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"SNAP Benefits and Crime: Evidence from Changing Disbursement Schedules"

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SNAP Benefits and Crime: Evidence from Changing Disbursement Schedules

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Abstract

Government transfer programs infuse a substantial amount of resources into the budgets of millions of low-income families each month. Under some states' aid disbursement schemes, there are extended periods of time within each month in which no recipients receive transfers, generally limiting the amount of resources in communities. In this paper, we study the effects of nutritional aid disbursement on crime, utilizing two main sources of variation: (i) a policy change in Illinois which 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 throughout the month leads to a 32 percent decrease in grocery store theft and reduces monthly cyclicity in grocery store crimes. Moreover, we find that the relationship between time since SNAP issuance and crime is nonlinear. Findings show that criminal behavior decreases in the second and third weeks following receipt, but increases in the last week of the benefit cycle, potentially due to resource constraints.

1 Introduction

While it is well-documented that income shocks due to monthly government cash transfers increase street crime, illicit drug and alcohol use, and disciplinary events for students, much less is known about how in-kind transfers affect criminal behavior (Dobkin and Puller (2007); Foley (2011); Wright, McClellan, Tekin, Dickinson, Topalli, and Rosenfeld (2014)). One such program, the Supplemental Nutrition Assistance Program (SNAP), provides food-purchasing assistance for nearly 45 million low-income Americans each year. Benefits are distributed in a lump sum, electronic payment once per month to be redeemed for foods at supermarkets

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or other authorized retailers. Given the large body of literature that documents that most SNAP recipients exhaust all benefits well before the end of the month, and because many SNAP recipients may be receiving assistance from other programs, such as Temporary Assistance for Needy Families (TANF), which issue benefits on the first week of the month, shifting SNAP benefit issuance towards later in the month may help recipients better smooth consumption and avoid financial desperation at the end of the month. Staggering benefit dates also has the potential to alleviate crime associated with first-of-the-month income shocks.

The objective of this paper is to estimate the effects of SNAP issuance on crime. First, we examine the effects of staggered SNAP benefits distribution using Chicago reported crime data before and after a policy change which increased the number of SNAP distribution dates. Second, we utilize individual-level conviction records from Indiana, where benefits dates are determined by first letter of last name, to measure how criminal behavior responds to the monthly disbursement of aid.

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 (Dobkin and Puller (2007); Castellari, Cotti, Gordanier, and Ozturk (2016); Carr and Koppa (2016)).

The second focuses on the fact that, unless recipients are fully smoothing their consumption of benefits, they may be forced to skip meals at the end of the month, 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 going hungry at the end of the benefits cycle, many studies have shown that recipients often run out of food by the end of the month, 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, Homonoff, and Meckel (2016)).

It is also possible that benefit distribution affects overall crime if there exist spillover effects on ineligible individuals. If ineligibles are aware of the distribution schedule, SNAP recipients may be more likely to be victimized on dates when benefits become available because they are lucrative targets. 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. Conversely, lean times may lead to less crime as individuals are less able to participate in activities that could lead to crime (as Evans and Moore (2011) suggest for mortality).

To study the effect of staggering the SNAP benefit schedule on crime, we utilize a 2010 policy change in Illinois that drastically changed the monthly SNAP distribution cycle. On February 16, 2010, Illinois switched from issuing 66% of benefits on the first of the month to more substantial distribution on the 4th, 7th and 10th days of the month.[1] We focus on this policy change for two reasons. First, the policy change is considerable, affecting nearly 1.12 million individuals.[2] Second, because the city of 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 the SNAP issuance policy. Increasing the number of SNAP distribution dates 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 drop from 30% and 60% to about 20% and 30%, 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 and find that grocery store crime and grocery store theft decrease 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 cyclicity of crime. SNAP issuance in Indiana has the distinct feature that benefit dates are based on first letter of last name. This feature 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% in the third week after SNAP issuance, but increases in the last week of the benefit cycle.

In this paper, we make three main contributions to the existing literature. First, we document the existence and magnitude of the monthly cycle in crime and theft at grocery stores in Chicago and determine how this cycle varies according to SNAP distribution. Second, we fill an important gap in the literature by estimatin the effects of *changes* to SNAP distribution on crime. In doing so, we address how in-kind income shocks and consumption smoothing affect criminal involvement and build upon Foley (2011) by examining the effects of a change to a staggered distribution schedule. Our third contribution to the existing literature is the use of arrest-level data to speak to how SNAP receipt, and monthly income shocks more generally, affects crime. 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 cyclicity from benefit effects.

[1]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)).

[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)).

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 change on crime and theft and estimate how monthly SNAP issuance affects the timing of criminal behavior. Finally, we provide a discussion on the overall impact of staggered SNAP distribution on welfare.

2 Background on SNAP Issuance Policies in Illinois and Indiana

Despite the fact that SNAP is an entitlement program administered by the United States Department of Agriculture, benefits are distributed by states, and states have the authority to determine rules for eligibility and funding. This authority extends to the organization and timing of benefits, and as a result, there is significant variation in state issuance schedules. Seven states currently distribute all benefits on one day of the month.[3] However, a majority of states stagger issuance throughout the month, meaning states distribute benefits over many days of the month and each recipient's benefits are made available once a month.

There are several reasons why states may choose to stagger benefits. First, staggering benefits 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. Third, by smoothing shopping spikes throughout the month, staggered disbursement policies could 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 crime. Prior to 2010, the Illinois Department of Health and Human Services distributed 66% of SNAP benefits on the first day of the month. On February 16, 2010, Illinois changed its issuance policy, adding many cases to the 4th, 7th and 10th day of each month. This change in issuance allows us to analyze within-state variation in SNAP policies to determine how later SNAP distribution dates can assist families in smoothing benefit consumption.

Additionally, we utilize a unique feature of Indiana's issuance policy to study how SNAP timing affects criminal behavior throughout the benefit month. Since Indiana issues benefits based on the first letter of the recipient's last name, we utilize this as-good-as-random variation to avoid bias due to other factors that may

[3]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.

be correlated with both SNAP receipt and criminal activity. Therefore, we are able to use individual-level crime data to estimate how monthly income shocks affect crime.

Table 1 provides the Indiana schedule of SNAP issuance dates throughout the month based on the first letter of the last name both before and after a policy change in 2014.[4] Prior to 2014, Indiana issued benefits from the 1st-10th of the month based on last name. Notably, this policy is different than the change in Illinois which increased the number of primary SNAP distribution dates; Indiana did not change the number of days of SNAP distribution, but rather made benefits available later in the month, and approximately the same number of recipients received benefits on each disbursement date before and after the policy change.

3 Data

We utilize crime data from two administrative datasets. The main advantage of these data is that the 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 store locations. Below we provide a detailed description of the data used in our analysis.

3.1 Chicago Crime Data

First, we use Chicago crime-level data from the City of Chicago's online data portal for 2007-2013.[5] 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 and whether it was domestic violence. We then group crimes into categories by their listed types and/or locations. The detailed descriptions of crimes in these data are a critical feature that we utilize to specifically analyze theft at grocery stores. Using geographic coordinates, we match crimes to their respective Census Tract locations to create a day-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.

Using a list of certified SNAP retailers from the USDA Food and Nutrition Service, we geocode retailer addresses using the Texas A&M GeoServices online batch processing system to count the number of certified SNAP retailers in each Census Tract in 2010 (the year the policy changed). We also integrate a measure from the American Communities Survey (2010 5-year estimates) of SNAP enrollment into our panel. We

[4] We will henceforth refer to these separate groups as "letter group."
[5] Available for download at https://data.cityofchicago.org/Public-Safety/Crimes-2001-to-present/ijzp-q8t2.

use both of these measures to examine heterogeneity by neighborhoods, and compare results across Census Tracts with high and low SNAP enrollment rates and numbers of SNAP retailers.

Table 2 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 11.607 and 7.512 crimes and thefts at grocery stores, respectively.

Table 2 Panel B separately displays the means for Chicago Census Tracts before and after the Illinois SNAP policy change. Notably, these statistics highlight that crime levels fell significantly over time, suggesting that other factors in addition to SNAP distribution policies likely contributed to the decline as well. One of the main goals of this paper is to separate out the effects of the policy change from the effects of other factors to better understand how staggering SNAP benefits affects crime.

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 from January 1, 2008, to December 31, 2014, in terms of the total dollar amount of benefits redeemed. During this time period, $7,480,298 were redeemed, on average, per day. We include these data to capture how beneficiaries alter consumption behavior when SNAP receipt dates 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, county of conviction, and category of crime 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 feature of these data is that they contain convicted 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.[6]

One of the limitations of these data is that all crimes are reported and classified by five main categories: person, drug, property, weapon, and sex offense.[7] Therefore, without more granular detail on exact crimes

[6]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`.

[7]Specifically, "person" crimes include, but are not limited to, assault, domestic violence, and kidnapping, "drug" crimes include drug possession and dealing, "property" crimes include burglary, theft, larceny and vandalism, "weapon" crimes include unlawful possession or use of a knife or firearm, and "sex offenses" include rape, molestation and indecency with a child.

committed, we are unable to distinguish between property crimes like vandalism, for example, and theft. Moreover, although these data contain information on the criminal's last name, we do not know which individuals received SNAP benefits prior to their conviction. Therefore, estimates on the effects of SNAP receipt and crime using these data will represent intent-to-treat effects and will understate the true effects of staggered SNAP disbursement.

Table 2 Panel C shows summary statistics for the Indiana convictions data. The average crimes committed per day in Indiana for each last name letter is 0.839, with the largest share of crimes due to property crimes (mean=0.237).

4 Methods

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

4.1 Within-State Policy Changes

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 benefit distribution.

The main model is a regression discontinuity-type 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 $outcome_{it}$ is the count of crimes (of various types) on day t in Census Tract i:

$$outcome_{it} = \beta_0 + \beta_1 * SNAP\,distributed\,2-23_t + f(days\,from\,cutoff_t) + \pi_d + \gamma_m + \psi_y + \lambda_i + u_{it} \quad (1)$$

β_1 is the coefficient of interest (the effect of dispersed SNAP distribution), π_d is day of week fixed effects, γ_m is month fixed effects, ψ_y is year fixed effects, and λ_i is Census Tract fixed effects. We control for the days from cutoff (running variable) in multiple ways and allow it to vary on either side of the cutoff. 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. Our preferred specifications uses this entire range of dates, but our results are not sensitive to this choice. Results from a range of bandwidths yield nearly identical results, and will be discussed in the Section 5.

Specifically, our identifying assumption is that characteristics related to crime vary smoothly across the time of treatment, namely February 2010. The fact that SNAP recipients cannot manipulate disbursement timing alleviates potential selection concerns. That said, with any RD design, it is important to consider whether there may be additional policy changes or general disruptions related to outcomes of interest that coincide with 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.[8] We also compare the effects on the full 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 SNAP disbursement (the 24th to the 31st). 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 various bandwidths.

For comparison, we also replicate the analysis using the February 2014 policy change in Indiana in which the number of days of SNAP issuance and the density of recipients per day did not change, but the distribution dates changed from the 1st-10th of the month to the 5th-23rd of the month. We estimate the effects of shifting SNAP dates later in the month using a day-level specification that corresponds to Equation 1.

To understand potential mechanisms, we consider the distribution of crimes across days of the month to

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

explore two possibilities. First, if recipients engage in criminal behavior the day of or day after receiving SNAP benefits, the number of crimes should spike on these days as a result of the policy change. Second, if disbursement on the 1st day of the month makes individuals more likely to commit crimes two weeks later when they have depleted their benefits, we would expect the average number of crimes around the 15th of the month go down after the policy. We find support for the latter.

