.0946)
Pre-Period Mean	0.055	0.061	0.094	0.056	0.053	0.061
N	45630	6214	936	1040	2704	1534
Bandwidth	Full	Optimal	Optimal	Optimal	Optimal	Optimal

Notes: Estimates are based on conviction-level crime data from the Indiana Department of Correction from 2012-2016. Each regression includes year, day-of-month, and day-of-week fixed effects, as well as controls for weather. Daily weather data for Indiana are from the Global Historical Climatology Network and are based on temperature, precipitation and average wind speeds from the Indianapolis Airport weather station. Robust standard errors are clustered on last name letter and are shown in parenthesis. We also report the mean of each outcome for the period before the policy change (January 1, 2012, to February 1, 2014).

*, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table A8: Summary Statistics by SNAP Letter Group

	A& B	C & D	E, F, & G	H & I	J, K, & L	M & N	O, P, Q & R	S	T, U, & V	W, X, Y & Z
Crime	1.44	1.33	0.75	0.97	0.80	1.17	0.61	2.22	0.35	0.44
Theft	0.16	0.16	0.09	0.10	0.09	0.14	0.07	0.25	0.04	0.05
Drugs	0.40	0.37	0.20	0.26	0.20	0.33	0.15	0.62	0.10	0.12
Alcohol	0.05	0.06	0.03	0.04	0.03	0.05	0.02	0.09	0.01	0.02
Percent Male	0.85	0.84	0.85	0.86	0.86	0.84	0.85	0.85	0.86	0.86
Percent White	0.68	0.69	0.68	0.69	0.65	0.69	0.69	0.73	0.63	0.62
Percent Black	0.28	0.26	0.26	0.28	0.32	0.27	0.25	0.24	0.31	0.36
Percent Hispanic	0.02	0.04	0.05	0.02	0.02	0.04	0.05	0.02	0.05	0.01
Number of Convictions	7594	7180	6081	5190	6438	6278	6576	5950	2898	4895

Notes: Crime data are from the Indiana Department of Correction. Each column displays means for crime types committed as well as convicted criminals' gender, race, ethnicity, and number of convictions by day and letter group in the state of Indiana from 2012-2016.

Table A9: Effect of Staggering SNAP Benefits on Crime, Controlling for Weekend SNAP Receipt

			Day of Month Range		
	Average Effect	Average Effect	1st of Month	Days 2-23	Days 24-31
Crime					
SNAP Staggered	-0.0520***	-0.1425***	-0.2595*	-0.1448***	2.0141
	(0.0085)	(0.0381)	(0.1367)	(0.0508)	(5.9737)
Weekend SNAP	0.9138***	0.9386***	1.2578***	0.9183***	0.9474***
	(0.0079)	(0.0303)	(0.1996)	(0.0365)	(0.0569)
Pre-Period Mean	1.377	1.101	1.592	1.137	1.011
N	1941114	72802	2454	53170	17178
Theft					
SNAP Staggered	-0.0316***	-0.0266***	0.2591	-0.0378***	0.0081
	(0.0040)	(0.0049)	(0.1881)	(0.0058)	(0.0133)
Weekend SNAP	0.0253***	0.0308***	-0.0090	0.0353***	0.0163
	(0.0028)	(0.0073)	(0.0491)	(0.0083)	(0.0132)
Pre-Period Mean	0.278	0.255	0.324	0.257	0.245
N	1941114	231494	7362	170144	53988
Crime at Grocery					
SNAP Staggered	-0.0039***	-0.0028**	-0.0014	-0.0041***	0.0001
	(0.0012)	(0.0013)	(0.0160)	(0.0016)	(0.0024)
Weekend SNAP	0.0012**	0.0012	-0.0083*	0.0011	0.0025
	(0.0006)	(0.0011)	(0.0043)	(0.0014)	(0.0022)
Pre-Period Mean	0.016	0.016	0.014	0.016	0.015
N	1941114	493254	15542	356648	121064
Theft at Grocery					
SNAP Staggered	-0.0030***	-0.0023**	-0.0013	-0.0037***	0.0015
	(0.0011)	(0.0011)	(0.0283)	(0.0014)	(0.0021)
Weekend SNAP	0.0005	-0.0001	-0.0040	0.0002	-0.0008
	(0.0004)	(0.0010)	(0.0038)	(0.0012)	(0.0020)
Pre-Period Mean	0.010	0.011	0.009	0.011	0.010
N	1941114	398366	13088	287936	97342
Bandwidth	Full	Optimal	Optimal	Optimal	Optimal

Notes: See Table 1 for main table notes. “Weekend SNAP" represents a dummy variable equal to one if any potential SNAP disbursement day of the month corresponds to a Friday or Saturday. Standard errors are clustered on the Census Tract level and reported in parentheses. We also report the mean of each outcome for the period before the policy change (January 1, 2007, to February 15, 2010).

*, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table A10: Effect of Staggering SNAP Benefits on Crime, Controlling for Weekend Paydays

			Day of Month Range		
	Average Effect	Average Effect	1st of Month	Days 2-23	Days 24-31
Crime					
SNAP Staggered	-0.0523***	-0.1426***	-0.2979**	-0.1479***	1.9850
	(0.0085)	(0.0381)	(0.1379)	(0.0509)	(5.9754)
Weekend Payday	0.8407***	0.8527***	1.1043***	0.8448***	0.8600***
	(0.0115)	(0.0304)	(0.2013)	(0.0356)	(0.0585)
Pre-Period Mean	1.377	1.101	1.592	1.137	1.011
N	1941114	72802	2454	53170	17178
Theft					
SNAP Staggered	-0.0316***	-0.0266***	0.2684	-0.0378***	0.0081
	(0.0040)	(0.0049)	(0.1883)	(0.0058)	(0.0133)
Weekend Payday	0.0240***	0.0277***	-0.0288	0.0318***	0.0165
	(0.0027)	(0.0073)	(0.0482)	(0.0082)	(0.0135)
Pre-Period Mean	0.278	0.255	0.324	0.257	0.245
N	1941114	231494	7362	170144	53988
Crime at Grocery					
SNAP Staggered	-0.0039***	-0.0028**	-0.0013	-0.0041***	0.0001
	(0.0012)	(0.0013)	(0.0160)	(0.0016)	(0.0024)
Weekend Payday	0.0014**	0.0016	-0.0081*	0.0015	0.0029
	(0.0006)	(0.0011)	(0.0044)	(0.0014)	(0.0023)
Pre-Period Mean	0.016	0.016	0.014	0.016	0.015
N	1941114	493254	15542	356648	121064
Theft at Grocery					
SNAP Staggered	-0.0030***	-0.0023**	-0.0012	-0.0037***	0.0015
	(0.0011)	(0.0011)	(0.0283)	(0.0014)	(0.0021)
Weekend Payday	0.0006	0.0002	-0.0037	0.0005	-0.0005
	(0.0004)	(0.0010)	(0.0039)	(0.0013)	(0.0020)
Pre-Period Mean	0.010	0.011	0.009	0.011	0.010
N	1941114	398366	13088	287936	97342
Bandwidth	Full	Optimal	Optimal	Optimal	Optimal