4.2 Random 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 unique feature of Indiana SNAP issuance policies, specifically that distribution dates are based on the first letters of SNAP recipient's 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 2012-2014 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.[9]

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

$$outcome_{lt} = \beta_0 + \beta_1 * week2_{lt} + \beta_2 * week3_{lt} + \beta_3 * week4_{lt} + \gamma_l + \pi_t + u_{lt} \tag{2}$$

where $outcome_{lt}$ 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 last name letter.

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

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 to more precisely estimate how SNAP disbursement affects crime:

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

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 month, year, day-of-month and day-of-week fixed effects. Notably, analyses allow errors to be correlated within last name letter over time when constructing standard-error estimates.

Finally, we note that, although we have information on each convicted criminal's last name, we do not have information on SNAP receipt. All estimates will measure intent-to-treat effects. Therefore, if every criminal was not previously participating in the SNAP program, any estimates based on the above methods will understate the benefits of staggered SNAP issuance.

5 Results

5.1 Baseline Results

First, to analyze the extent to which staggering SNAP benefits reduces crime, we present graphical evidence of crimes levels over time in Figure 1. Each figure plots monthly means of daily, Census Tract-level counts (after differencing out month fixed effects).[10] 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 display linear fits and confidence intervals for the Census Tract by day counts (after removing month fixed effects) of the crimes.

Crime and theft occurring at grocery stores (the bottom row) both exhibit large drop-offs after the policy

[10]Monthly cyclicity in crime is particularly pronounced in Chicago given its cold winters. Appendix Table A1 replicates these figures for crime at grocery stores and theft at grocery stores without differencing out month effects, and the conclusions are similar.

change, and the effect on theft at grocery stores is particularly striking. Conversely, for crime and theft anywhere (top row) the visual evidence is less convincing. Estimates for these types of crimes are less robust across specifications, and we primarily focus on the effect on grocery store crime and grocery store theft.

Table 3 presents estimates from the same comparisons shown in Figure 1 based on the OLS model described in Equation 1. The baseline results include all days (Column 1) and results by day of month ranges for all four crime outcomes (Columns 2-4). We also report the pre-period means for each time span by type. Standard errors are clustered on the Census Tract level, although results are robust to clustering on the days from the cutoff.[11,12]

These empirical results in Column 1 largely reinforce the conclusions that can be drawn from the figures - staggering SNAP benefits leads to a large reduction in crime at grocery stores and theft at grocery stores of approximately 15-20%. Moreover, we find some evidence of a decrease in crime and theft in general, however these estimates are more sensitive to specification changes and are therefore less convincing.

5.2 Timing Results

5.2.1 Results from Illinois

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 likely to be most affected by the policy change and the locations that are more likely to be responsive to the change. If the 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. 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% 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 reduction in the benefits given out on the 1st, and an increase in those given out on 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 dates to affect behavior. To show how consumers respond to this change, we

[11] Clustering on the days from the cutoff would be the analog to 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.

[12] These results hold even when we do not account for time fixed effects. See Figure A1 for a replication of Figure 1 for grocery crime and theft with non-residualized mean.

present SNAP redemptions data in Figure 2. Prior to the policy change, 8 percent of all SNAP benefit redemptions occurred on the first of the month, 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 4 percent and remained more consistent throughout the month. Therefore, Figure 2 indicates that consumers do alter shopping behavior when benefit dates 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 3 Columns 2-4 present estimates based on the OLS model in Equation 1 that restricts the sample to the corresponding day groups (1st of the month, 2nd to 23rd, 24th to 31st). Estimates in Column 2 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 positive and statistically significant. This may be because staggered SNAP distribution influences other types of criminal behavior not captured in the grocery theft or grocery crime estimates.

Columns 3 and 4 of Table 3 present findings for days 2-23 and days 24-31, respectively. While all of the estimates in Column 3 are negative and statistically significant, implying that the policy caused a reduction in all reported types of crime, estimates in Column 4, with the exception of overall crime, are negative and statistically insignificant. Moreover, the reductions are larger in the 2-23 range than the 24-31 range. The relative magnitudes of these effects are suggest that staggered SNAP distribution led to a 32% reduction in grocery store theft and approximately a 21% decrease for grocery store crimes in days 2-23, but did not change behavior in the never-treated range (days 24-31).

Given that monthly fluctuations in crime are driven by weather patterns, we additionally replicate these main results, adding controls for weather variables, which include average daily high and low temperatures, snowfall, wind speed and precipitation. [13] Estimates, shown in Table 4 indicate that SNAP staggering reduced overall crime levels by 3.6 percent and reduced grocery store crime by 24 percent. Similar to results in Table 3, the reduction in grocery store crime and theft is driven by effects in the 2-23 range, which indicate a 27 percent and 35 percent decrease, respectively. Moreover, when accounting for weather, crime at grocery stores also falls in the fourth week, albeit to a lesser extent.

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.[14] The solid line is a polynomial fit of these means for the months after the policy change (when SNAP benefits were staggered

[13]Notably, all of these variables are smooth across the treatment threshold, as shown in Appendix Table A3.

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

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 dates over which many more SNAP disbursements were given out after the policy change.

Overall crime and thefts are shown in the top row and 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).

5.2.2 Results from Indiana

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 an individual who committed a crime would have received SNAP benefits, based on the first letter of their last name.[15] Figure 4 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 fixed effects. These figures suggest that criminal behavior 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, cyclicity is much more pronounced.

Table 5 presents estimates that measure how crime fluctuates in the weeks following SNAP distribution. Estimates are presented 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 these weeks. 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, both property crimes as well as the overall crime level fall by about 8%, and 4%, respectively, although estimates for all other crime types are statistically insignificant. By the fourth week of the benefit month, there are no statistically significant effects of SNAP distribution on any crime type. Estimates for the fourth week of the month are precise enough to rule out effects of 5-7 percent.[16,17]

[15] For example, if John Smith committed a crime on the 27th, 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.

[16] For a graphical depiction of these main results, see Figure A5.

[17] Following Foley (2011) we additionally show the main results, grouping by three days instead of weeks. See Figure A6 and Table A1. When grouping effects by into more bins, estimates for overall crime levels and property crimes become statistically insignificant for all day groups. Notably, estimates follow a quadratic pattern, with crime increasing in the fourth week of the benefit month.

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 month) or, as a recent study has found, that individuals do not view SNAP benefits as fungible (Hastings and Shapiro, 2017). Conversely, they do appear to suggest that crime attains its nadir the third week after disbursement. These findings may indicate that crime decreases when recipients begin to exhaust SNAP benefits, potentially because the household has little resources to spend, limiting social interactions and access to complements to crime, such as alcohol or drugs.

It may be the case that individuals with different race, ethnicity and gender are affected by SNAP policies differently. To explore the extent to which criminal behavior between these subgroups vary, we estimate effects of staggered SNAP benefits on convicted crimes and show these results in Table 6. Notably, about 3 percent of the sample is Hispanic, 28 percent is black, 68 percent is white and 15 percent is female. Panel A shows the effects of staggering SNAP benefits on crimes committed by whites; estimates are similar to the main results and indicate a decrease of overall crime and property crime 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. Interestingly, estimates indicate that property crimes increase in the second and fourth weeks of the month after receiving SNAP benefits. This could suggest that females are more likely to steal food or other resources after exhausting their benefits.

Notably, the results presented above suggest that recipients stay home and commit less crimes during the second and third weeks of the month, relative to the first week, and increase criminal involvement near the end of the benefit month. Since Figure 4 and results in Table 5 indicate that SNAP distribution dates and criminal behavior are related nonlinearly, Table 7 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. We do not find statistically significant effects for drug or property crimes, further highlighting that SNAP recipients are not experiencing an income shock that encourages reckless behavior at the beginning of the month. As in the week-by-week results in Table 5, crime actually reaches a low when we expect beneficiaries to exhaust benefits. Furthermore, given that average crime levels increase at the end of the month, it is likely the case that individuals commit crimes due to a lack of financial resources.

Finally, we consider the extent to which shifting benefit issuance towards the middle of the month can affect crime. 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.[18] Therefore, we additionally utilize this within-state variation to analyze how shifting benefit issuance towards the middle of the month affected criminal behavior. To do so, we provide corresponding RD-type figures to show how crime levels responded to the change in policy just after February 1, 2014. Figure 5 presents average monthly crime levels over time, controlling for month fixed effects. Table 8 contains the analogous point estimates (from estimating a state-level version of Equation 1), as well as estimates for the 1st of the month, days 2-23, and days 24-31 separately. While overall crime levels, drug arrests and property crimes do not decrease overall, we find large and statistically significant reductions of about 100 percent in these crimes on the first of the month. Moreover, weapon crimes increase by about 77 percent during the first three weeks of the month following the policy change. We do not find consistent results for person crimes or sex offenses, suggesting that crimes committed at the end of the month are financially motivated. Furthermore, we recognize that the RD-style figures are less compelling in Table 8, and primarily include them for completeness.

5.3 Geographic Results

If SNAP distribution affects 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. We explore this possibility 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.[19]

Table 9 contains results for these subgroups of Census Tracts. Column 1 replicates the baseline estimates presented in Table 3 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, there are only statistically significant declines in crime in high SNAP enrollment areas, although all coefficients are negative. For crime and theft at grocery stores, the effects for low SNAP enrollment areas are smaller than those for high enrollment areas, and only high enrollment areas experienced a statistically significant decline. Crime at grocery stores declined by 3% in low SNAP enrollment Census Tracts, and by 24% in high enrollment Census Tracts. Theft at grocery stores declined by 17% and 37% in low and high enrollment Census Tracts, respectively.

Differences between these areas could also reasonably be attributed to the lack of grocery stores in certain

[18] See Table 1 for the SNAP issuance schedule as of February 2014.

[19] In practice, the median percentage of SNAP enrollees by Census Tracts in Chicago in 2010 according to the ACS is 13.6%. The median number of SNAP retailers is 2, and the number ranges from 0 to 18.

areas.[20] The last two columns in Table 9 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. Crime at grocery stores declined by 2% in Census Tracts with a low concentration of SNAP retailers, and by 25% in Census Tracts with a high concentration of SNAP retailers. Theft at grocery stores declined by 8% and 33% in Census Tracts with a low and high concentration of SNAP retailers, respectively.[21]

5.4 Robustness Checks

This section provides support for the identification assumptions described in Section 4 and support that the main results are consistent across a wide range of specifications and bandwidths.

We first turn to the regression discontinuity (RD) specification. Given the fact that estimates for models that consider overall crime and theft are somewhat unreliable, we now focus solely on the effects of staggered SNAP benefits on crimes and thefts at grocery stores. A standard concern in RD 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 main results for grocery store crime and grocery store theft are robust to these other specifications.

First, we allow the function of the days to the policy change (the running variable) to vary in order. Column 1 in Table 10 replicates the main baseline results. Column 2 contains the results when we control for the days to the cutoff quadratically, and results in the 3rd column allow for it to vary cubically. (Again, we allow the polynomials to vary on either side of the cutoff.) For both crime and theft at grocery stores, the quadratic models are similar to the baseline models. Under a cubic fit, crime at grocery stores still appears to decrease, but the magnitude of the coefficient is about two-thirds of the linear and quadratic models and is not statistically significant. For theft at grocery stores, the cubic model yields very similar results to the baseline and quadratic models.

Additionally, we estimate a Poisson model because the number of crimes is count data. These results are shown in Table 10 Column 4. Because some tracts never have a crime of either of these types (perhaps because they have no grocery stores) a number of observations are dropped in this model. Again, the estimates are very close to those found in the baseline models - that these crimes go down by approximately 20-30 percent.

[20]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.

[21]We similarly estimate effects of SNAP staggering in Indiana counties with below and above average rates of SNAP usage and display these results in Table A2. Estimates indicate similar patterns in each subgroup, which suggests that SNAP timing drives criminal behavior more than the financial state of the community. However, it could also be the case that since data on census tracts contain more granular information, these data better represent communities than counties, and thus county-level data does not accurately measure potential spillover effects that SNAP benefits have on communities as a whole.

Second, we explore how sensitive the estimates are to kernel selection and bandwidth. In keeping with the current methodology in regression discontinuity models, we follow Calonico, Cattaneo, Farrell, and Titiunik (2016) (and utilize their STATA package rdrobust) to estimate the model with a triangular kernel and to determine the mean square error optimal bandwidth for the RD estimator.[22] We first estimate our baseline model with a triangular kernel (our results above use a uniform kernel). For both crime at grocery stores and theft at grocery stores, the point estimate is again stable (when compared to the baseline results) and statistically significant. The MSE-optimal bandwidths are 287 days for crime at grocery stores and 256 days for theft at grocery stores. When we estimate models with these smaller bandwidths, we obtain much larger estimates (that are still negative and statistically significant)[23]

To further test bandwidth sensitivity, we replicate the models under a range of bandwidths. We test bandwidths from 12 months on either side to the full 39 months used in the baseline specification in increments of one month at a time. Figure 7 reports the coefficients and standard errors from models using each of these alternative bandwidths. For both outcomes, the estimated coefficient on the policy change is stable across the different bandwidths and is nearly always statistically significant on the 95% level.

Moreover, to show that our estimated effect in 2010 is not simply representative of a yearly cycle of recurring monthly fluctuations of crime levels, we present average crime levels by month in Table 11. Panels A and B display mean monthly grocery crimes and grocery thefts, respectively, for the four months before and after February, the first effective month of the 2010 policy change. Column 1 presents average crime levels for October to June in pre-treatment years, 2007-2009, and Column 2 shows average crime levels for the four months leading up to the policy change and first five months after the policy change was enacted. Notably, there is clear cyclicality in crime levels across months. However, in February 2010 both grocery crimes and grocery thefts fell by three times that of previous years, reinforcing the idea that changes in SNAP issuance policy led to lower overall levels of crime. Figure A2 mirrors this by showing trends in crime across months, comparing average grocery store crimes and grocery store thefts for 2009 and 2010.[24]

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, and assign it as a treatment cutoff date, without replacement. We then generate distributions of RD estimates, using the preferred specification in Equation 1 and optimal bandwidths, as suggested by (Calonico, Cattaneo, Farrell,

[22]Although the newest version of the rdrobust package does allow for the consideration of covariates in the bandwidth selection, we do not use the fixed effects controls from the main model in this step. This is a computational choice - because some of the fixed effects are zero in smaller bandwidths, it is unable to select one when we include the fixed effects.

[23]We believe this is due to the fact that some month fixed effects are only equal to one on one side of the cutoff, and we get similarly large estimates using OLS on bandwidth of less than a year on either side of the cutoff.

[24]We additionally show that our results are not being driven by sharp changes in weather or labor market conditions. See Figures A3 and A4.

and Titiunik, 2016), to determine what percent of the simulated estimates from 1,000 random draws are less than our actual estimate reported in Table 3. The distributions of placebo estimates for grocery store crimes and grocery store thefts are shown in Figure 8. Based on these placebo distributions, 8.9 percent and 9.1 percent of placebo estimates are less than the actual estimates for grocery store crimes and thefts, respectively, which provides some 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 sufficiently random to provide causal estimates. Table 12 displays the average crimes committed by each SNAP letter group and the available demographic characteristics by letter. These statistics suggest that the letter groups are quite similar, although our use of letter group fixed effects does not require this to be the case.

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 crimes and thefts that occur in grocery stores. To measure this effect, we examine the response in these outcomes to a large policy change in the city of Chicago. Prior to this change, over 60% 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 both of these types of crimes fall by about 20-30% after the policy change, which corresponds to approximately 3 grocery store crimes across the city per day. Therefore, our results suggest that any policies that stagger benefits have the potential to reduce negative externalities associated with income shocks on the first of the month.

Importantly, 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 an increase in SNAP redemptions on the 12 issuance dates as a percent of total sales before and after the policy change. Based on SNAP redemption data, we can also infer that although the reduction in shopping on the first of the month is substantial, the increase on other days small - around 1% more in spending each day.[25]

We also analyze how the benefits 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 4.3 percent in the third week after disbursement. We find evidence of a quadratic relationship between SNAP benefits and criminal behavior,

[25] 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 A3 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 of the month.

where crime increases immediately after SNAP receipt and again at the end of the benefit month, following similar patterns in income receipt (Evans and Moore (2011)). While we find effects of SNAP disbursement on overall crime level, we do not see effects for drug crimes, indicating that recipients do not engage in more reckless behavior right after receiving benefits.

These findings are important for understanding the choices that families in poverty make in response to the programs in which they participate. 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 findings support and refine the results in Foley (2011) establishing that financial 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, we believe that there are substantial policy implications of our findings. Most importantly, staggering SNAP benefits over the course of the month decreases crime. In the case of Chicago, it reduced the number of annual grocery store crimes by over 800 and annual grocery store thefts by over 500. If SNAP benefits were the only income sources families received, the result of this shift would not be a change in levels of this magnitude, but merely a shift over the days of the month. Our results indicate more broadly 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 Temporary Aid to Needy Families) could also help to alleviate consumption shocks, as could splitting families' monthly benefits into multiple staggered payments per month.

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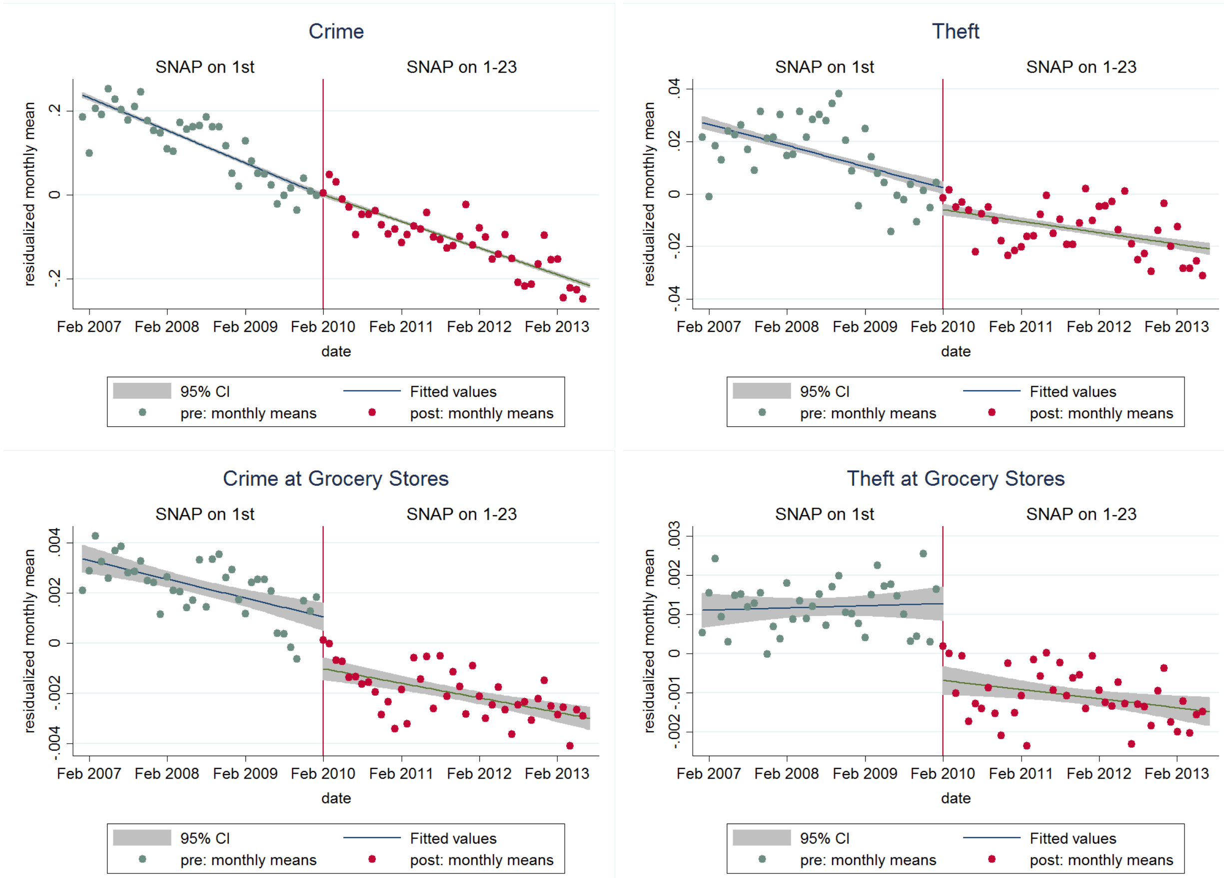
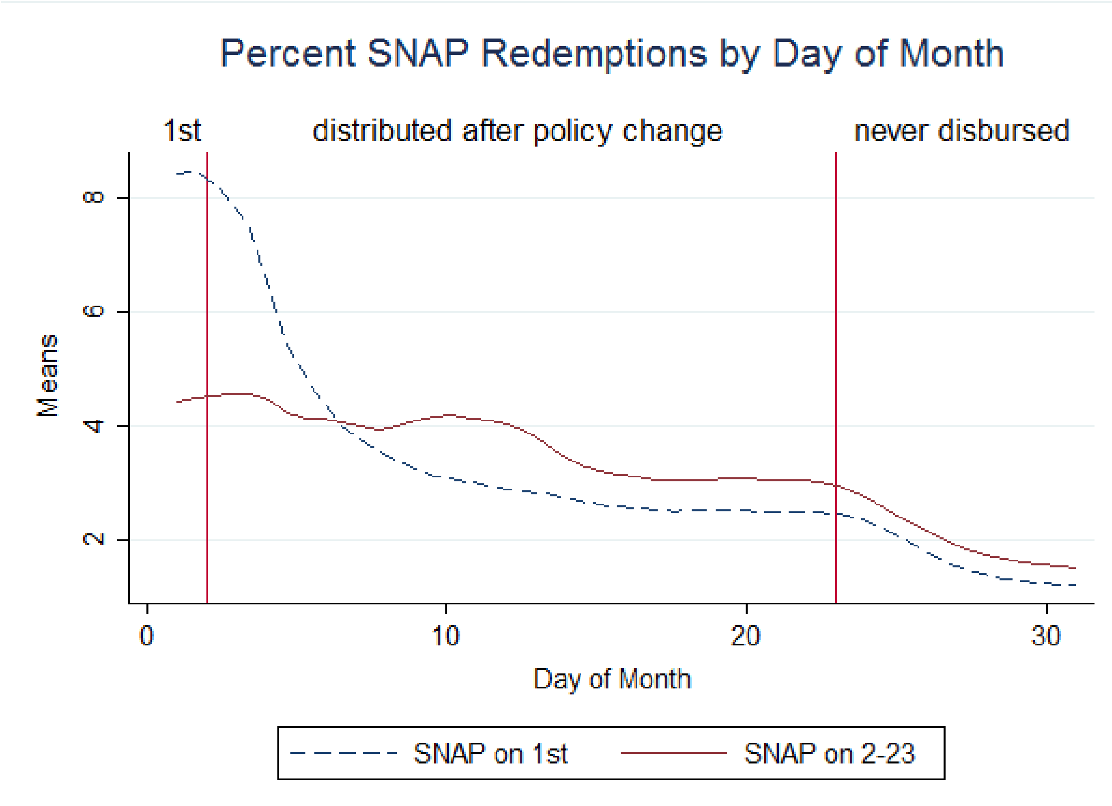
Tables and Figures