Notes: See Table 1 for main table notes. “Weekend Payday" represents a dummy variable equal to one if the 1st or 15th day of the month corresponds to a Friday or Saturday. Standard errors are clustered on the Census Tract level and reported in parentheses. We also report the mean of each outcome for the period before the policy change (January 1, 2007, to February 15, 2010).
*, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

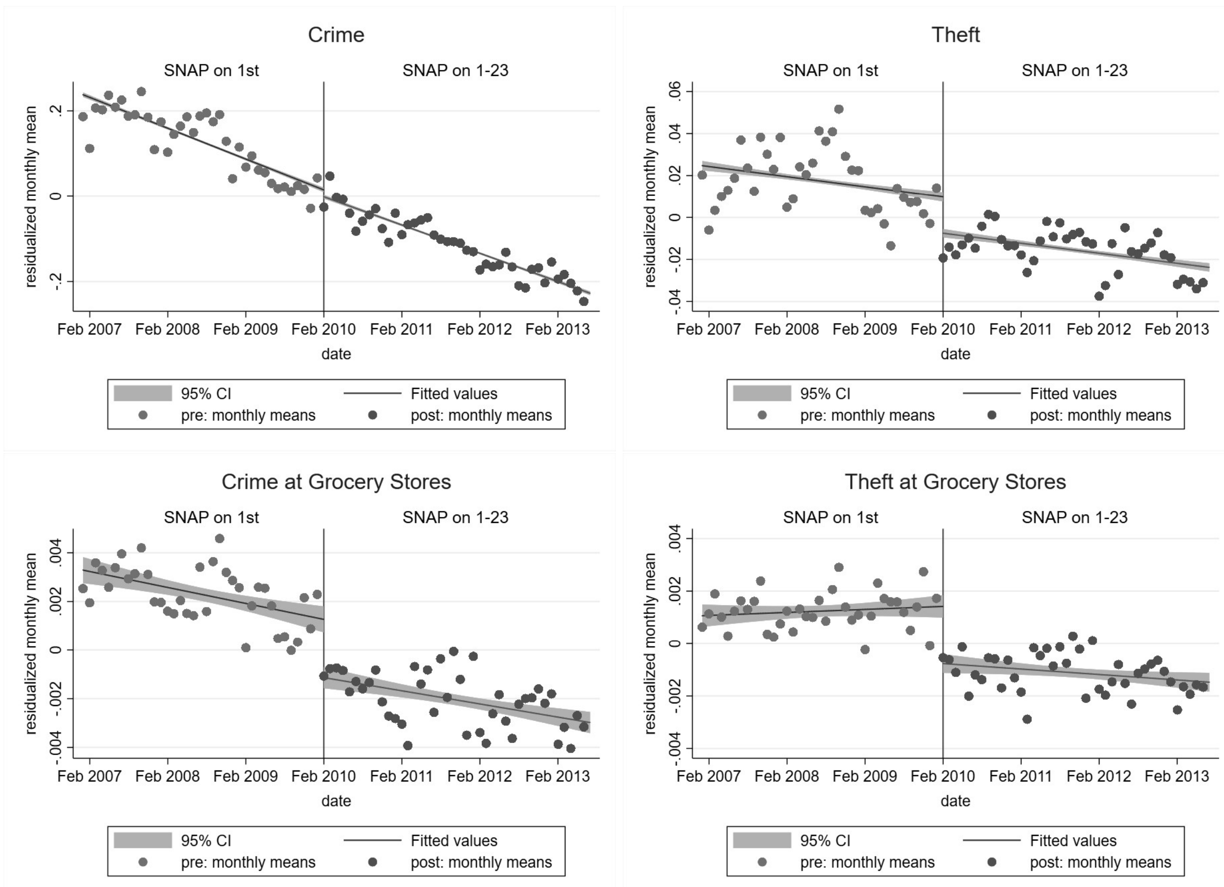
Table A11: Effect of Staggering SNAP Benefits on Crime in Census Tracts with Supermarkets

		Day of Month Range			
	Average Effect	Average Effect	1st of Month	Days 2-23	Days 24-31
Crime					
SNAP Staggered	-0.1019***	-0.0935	-0.7589**	-0.1564	16.3650
	(0.0265)	(0.1153)	(0.3133)	(0.1443)	(20.9092)
Pre-Period Mean	1.377	1.101	1.592	1.137	1.011
N	315589	11735	435	8975	2325
Theft					
SNAP Staggered	-0.0646***	-0.0437***	0.3561	-0.0700***	-0.0043
	(0.0136)	(0.0147)	(0.8875)	(0.0177)	(0.0420)
Pre-Period Mean	0.278	0.255	0.324	0.257	0.245
N	315589	31135	1035	23230	6870
Crime at Grocery					
SNAP Staggered	-0.0146***	-0.0140**	0.0535	-0.0171**	-0.0005
	(0.0052)	(0.0054)	(0.0605)	(0.0069)	(0.0078)
Pre-Period Mean	0.016	0.016	0.014	0.016	0.015
N	315589	63135	2035	45760	15340
Theft at Grocery					
SNAP Staggered	-0.0105**	-0.0086*	0.2200*	-0.0121*	0.0073
	(0.0048)	(0.0047)	(0.1255)	(0.0066)	(0.0074)
Pre-Period Mean	0.010	0.011	0.009	0.011	0.010
N	315589	51535	1780	37270	12485

Notes: See Table 1 for main table notes. Each regression includes year, day-of-month, and day-of-week fixed effects. Store data is from the USDA authorized retailer list. Supermarkets include Walmart, Target, Publix, Save A Lot, Kroger, Safeway, Albertson, Costco, Winn Dixie, and Walgreens.