Figure 1: Effect of Illinois SNAP Disbursement Change on Crime



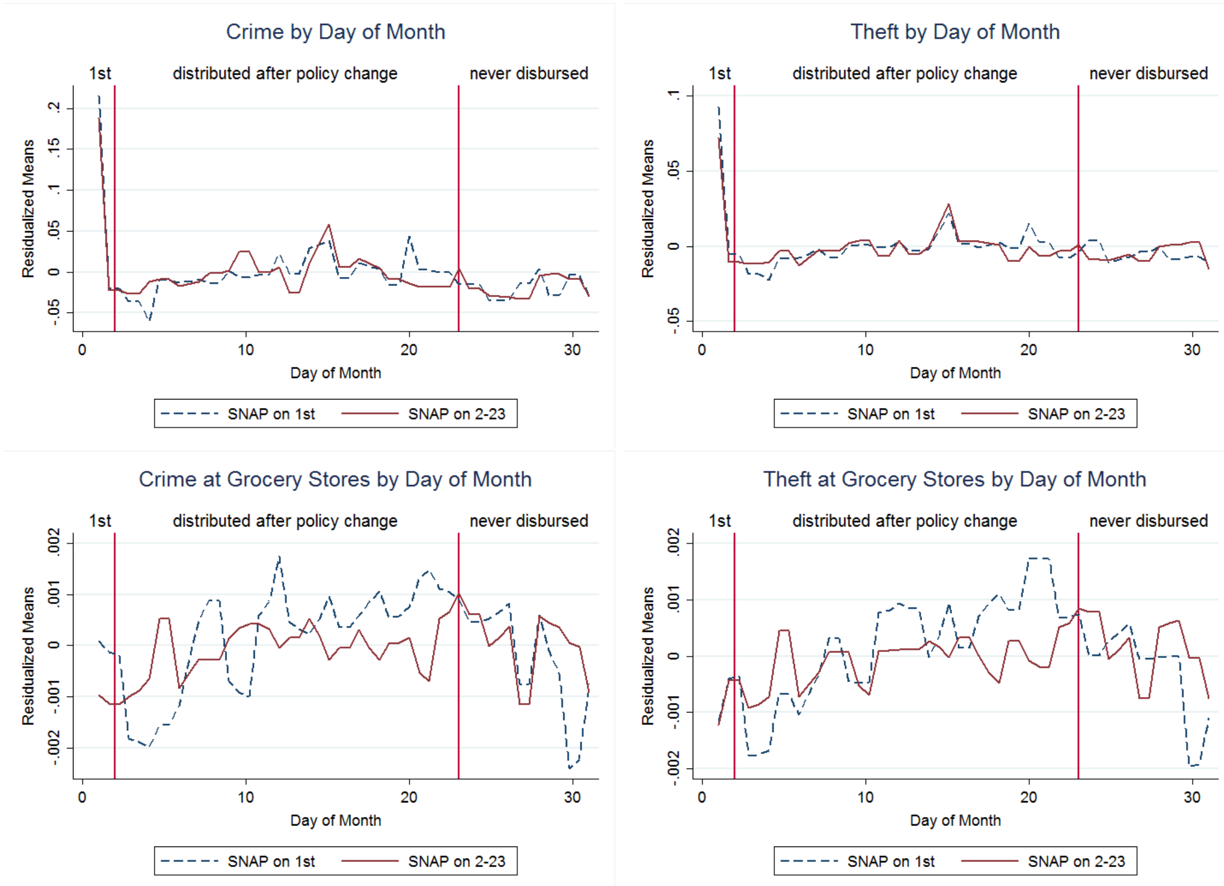
Notes: Each figure plots month-level means of residuals (after differencing out month fixed effects) and linear fits (with 95% confidence intervals) of each of the crimes listed. To the left of the vertical line, SNAP benefits were given out primarily on the 1st of the month, and to the right, they were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

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



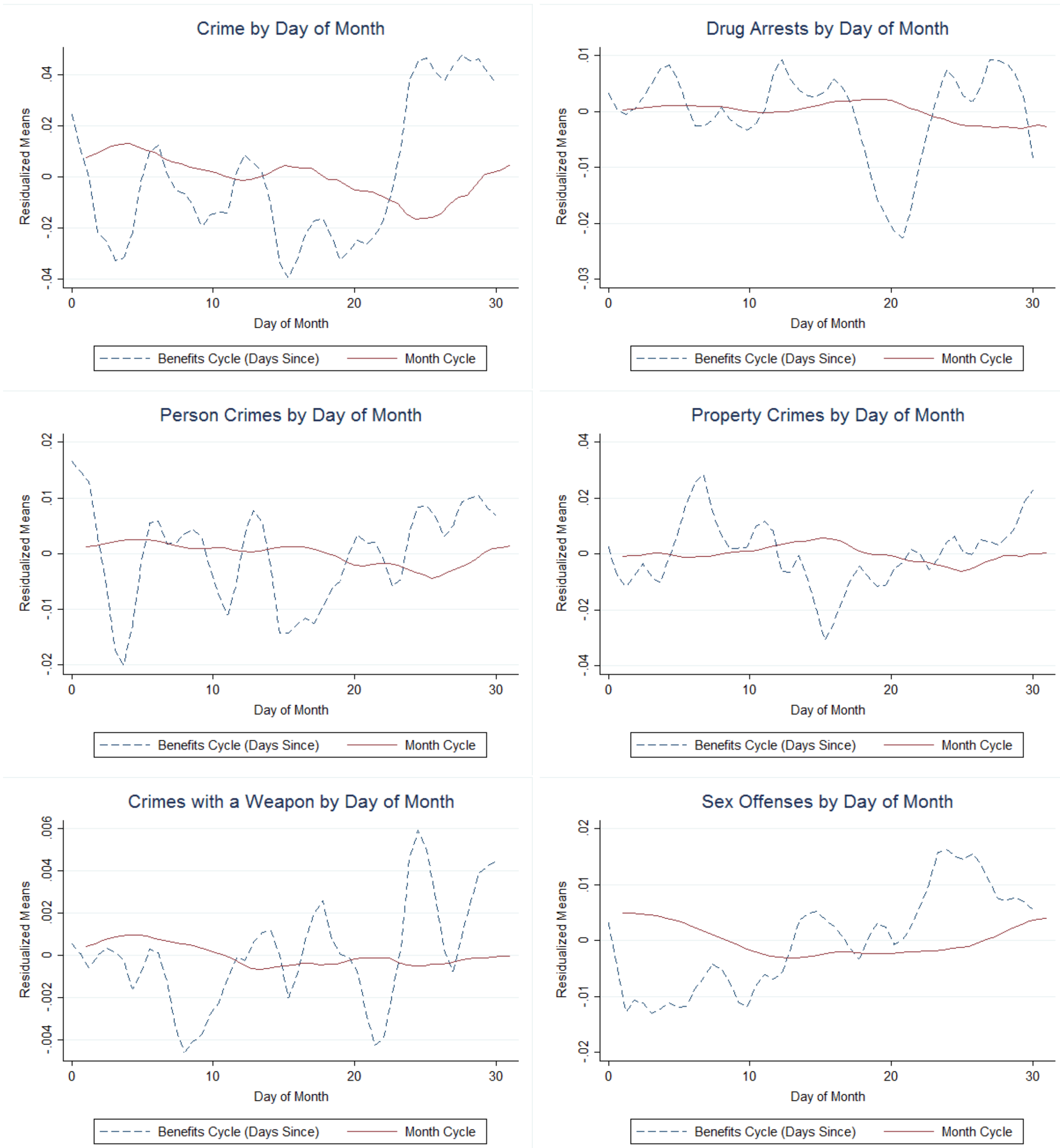
Notes: Authors' calculation based on daily SNAP redemptions data from the Illinois Department of Health and Human Services. The dotted line is calculated for January 2007 - January 2010. The solid line, indicating the post-period after the policy change, is calculated for February 2010 - May 2013.

Figure 3: Crime by Day of Month



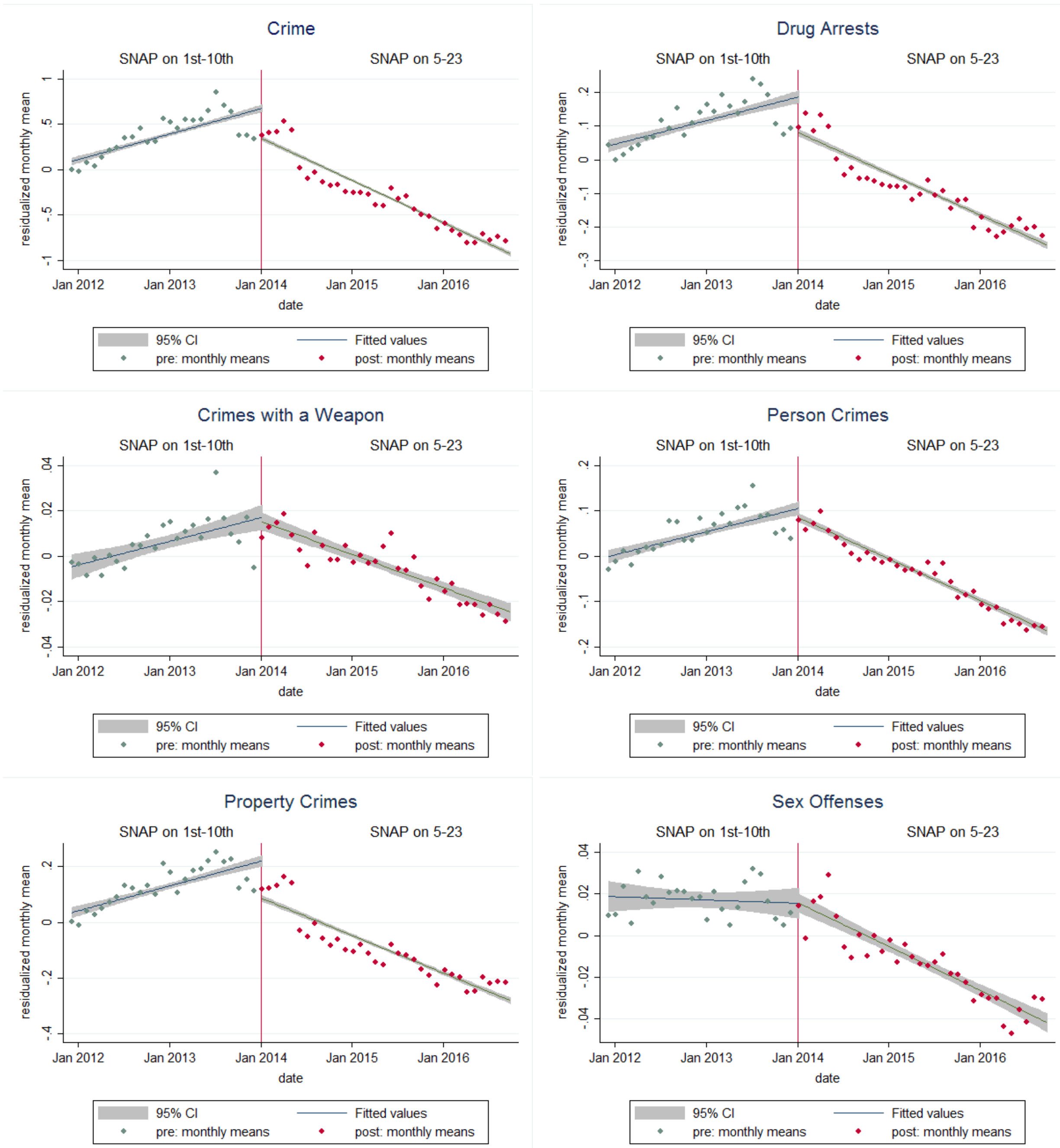
Notes: Each figure displays residualized (for month and year differences in levels) kernel-weighted local polynomial plots of crimes of each denoted type on the Census Tract level across days of the month. The range of days between the vertical lines contains the "new" distribution dates after the policy change. The area to the right (the 24th-31st) includes days on which SNAP benefits were never distributed. Crime data from 2007-2013 are from the city of Chicago.