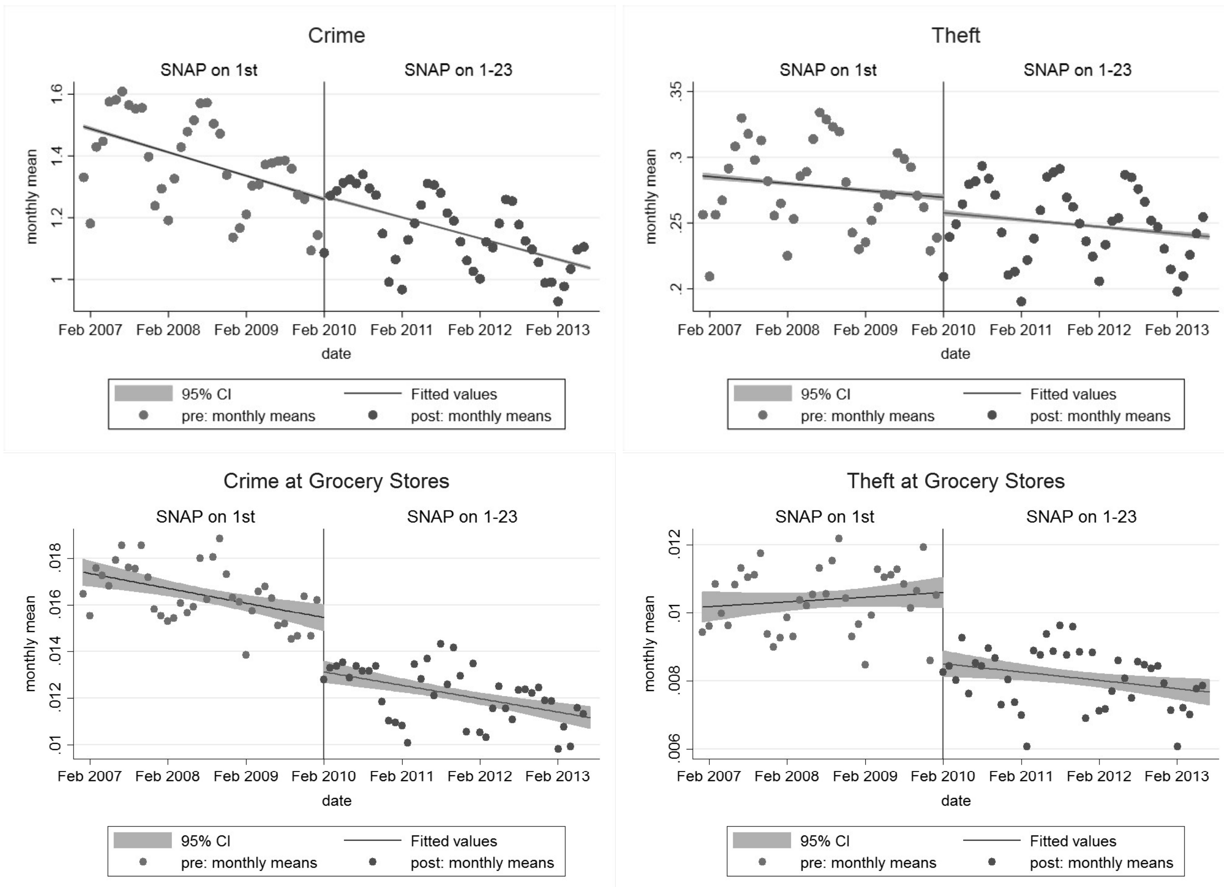
*, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Figure A1: Effect of Illinois SNAP Disbursement Change on Crime, Full Bandwidth



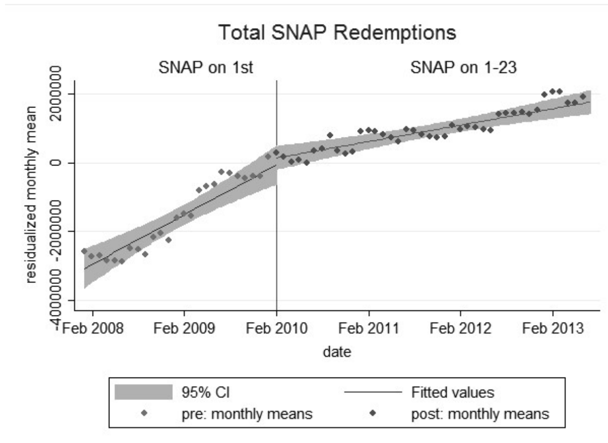
Notes: Each figure plots month-level means of residuals (after differencing out weather effects and Census Tract fixed effects) and linear fits (with 95% confidence intervals) of each of the crimes listed. To the left of the vertical line, SNAP benefits were given out primarily on the 1st of the month, and to the right, they were distributed over the 1st to the 23rd. Crime data are from the city of Chicago. Daily weather data for Chicago are from the Global Historical Climatology Network and are based on temperature, precipitation and average wind speeds from the Chicago O'Hare International Airport weather station.

Figure A2: Effect of Illinois SNAP Disbursement Change on Crime Without Residualizing



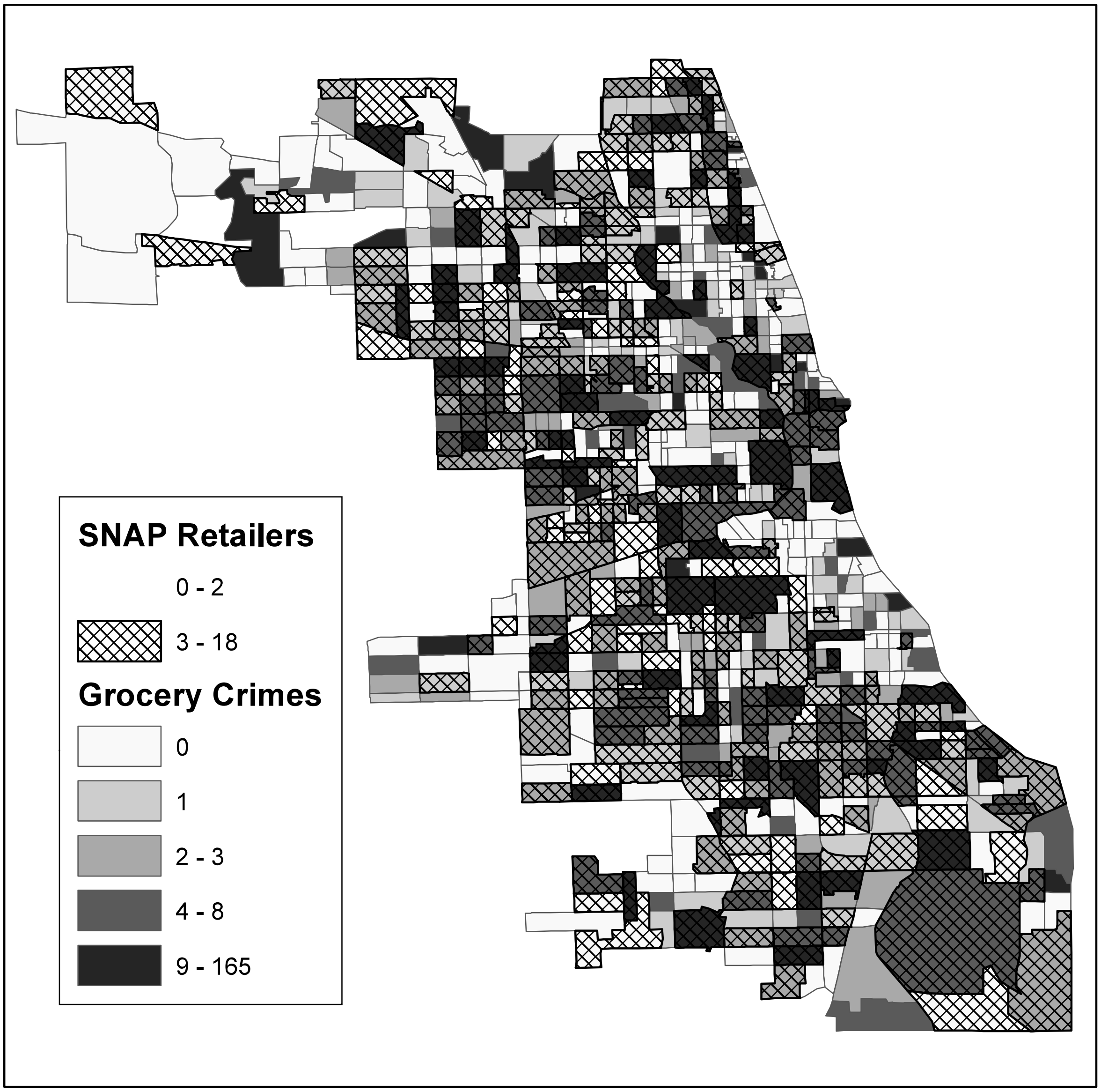
Notes: Each figure plots month-level means and linear fits (with 95% confidence intervals) of each of the crimes listed. To the left of the vertical line, SNAP benefits were given out primarily on the 1st of the month, and to the right, they were distributed over the 1st to the 23rd. Crime data are from the city of Chicago.

Figure A3: Effect of Illinois SNAP Disbursement Change on Total SNAP Redemptions



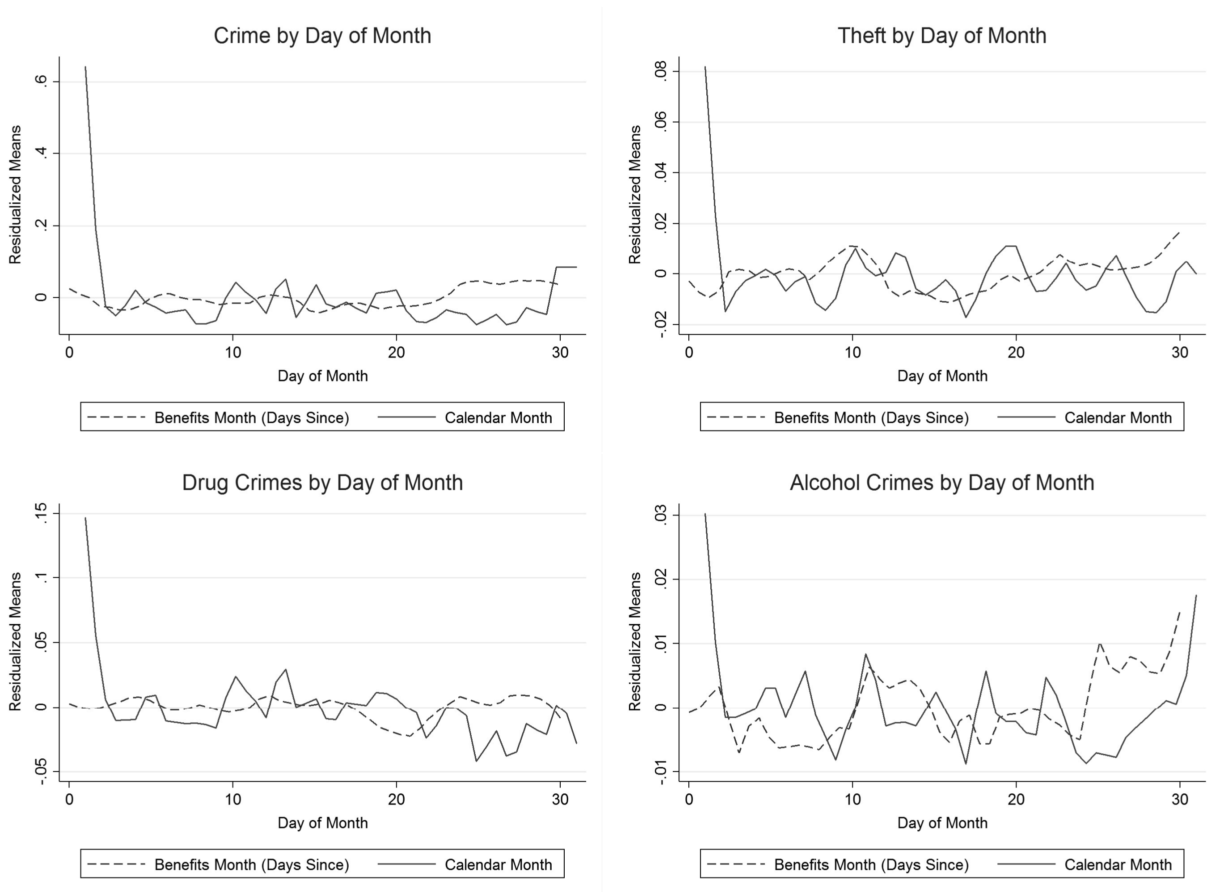
Notes: This figure plots month-level means and linear fits (with 95% confidence intervals) of total SNAP redemptions for the state of Illinois. To the left of the vertical line, SNAP benefits were given out primarily on the 1st of the month, and to the right, they were distributed over the 1st to the 23rd. Data on daily SNAP redemptions are from the Illinois Department of Health and Human Services.

Figure A4: SNAP Retailers and Grocery Store Crimes (2010)



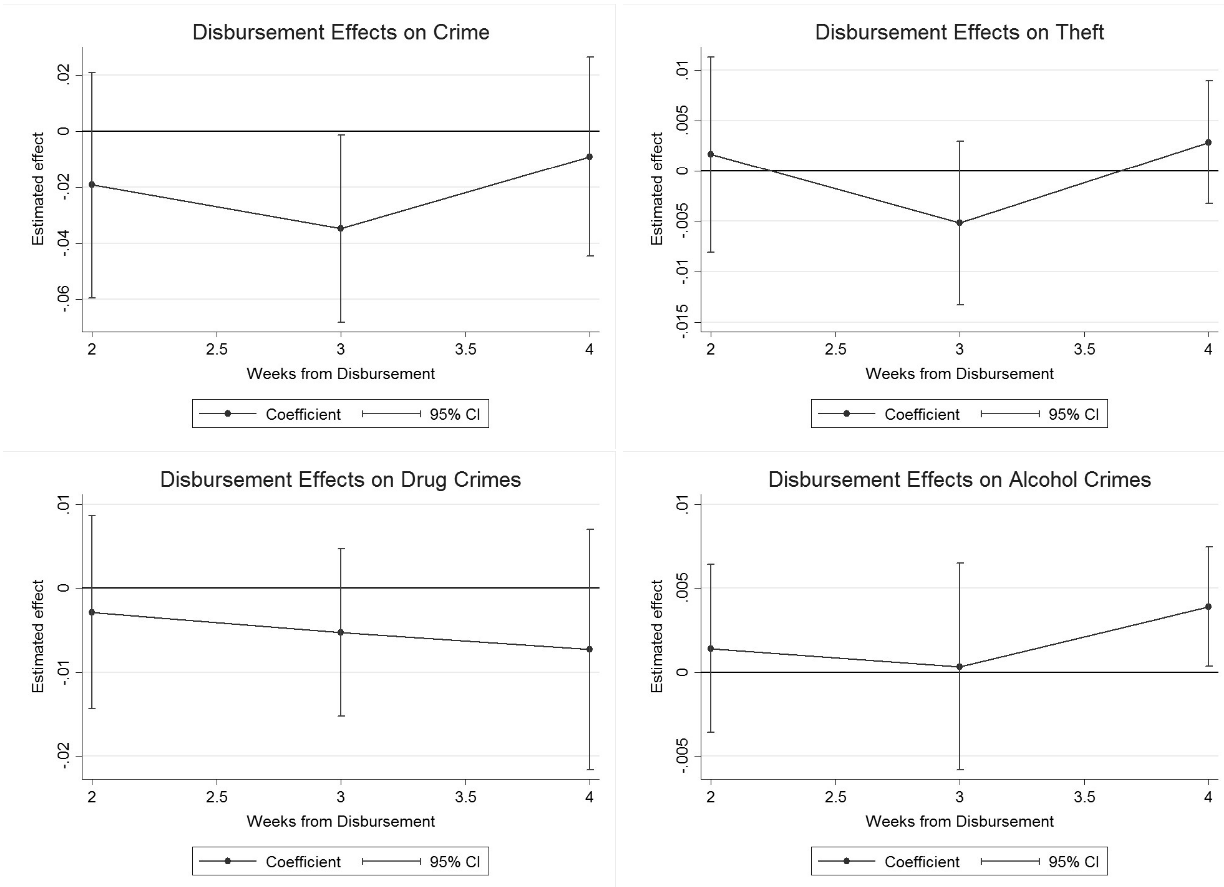
Notes: Census Tracts are grouped by the count of SNAP retailers, and the cross-hatched texture denotes “high SNAP retailer" (above median count) Census Tracts. Census Tracts are also grouped by quintiles of the number of crimes reported to have occurred at grocery stores in 2010. Crime data are from the City of Chicago and SNAP retailer data are from United States Department of Agriculture Food and Nutrition Service.