Figure 4: Average Crimes Committed: Benefit Month vs. Calendar Month



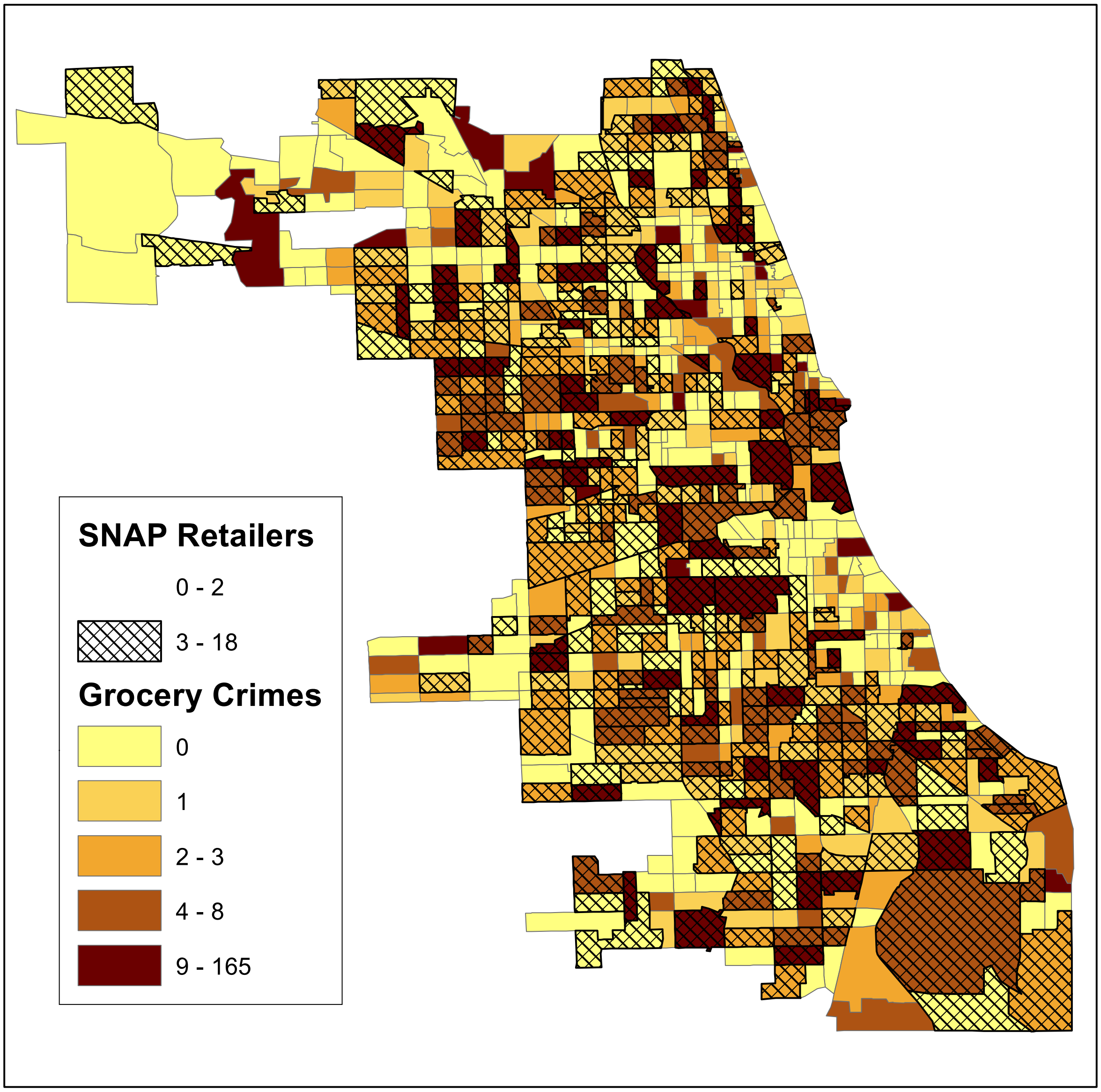
Notes: Each figure plots month-level means of residuals (after differencing out month fixed effects) of each of the crimes listed. The dotted line displays the average crimes committed by the number of days since each letter group potentially received SNAP benefits, while the solid line plots the average number of crimes for each day of the month. Crime data from 2012-2016 are from Indiana Department of Correction.

Figure 5: Effect of Indiana SNAP Disbursement Change on Crime



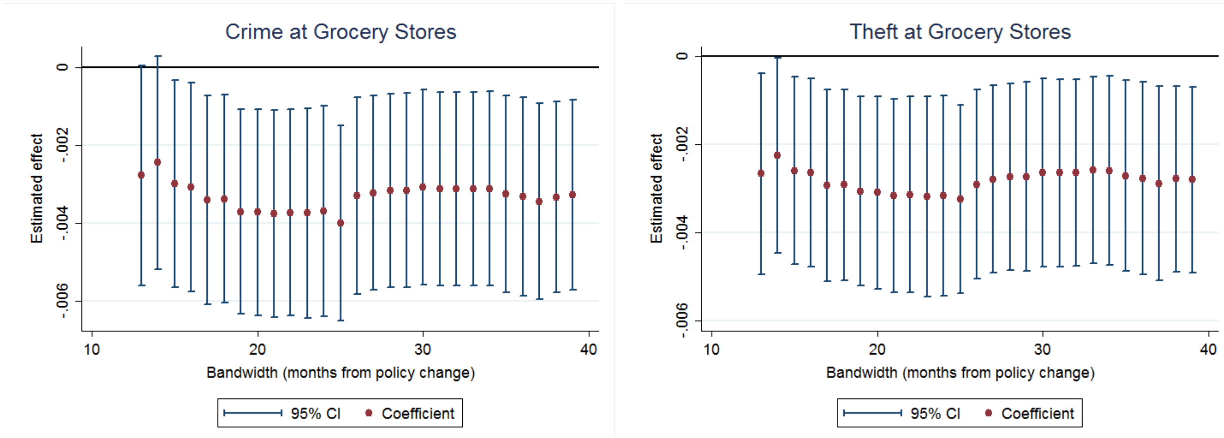
Notes: Each figure plots month-level means of residuals (after differencing out month fixed effects) and linear fits (with 95% confidence intervals) of each of the crimes listed. To the left of the vertical line, SNAP benefits were given out each day from the 1st-10th, and to the right, they were distributed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

Figure 6: SNAP Retailers and Grocery Store Crimes 2010



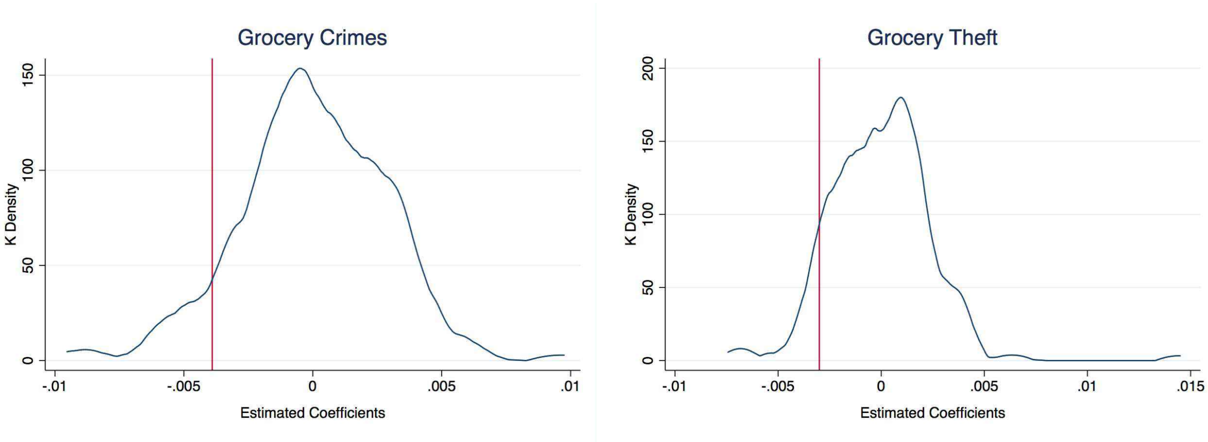
Notes: Census Tracts are grouped by the count of SNAP retailers, and the cross-hatched texture denotes "high SNAP retailer" (above median count) Census Tracts. Census Tracts are also grouped by quintiles of the number of crimes reported to have occurred at grocery stores in 2010. Crime data are from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

Figure 7: 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 8: Placebo Estimates



Notes: Each figure plots the distribution of 1,000 randomly drawn placebo estimates from the regression discontinuity specification in Equation 1 using pre-period crime data. For grocery store crimes, 9.1 percent of placebo estimates are smaller than the estimate reported in Table 3. For grocery store thefts, 8.9 percent of placebo estimates are smaller than the baseline estimate reported in Table 3. Optimal bandwidths are selected as suggested by Calonico, Cattaneo, Farrell, and Titiunik (2016) and are 256 days. Crime data from are from the city of Chicago.

Table 1: Indiana Monthly Benefit Issuance Schedule

	Disbursement Date	
First Letter of Last Name	Before	After
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" denotes Indiana's SNAP disbursement schedule prior to 2014, while "After" denotes the current SNAP schedule, which changed in January 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 2: Summary Statistics

Panel A: Summary Statistics - Chicago				
	Mean	St.Dev.		
Census Tract Crime	1.260	1.572		
Census Tract Theft	0.262	0.605		
Census Tract Crime at Grocery Stores	0.014	0.126		
Census Tract Theft at Grocery Stores	0.009	0.102		
City-Wide Crime	1030.396	166.163		
City-Wide Theft	214.720	39.193		
City-Wide Crime at Grocery	11.607	4.148		
City-Wide Theft at Grocery	7.512	3.092		
City-Wide Yearly Crime	364664.691	70313.858		
City-Wide Yearly Theft	75865.039	12995.485		
City-Wide Yearly Crime at Grocery	4115.008	934.778		
City-Wide Yearly Theft at Grocery	2661.636	548.914		
Percent Household on SNAP (2010)	0.171	0.143		
Number of SNAP Retailers (2010)	2.979	2.680		
Panel B: Pre vs. Post Policy - Chicago				
	Before Policy Change (1/1/07-2/15/10)		**After Policy Change (2/16/10-6/30/13)**	
	Mean	St.Dev.	Mean	St.Dev.
Crime	1.377	1.675	1.153	1.464
Theft	0.278	0.623	0.249	0.588
Crime at Grocery Stores	0.016	0.136	0.012	0.116
Theft at Grocery Stores	0.010	0.109	0.008	0.095
Panel C: Summary Statistics - Indiana				
	Mean	St.Dev.		
All Crimes	0.839	1.378		
Drug Crimes	0.227	0.575		
Weapon Crimes	0.028	0.175		
Person Crimes	0.166	0.460		
Property Crimes	0.237	0.588		
Sex Offenses	0.040	0.225		

Notes: 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 Communities Survey and SNAP retailer data are from the USDA Food and Nutrition Service. Indiana crime data are from the Indiana Department of Correction. Panel A displays means and corresponding standard deviations for data from Chicago spanning 2007-2013, Panel B displays means and standard deviations for Chicago Census Tracts before and after a change to the Illinois SNAP issuance schedule, and Panel C displays means and standard deviations for crime types committed by day and last name letter in the state of Indiana from 2012-2016.