Figure A5: Average Crimes Committed: Benefit Month vs. Calendar Month (Indiana)



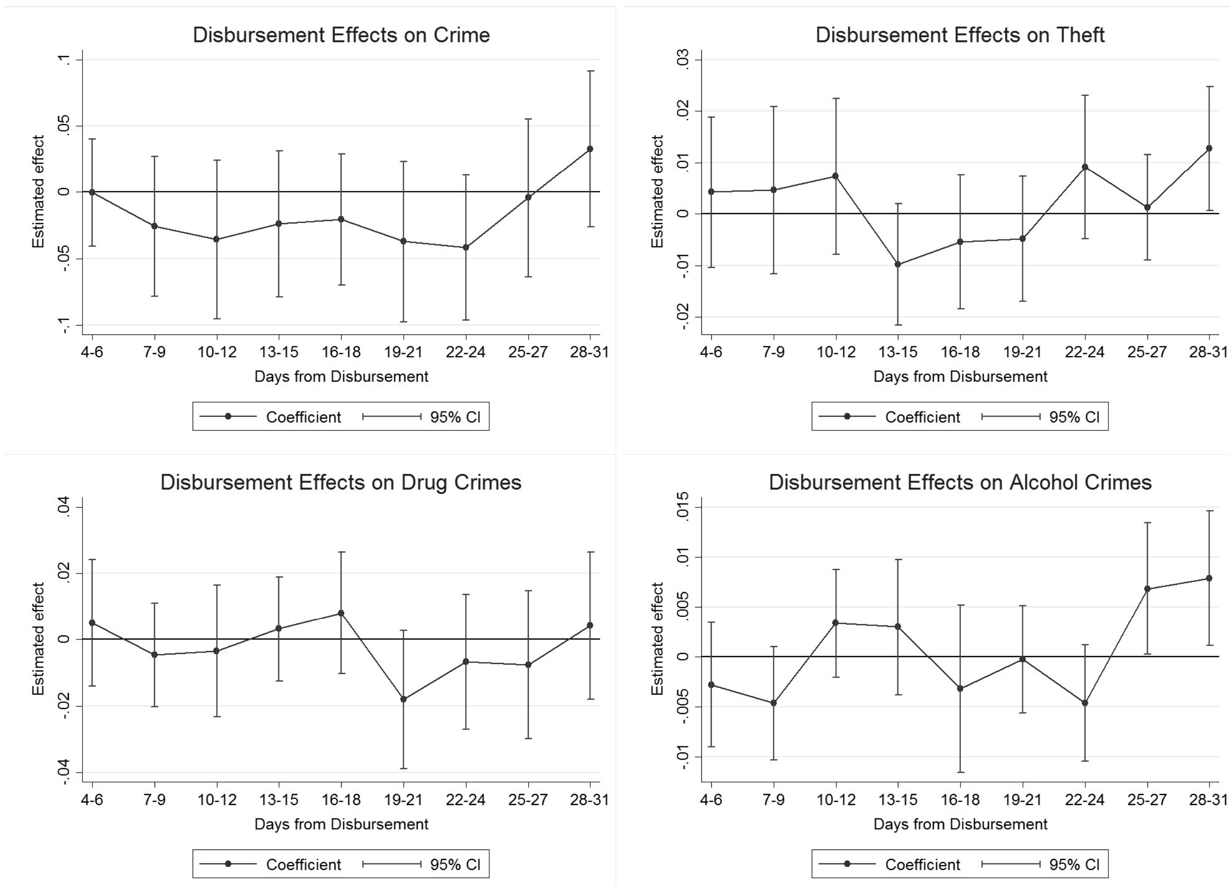
Notes: Each figure plots month-level means of residuals (after differencing out month and year fixed effects) of each of the crimes listed. The dotted line displays the average crimes committed by the number of days since each letter group potentially received SNAP benefits, while the solid line plots the average number of crimes for each day of the month. Crime data are from Indiana Department of Correction.

Figure A6: Estimates of SNAP Receipt on Crime, by Crime Type (Indiana)



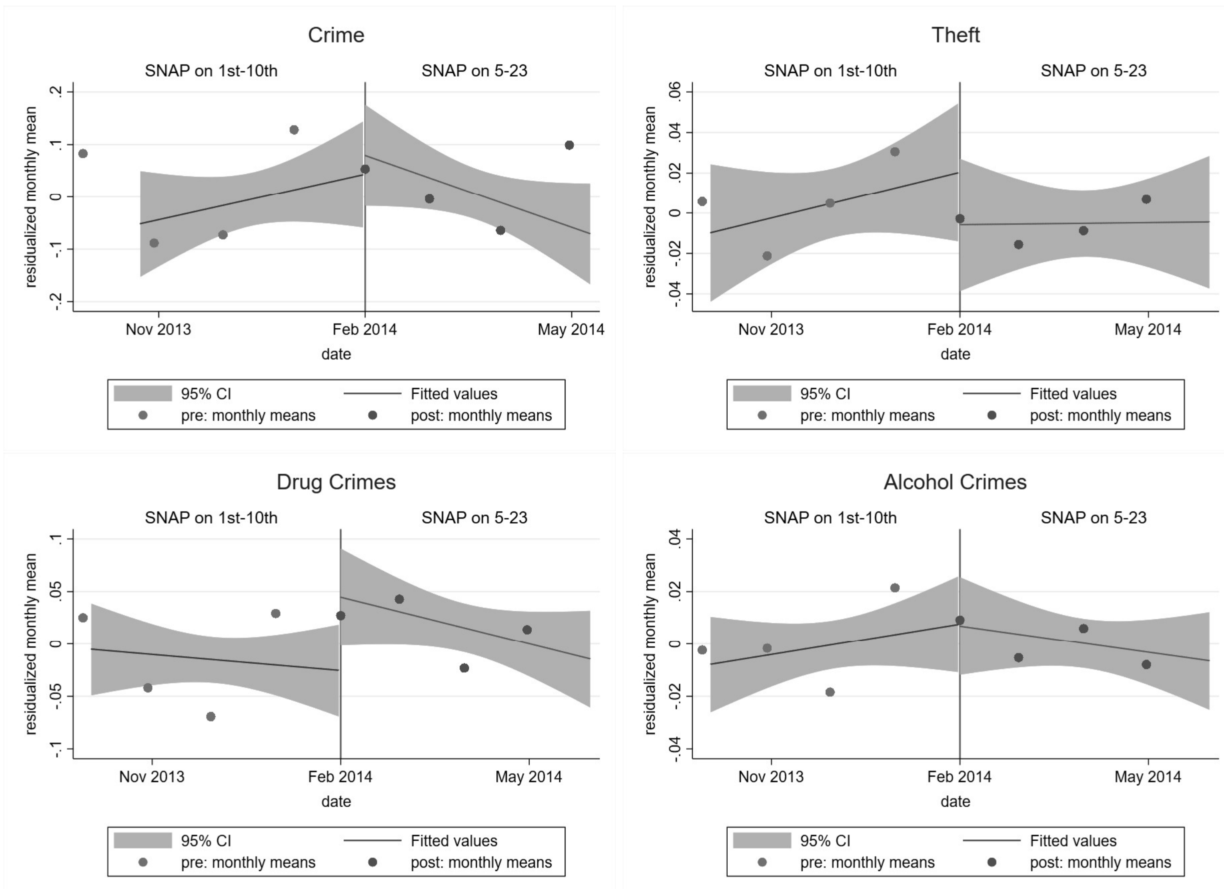
Notes: Each figure plots coefficients from Equation 3 for each of the outcomes listed with a 95% confidence interval. Estimates are based on conviction-level data from the Indiana Department of Correction from 2012-2016. Standard errors are clustered at the last name letter.

Figure A7: Estimates of SNAP Receipt on Crime, by Crime Type by Every Three Days Since Issuance (Indiana)



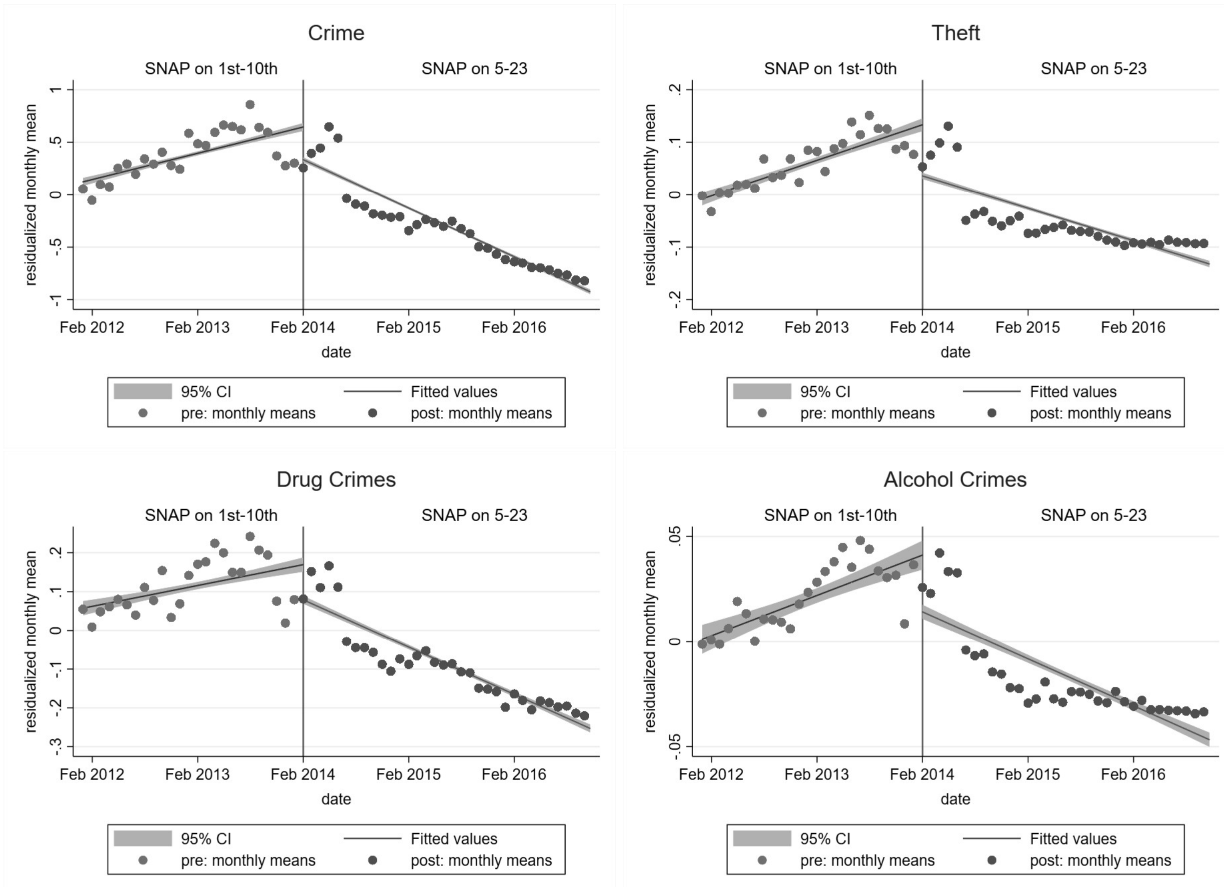
Notes: Each figure plots coefficients from Equation 2 using three day bins for each of the outcomes listed with a 95% confidence interval. Estimates are based on conviction-level data from the Indiana Department of Correction from 2012-2016. Standard errors are clustered on last name letter.