Table 3: The Effect of Staggering SNAP Benefits on Crime

		Day of Month Range		
	Baseline	1st of Month	Days 2-23	Days 24-31
Crime				
SNAP dispersed	-0.0041	0.2338***	-0.0230**	0.0218
	(0.0088)	(0.0556)	(0.0104)	(0.0166)
Pre-Period Mean	1.377	1.592	1.373	1.360
Theft				
SNAP dispersed	-0.0123***	0.0322	-0.0141***	-0.0113
	(0.0041)	(0.0271)	(0.0047)	(0.0073)
Pre-Period Mean	0.278	0.370	0.275	0.273
Crime at Grocery				
SNAP dispersed	-0.0032***	0.0050	-0.0036**	-0.0028
	(0.0012)	(0.0046)	(0.0015)	(0.0018)
Pre-Period Mean	0.016	0.016	0.017	0.016
Theft at Grocery				
SNAP dispersed	-0.0028***	-0.0005	-0.0035***	-0.0009
	(0.0011)	(0.0039)	(0.0013)	(0.0014)
Pre-Period Mean	0.010	0.009	0.011	0.010
N	1941114	63804	1403688	473622

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 (Column 1) or the ranges listed at the top of each column. Each regression includes month, 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 4: The Effect of Staggering SNAP Benefits on Crime, Controlling for Weather

		Day of Month Range		
	Baseline	1st of Month	Days 2-23	Days 24-31
Crime				
SNAP dispersed	-0.0512***	-0.2536***	-0.0697***	0.0200
	(0.0085)	(0.0522)	(0.0100)	(0.0164)
Pre-Period Mean	1.377	1.592	1.373	1.360
Theft				
SNAP dispersed	-0.0309***	-0.0896***	-0.0341***	-0.0163**
	(0.0040)	(0.0256)	(0.0046)	(0.0072)
Pre-Period Mean	0.278	0.370	0.275	0.273
Crime at Grocery				
SNAP dispersed	-0.0039***	0.0044	-0.0046***	-0.0031*
	(0.0012)	(0.0038)	(0.0015)	(0.0018)
Pre-Period Mean	0.016	0.016	0.017	0.016
Theft at Grocery				
SNAP dispersed	-0.0030***	0.0001	-0.0038***	-0.0013
	(0.0011)	(0.0035)	(0.0013)	(0.0014)
Pre-Period Mean	0.010	0.009	0.011	0.010
N	1941114	63804	1403688	473622

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 (Column 1) or the ranges listed at the top of each column. Each regression includes year, day-of-month, and day-of-week fixed effects and daily controls for weather. 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 5: Effects of SNAP Receipt on Crimes Committed by Weeks Since Issuance

	Any Crime	**Drugs**	**Property**	**Weapon**	**Person**	**Sex Offense**
Second Week of Month	-0.020	-0.003	0.001	-0.003	0.000	-0.006
	(0.021)	(0.006)	(0.009)	(0.003)	(0.005)	(0.004)
Third Week of Month	-0.036**	-0.005	-0.018**	0.001	-0.010	0.002
	(0.017)	(0.005)	(0.008)	(0.002)	(0.007)	(0.003)
Fourth Week of Month	-0.010	-0.008	-0.003	0.001	-0.001	0.005
	(0.018)	(0.007)	(0.007)	(0.002)	(0.006)	(0.003)
N	45630	45630	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. "Person" crimes include assault, domestic violence, and kidnapping, "drug" crimes include drug possession and dealing, "property" crimes include buglary, theft, larceny and vandalism, "weapon" crimes include unlawful possession or use of a knife or firearm, and "sex offenses" include rape, molestation and indecency with a child. Robust standard errors are clustered on last name group and are shown in parenthesis.

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

Table 6: The Effect of Indiana SNAP Receipt on Crime by Race, Ethnicity, and Gender

	Any Crime	Drugs	Property	Weapon	Person	Sex Offense
Panel A. White						
Second Week of Month	-0.0067	-0.0063	0.0042	0.0001	0.0049	-0.0036
	(0.0138)	(0.0047)	(0.0073)	(0.0010)	(0.0040)	(0.0032)
Third Week of Month	-0.0300**	-0.0068	-0.0146*	-0.0004	-0.0046	0.0003
	(0.0125)	(0.0042)	(0.0078)	(0.0011)	(0.0040)	(0.0025)
Fourth Week of Month	-0.0081	-0.0072	-0.0044	0.0013	-0.0005	0.0054**
	(0.0144)	(0.0065)	(0.0057)	(0.0011)	(0.0045)	(0.0025)
Panel B. Black						
Second Week of Month	-0.0169*	0.0029	-0.0046	-0.0033	-0.0063	-0.0013
	(0.0092)	(0.0024)	(0.0031)	(0.0026)	(0.0037)	(0.0014)
Third Week of Month	-0.0100	0.0014	-0.0040	0.0017	-0.0074*	0.0011
	(0.0064)	(0.0023)	(0.0030)	(0.0021)	(0.0040)	(0.0013)
Fourth Week of Month	-0.0086	-0.0003	-0.0011	-0.0002	-0.0037	-0.0002
	(0.0071)	(0.0030)	(0.0026)	(0.0019)	(0.0037)	(0.0015)
Panel C. Hispanic						
Second Week of Month	0.0014	-0.0001	0.0011	0.0004	0.0010	-0.0003
	(0.0018)	(0.0011)	(0.0007)	(0.0004)	(0.0007)	(0.0006)
Third Week of Month	0.0018	-0.0001	-0.0001	-0.0003	0.0016	0.0007
	(0.0015)	(0.0008)	(0.0010)	(0.0003)	(0.0010)	(0.0009)
Fourth Week of Month	0.0025	-0.0001	0.0011	-0.0003	0.0015*	0.0002
	(0.0022)	(0.0011)	(0.0009)	(0.0002)	(0.0008)	(0.0006)
Panel D. Female						
Second Week of Month	0.0018	-0.0032	0.0048*	0.0002	0.0009	-0.0006**
	(0.0055)	(0.0045)	(0.0025)	(0.0004)	(0.0023)	(0.0003)
Third Week of Month	0.0017	-0.0011	0.0012	0.0003	0.0009	0.0004
	(0.0053)	(0.0035)	(0.0040)	(0.0005)	(0.0019)	(0.0005)
Fourth Week of Month	0.0048	-0.0025	0.0059**	0.0002	-0.0006	0.0007*
	(0.0052)	(0.0031)	(0.0027)	(0.0004)	(0.0022)	(0.0004)
N	46,530	46,530	46,530	46,530	46,530	46,530

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. "Drug" crimes include drug possession and dealing, "property" crimes include buglary, theft, larceny and vandalism, "weapon" crimes include unlawful possession or use of a knife or firearm, "person" crimes include assault, domestic violence, and kidnapping, and "sex offenses" include rape, molestation and indecency with a child. Robust standard errors are clustered on last name group and are shown in parenthesis.
, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table 7: Quadratic Effects of Indiana SNAP Receipt on Crime

	Any Crime	**Drugs**	**Property**	**Weapon**	**Person**	**Sex Offense**
Days Since SNAP	-0.00758**	-0.00029	-0.00249	-0.00018	-0.00175*	-0.00105*
	(0.00340)	(0.00100)	(0.00152)	(0.00032)	(0.00086)	(0.00059)
Days Since SNAP Squared	0.00026**	0.00000	0.00008	0.00001	0.00006*	0.00005**
	(0.00011)	(0.00003)	(0.00005)	(0.00001)	(0.00003)	(0.00002)
N	45630	45630	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. "Person" crimes include assault, domestic violence, and kidnapping, "drug" crimes include drug possession and dealing, "property" crimes include buglary, theft, larceny and vandalism, “weapon" crimes include unlawful possession or use of a knife or firearm, and "sex offenses" include rape, molestation and indecency with a child. 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 8: The Effect of Shifting SNAP Benefits Dates on Crime

		Day of Month Range		
	Baseline	1st of Month	Days 2-23	Days 24-31
Any Crime				
SNAP dispersed	-0.0302	-2.2832***	0.0255	0.0799
	(0.0447)	(0.5865)	(0.0479)	(0.0925)
Pre-Period Mean	1.222	2.431	1.181	1.181
Drugs				
SNAP dispersed	-0.0252	-1.0104***	0.0465**	-0.1030**
	(0.0212)	(0.2752)	(0.0206)	(0.0466)
Pre-Period Mean	0.341	0.638	0.338	0.311
Property				
SNAP dispersed	-0.0284	-0.7570**	-0.0202	0.0389
	(0.0267)	(0.3474)	(0.0279)	(0.0549)
Pre-Period Mean	0.366	0.686	0.355	0.356
Weapon				
SNAP dispersed	0.0228***	0.0436*	0.0255***	0.0141
	(0.0063)	(0.0236)	(0.0075)	(0.0136)
Pre-Period Mean	0.034	0.046	0.033	0.035
Person				
SNAP dispersed	0.0407**	-0.1018	0.0273	0.0894*
	(0.0193)	(0.1644)	(0.0245)	(0.0458)
Pre-Period Mean	0.218	0.365	0.215	0.208
Sex Offense				
SNAP dispersed	-0.0000	0.0012	-0.0046	0.0149
	(0.0088)	(0.1357)	(0.0083)	(0.0160)
Pre-Period Mean	0.056	0.318	0.041	0.065
Observations	45630	1508	33098	11024

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. "Person" crimes include assault, domestic violence, and kidnapping, "drug" crimes include drug possession and dealing, "property" crimes include buglary, theft, larceny and vandalism, "weapon" crimes include unlawful possession or use of a knife or firearm, and "sex offenses" include rape, molestation and indecency with a child. 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 9: Neighborhood Subgroups

	Baseline	SNAP Enrollment low	SNAP Enrollment high	SNAP Retailers low	SNAP Retailers high
SNAP dispersed	-0.0041	0.0098	-0.0179	0.0125	-0.0213
	(0.0088)	(0.0116)	(0.0133)	(0.0098)	(0.0148)
Pre-Period Mean		0.927	1.828	0.924	1.851
Theft					
SNAP dispersed	-0.0123***	0.0007	-0.0252***	-0.0009	-0.0241***
	(0.0041)	(0.0057)	(0.0057)	(0.0049)	(0.0065)
Pre-Period Mean		0.286	0.270	0.204	0.355
Crime at Grocery					
SNAP dispersed	-0.0032***	-0.0020	-0.0044**	-0.0002	-0.0063***
	(0.0012)	(0.0015)	(0.0020)	(0.0010)	(0.0023)
Pre-Period Mean		0.015	0.018	0.009	0.025
Theft at Grocery					
SNAP dispersed	-0.0028***	-0.0019	-0.0037**	-0.0004	-0.0053***
	(0.0011)	(0.0012)	(0.0018)	(0.0008)	(0.0020)
Pre-Period Mean		0.011	0.010	0.005	0.016
Observations	1941114	970557	970557	991914	949200

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 (Column 1) or the Census Tracts described at the top of each column. Each regression includes month, 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 10: Robustness Checks

	Baseline	Quad Fit	Cubic Fit	Poisson	Triangular Kernel Full Bandwidth	Triangular Kernel MSERD Bandwidth
Crime at Grocery						
SNAP dispersed	-0.0032***	-0.0027**	-0.0019	-0.2233***	-0.0033***	-0.0226***
	(0.0012)	(0.0012)	(0.0012)	(0.0745)	(0.0004)	(0.0009)
Theft at Grocery						
SNAP dispersed	-0.0028***	-0.0026**	-0.0022**	-0.3029***	-0.0028***	-0.0175***
	(0.0011)	(0.0011)	(0.0010)	(0.0980)	(0.0003)	(0.0006)
Observations	1941114	1941114	1941114	1476006	1941114	470350, 419634

Notes: Each coefficient if 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 effect of 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, and Column 6 uses a MSE-driven bandwidth. Crime data are from the city of Chicago.

Table 11: Differences in Chicago Crime Levels Across Months

	Pre-2010	2009-2010	Diff Pre-2010	Diff in 2010
Panel A. Grocery Crimes				
October	0.02	0.01	.	.
November	0.015	0.016	-0.002	0.002
December	0.014	0.015	-0.001	-0.002
January	0.016	0.016	0.002	0.002
February	0.015	0.013	-0.001	-0.003
March	0.016	0.013	0.001	0.000
April	0.016	0.013	0.001	0.000
May	0.016	0.014	-0.000	0.000
June	0.016	0.013	-0.000	-0.001
Panel B. Grocery Theft				
October	0.01	0.01	.	.
November	0.009	0.012	-0.002	0.001
December	0.009	0.009	-0.000	-0.003
January	0.009	0.011	0.001	0.002
February	0.009	0.008	-0.000	-0.002
March	0.010	0.008	0.000	0.000
April	0.011	0.008	0.001	-0.000
May	0.011	0.009	-0.000	0.001
June	0.011	0.008	0.000	-0.002

Notes: Columns 1 and 2 display the monthly average crime levels for grocery crimes and grocery theft in Chicago from October 2008-June 2009 and October 2009-June 2010. "Diff Pre-2010" denotes the month-to-month difference in crime levels for months prior to October 2009. "Diff in 2010" denotes the month-to-month difference in crime levels for 2009-2010, the year that Illinois increased the number of SNAP distribution days. Crime data are from the city of Chicago.

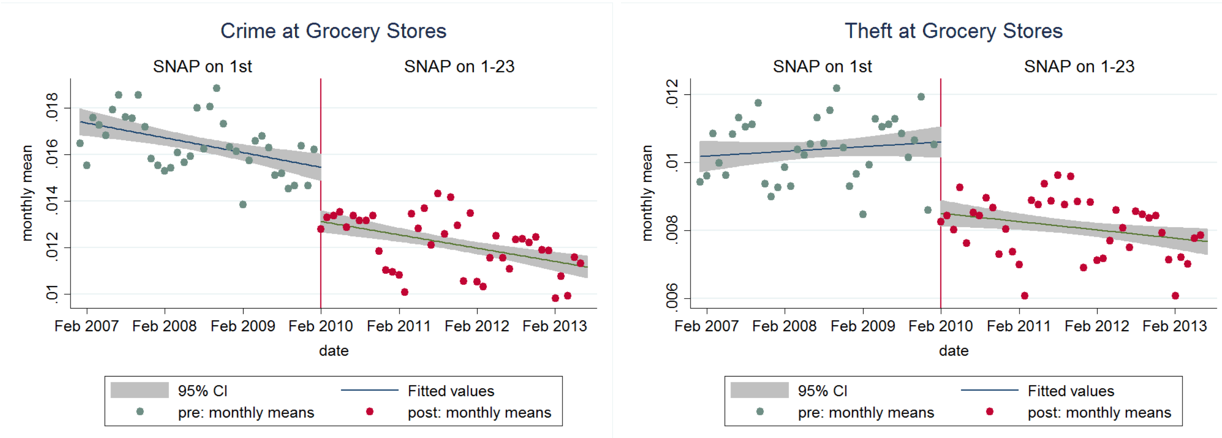
Table 12: Average Crime Levels by SNAP Letter Group

	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
All Crimes	1.43	1.33	0.75	0.96	0.79	1.16	0.60	2.20	0.35	0.44
Drug Crimes	0.40	0.37	0.20	0.26	0.20	0.33	0.15	0.62	0.10	0.12
Weapon Crimes	0.05	0.04	0.02	0.03	0.03	0.04	0.02	0.07	0.01	0.02
Person Crimes	0.27	0.25	0.14	0.19	0.17	0.22	0.12	0.43	0.07	0.09
Property Crimes	0.40	0.38	0.21	0.26	0.22	0.33	0.18	0.64	0.10	0.12
Sex Offenses	0.06	0.06	0.04	0.05	0.04	0.06	0.03	0.09	0.02	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: Indiana crime data are from the Indiana Department of Correction. Each column displays means for crime types committed by day and letter group in the state of Indiana from 2012-2016. "Person" crimes include assault, domestic violence, and kidnapping, "drug" crimes include drug possession and dealing, "property" crimes include buglary, theft, larceny and vandalism, "weapon" crimes include unlawful possession or use of a knife or firearm, and "sex offenses" include rape, molestation and indecency with a child.

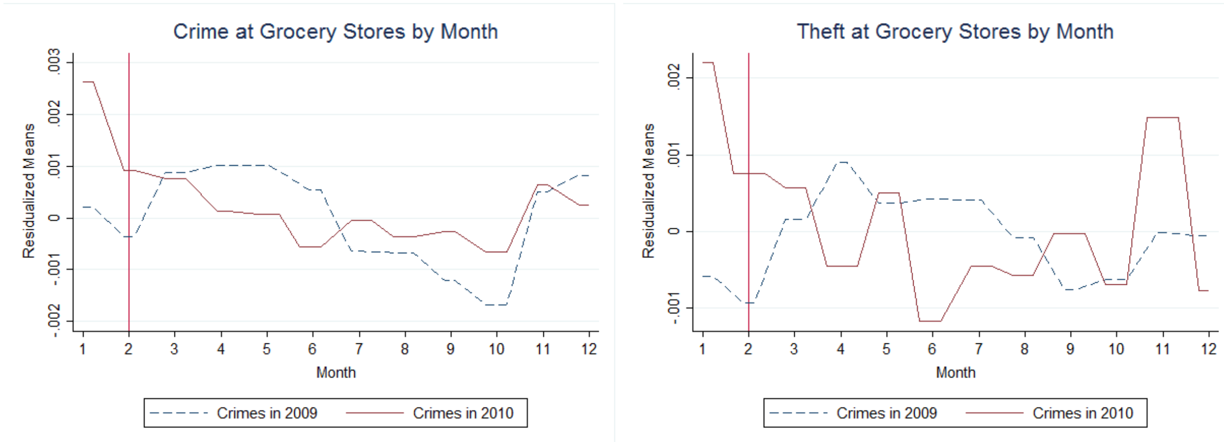
Appendix

Figure A1: Effect of Illinois SNAP Disbursement Change on Crime Without Residualizing



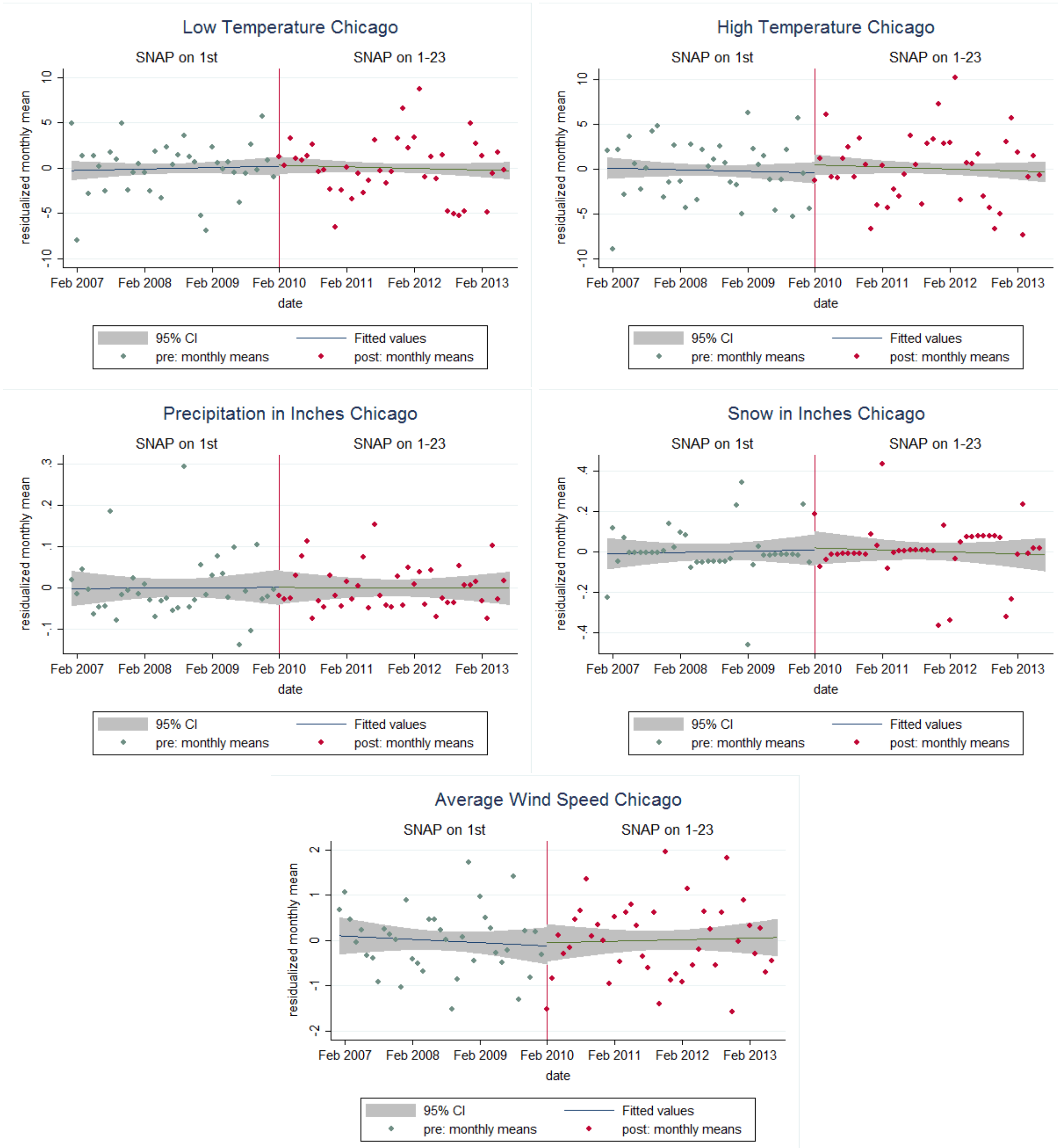
Notes: Each figure plots month-level means and linear fits (with 95% confidence intervals) of each of the crimes listed. To the left of the vertical line, SNAP benefits were given out primarily on the 1st of the month, and to the right, they were distributed over the 1st to the 23rd. Crime data are from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

Figure A2: Average Crimes by Month, Comparing 2009 and 2010



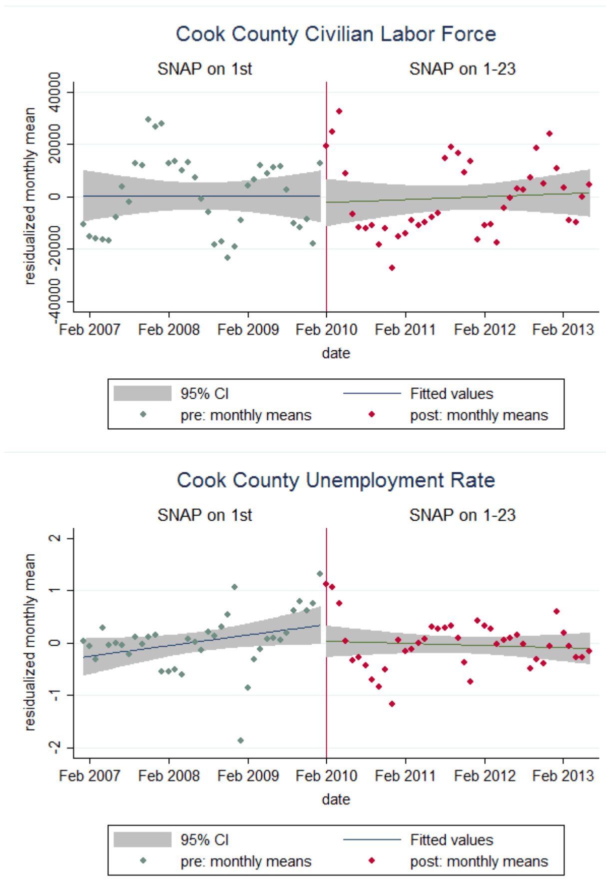
Notes: Each figure plots day-level means of each of the crimes listed. The vertical line represents the month when Illinois increased the number of SNAP distribution dates. Crime data are from the city of Chicago.