Figure A8: Effect of SNAP Disbursement Change on Crime, Estimated Optimal Bandwidth (Indiana)



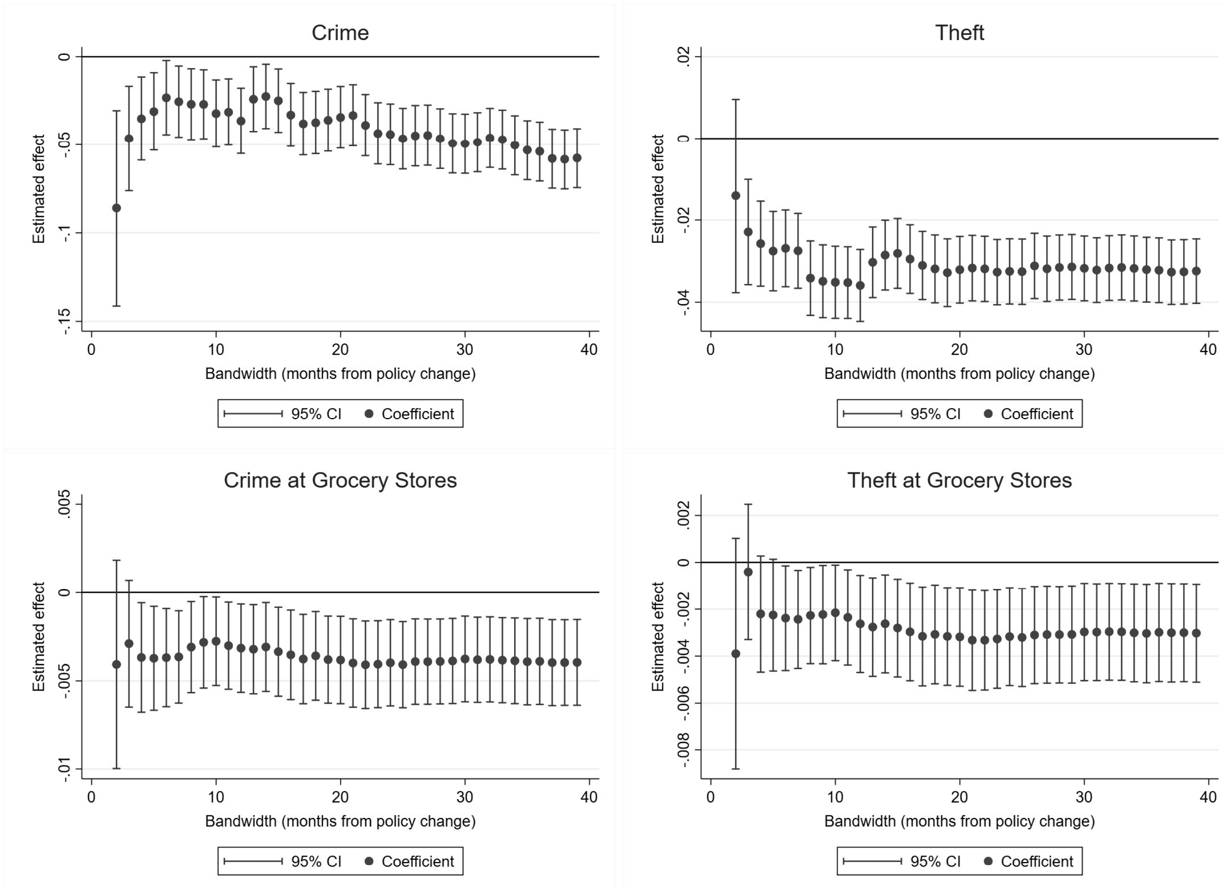
Notes: Each figure plots month-level means of residuals (after differencing out weather effects) and linear fits (with 95% confidence intervals) of each of the crimes listed. To the left of the vertical line, SNAP benefits were given out each day from the 1st-10th, and to the right, they were distributed from the 5th-23rd. Crime data are from Indiana Department of Correction.

Figure A9: Effect of SNAP Disbursement Change on Crime, Full Bandwidth (Indiana)



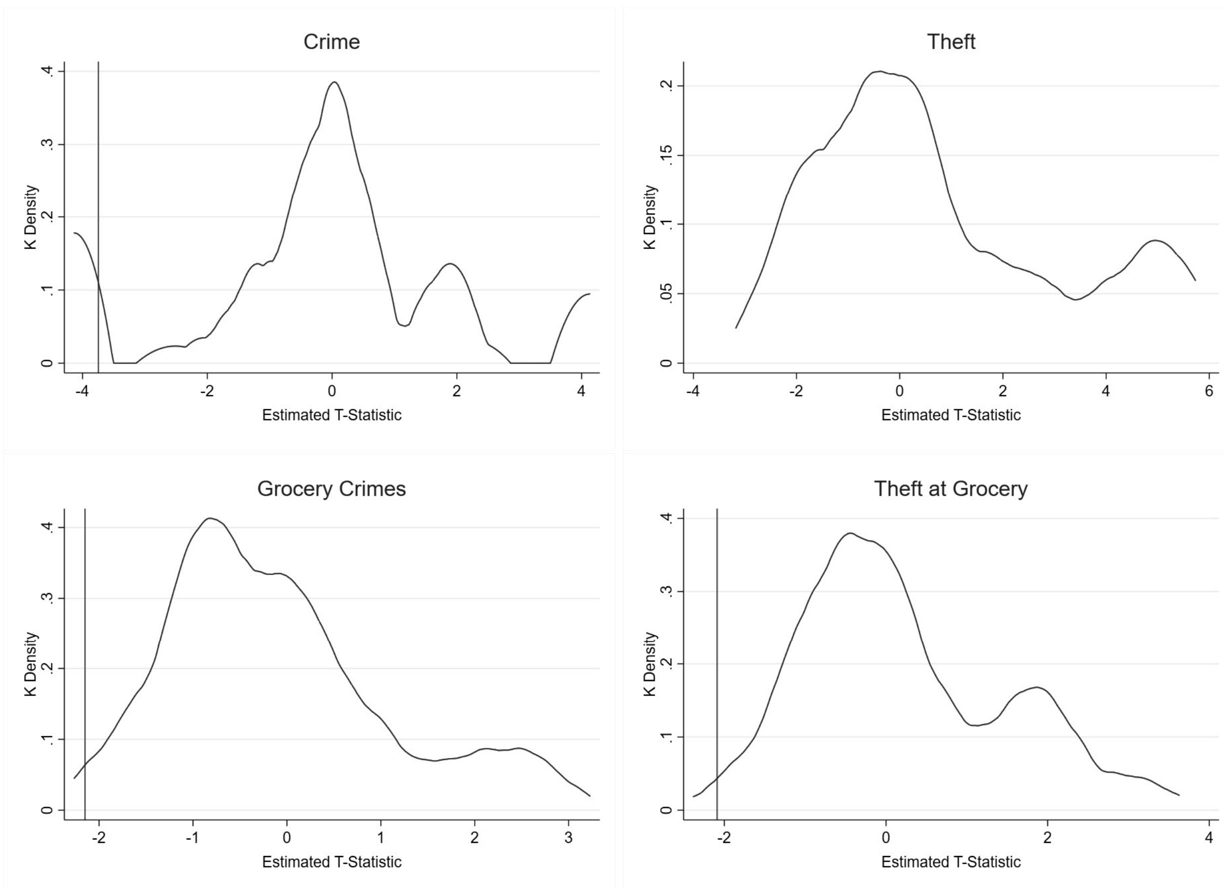
Notes: Each figure plots month-level means of residuals (after differencing out weather fixed effects) and linear fits (with 95% confidence intervals) of each of the crimes listed. To the left of the vertical line, SNAP benefits were given out each day from the 1st-10th, and to the right, they were distributed from the 5th-23rd. Crime data are from Indiana Department of Correction.

Figure A10: Effect of Varying Bandwidth on Estimates



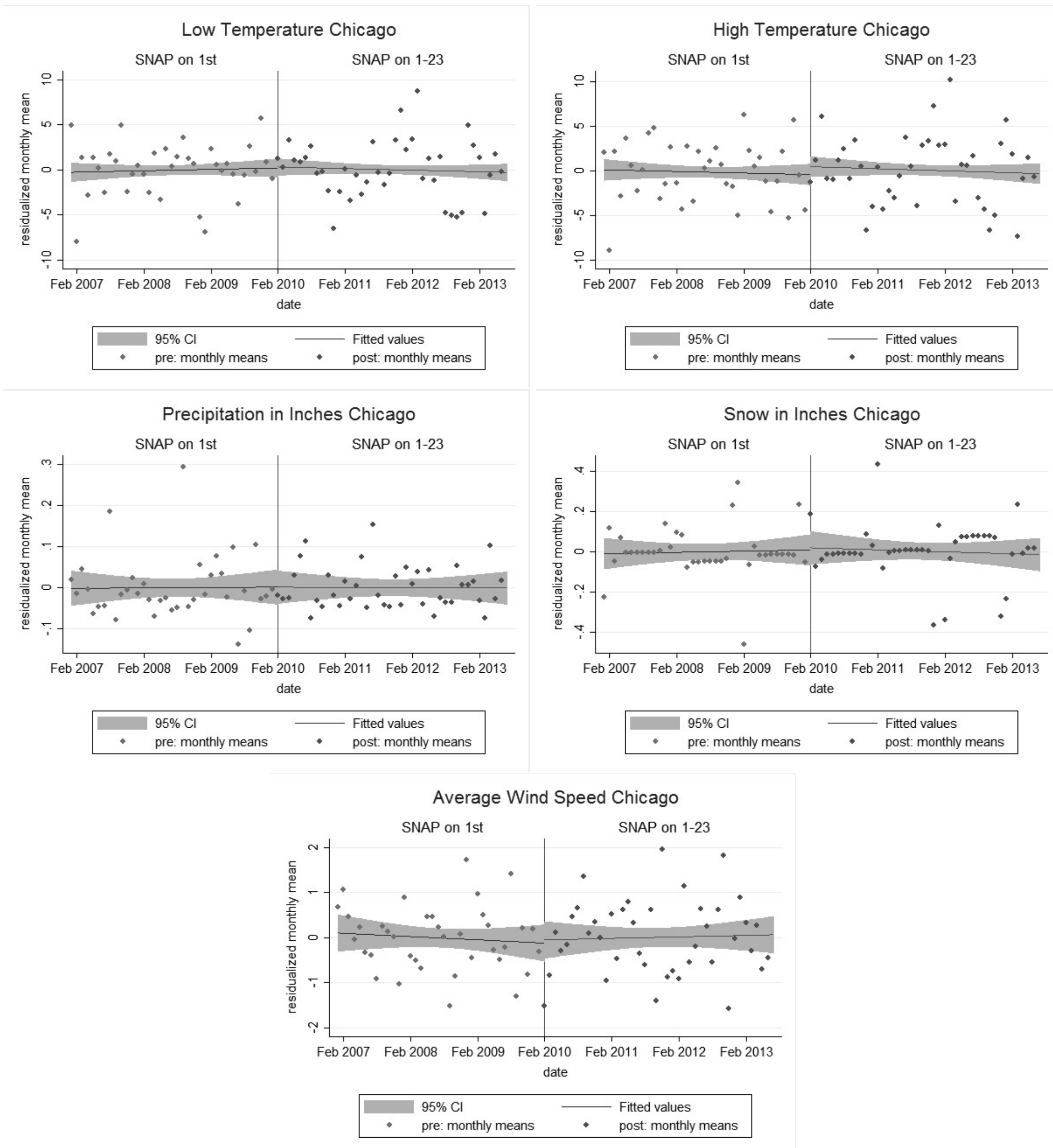
Notes: Each dot represents the coefficient of interest generated by a separate regression. The various bandwidths on which these regressions were performed are represented on the x-axis. We also report the 95% confidence interval of the coefficient. Crime data from 2007-2013 are from the city of Chicago.

Figure A11: Placebo Estimates



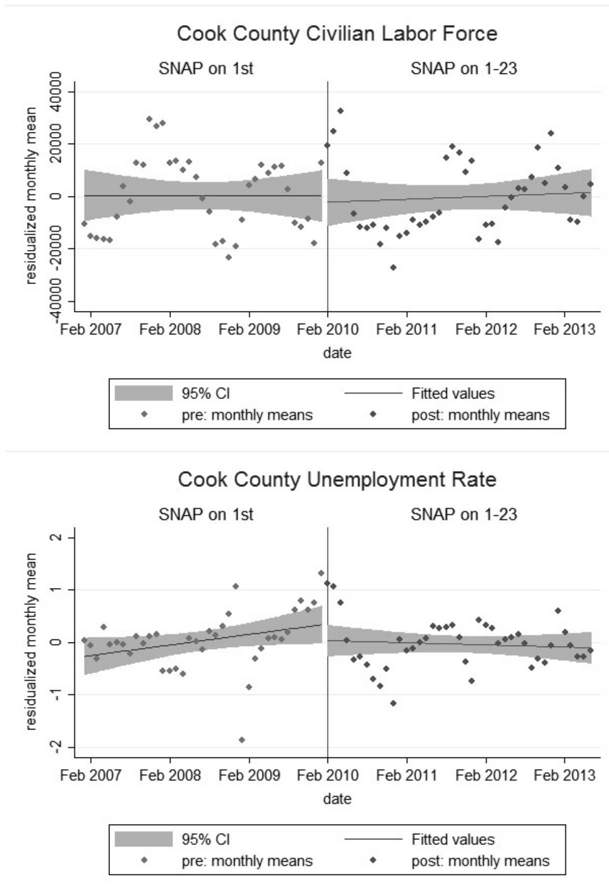
Notes: Each figure plots the distribution of 1,000 randomly drawn placebo t-scores from the regression discontinuity specification in Equation 1 using pre-period crime data. For overall crime and theft, 14.5 percent and 0 percent of estimates are less than the estimate reported in Table 1, respectively. For grocery store crimes, 0.4 percent of placebo estimates are smaller than the estimate reported in Table 1. For grocery store thefts, 0.9 percent of placebo estimates are smaller than the baseline estimate reported in Table 1. Crime data from are from the city of Chicago.

Figure A12: Effect of Illinois SNAP Disbursement Change on Weather



Notes: Each figure plots month-level means and linear fits (with 95% confidence intervals) of each of the weather outcomes listed. To the left of the vertical line, SNAP benefits were given out primarily on the 1st of the month, and to the right, they were distributed over the 1st to the 23rd. Daily weather data for Chicago are from the Global Historical Climatology Network.

Figure A13: Effect of Illinois SNAP Disbursement Change on Labor Force



Notes: Each figure plots month-level means, accounting for month and year fixed effects, and linear fits (with 95% confidence intervals) of the monthly civilian labor force and unemployment rate in Cook County. To the left of the vertical line, SNAP benefits were given out primarily on the 1st of the month, and to the right, they were distributed over the 1st to the 23rd. Monthly labor force and unemployment data are from the U.S. Bureau of Labor Statistics.