Figure A3: Effect of Illinois SNAP Disbursement Change on Weather



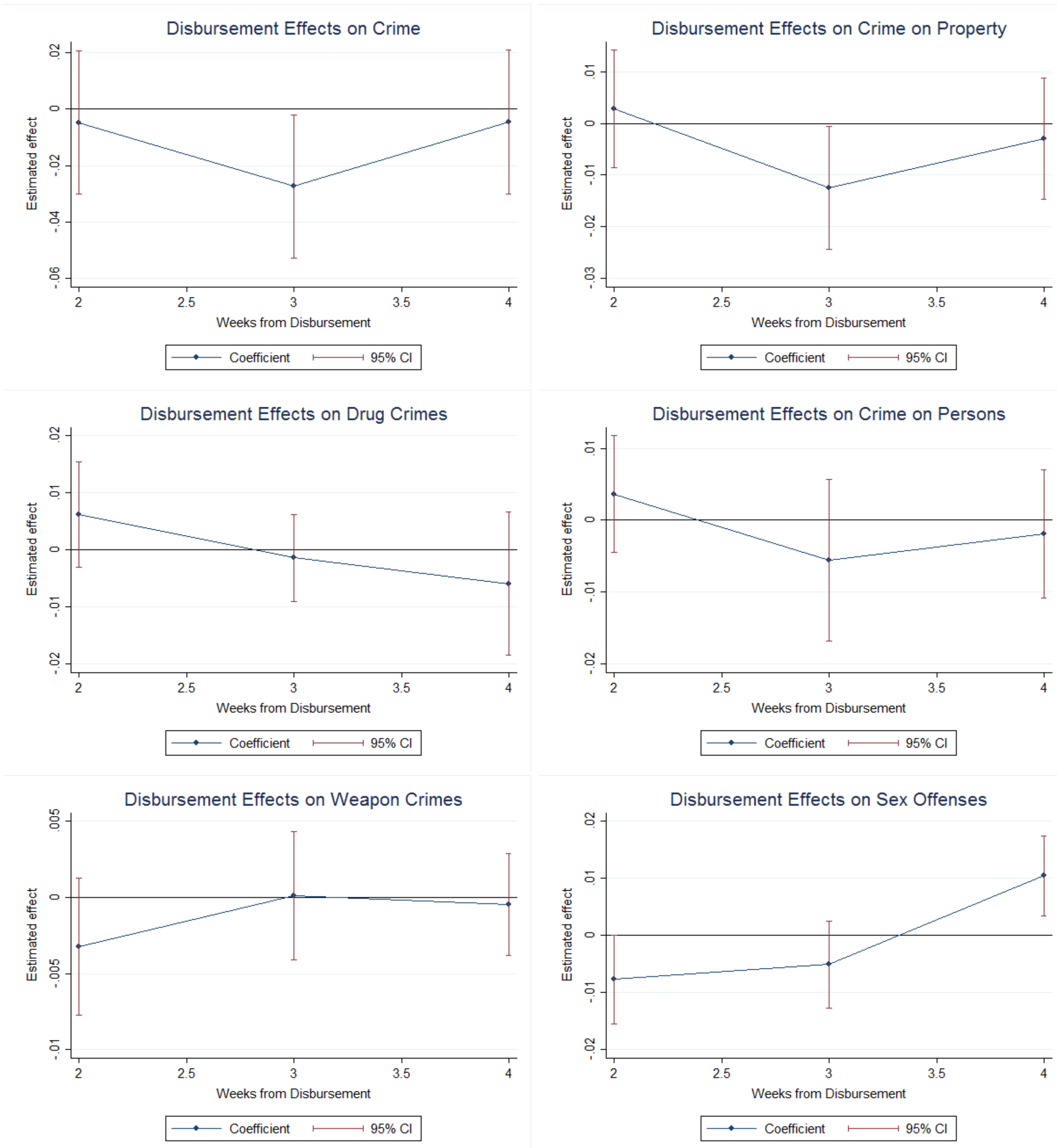
Notes: Each figure plots month-level means and linear fits (with 95% confidence intervals) of each of the weather outcomes listed. To the left of the vertical line, SNAP benefits were given out primarily on the 1st of the month, and to the right, they were distributed over the 1st to the 23rd. Daily weather data for Chicago are from the global historical climatology network and are based on temperature, precipitation and average wind speeds from the Chicago O'Hare International Airport weather station.

Figure A4: Effect of Illinois SNAP Disbursement Change on Labor Force



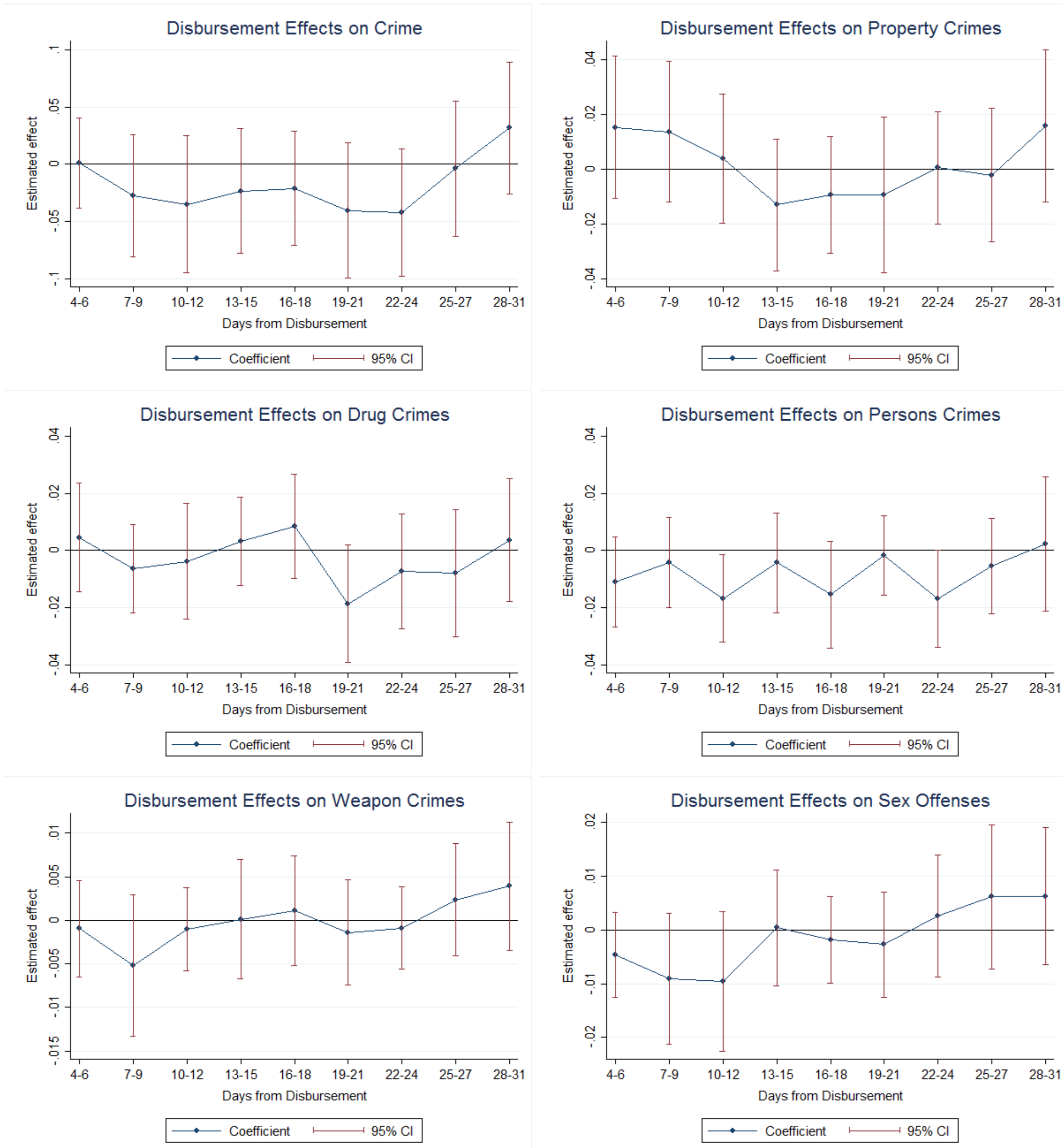
Notes: Each figure plots month-level means, accounting for month and year fixed effects, and linear fits (with 95% confidence intervals) of the monthly civilian labor force and unemployment rate in Cook County. To the left of the vertical line, SNAP benefits were given out primarily on the 1st of the 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.

Figure A5: Estimates of SNAP Receipt on Crime, by Crime Type



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

Figure A6: Estimates of SNAP Receipt on Crime, by Crime Type by Every Three Days Since Issuance



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

Table A1: The Effect of Indiana SNAP Receipt on Crime by Every Three Days Since Issuance

	Any Crime	**Drugs**	**Property**	**Weapon**	**Person**	**Sex Offense**
3rd-5th of Month	0.001	0.005	0.015	-0.001	-0.011	-0.005
	(0.020)	(0.010)	(0.013)	(0.003)	(0.008)	(0.004)
6th-8th of Month	-0.027	-0.006	0.014	-0.005	-0.004	-0.009
	(0.027)	(0.008)	(0.013)	(0.004)	(0.008)	(0.006)
9th-11th of Month	-0.035	-0.004	0.004	-0.001	-0.017**	-0.010
	(0.031)	(0.010)	(0.012)	(0.002)	(0.008)	(0.007)
12th-14th of Month	-0.023	0.003	-0.013	0.000	-0.004	0.000
	(0.028)	(0.008)	(0.012)	(0.003)	(0.009)	(0.005)
15th-17th of Month	-0.021	0.008	-0.009	0.001	-0.015	-0.002
	(0.026)	(0.009)	(0.011)	(0.003)	(0.010)	(0.004)
18th-20th of Month	-0.040	-0.019*	-0.009	-0.001	-0.002	-0.003
	(0.030)	(0.011)	(0.015)	(0.003)	(0.007)	(0.005)
21st-23rd of Month	-0.042	-0.007	0.000	-0.001	-0.017*	0.003
	(0.028)	(0.010)	(0.011)	(0.002)	(0.009)	(0.006)
24th-26th of Month	-0.004	-0.008	-0.002	0.002	-0.005	0.006
	(0.030)	(0.011)	(0.012)	(0.003)	(0.009)	(0.007)
27th-31st of Month	0.032	0.004	0.016	0.004	0.002	0.006
	(0.030)	(0.011)	(0.014)	(0.004)	(0.012)	(0.006)
N	45630	45630	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. "Drug" crimes include drug possession and dealing, "property" crimes include buglary, theft, larceny and vandalism, "weapon" crimes include unlawful possession or use of a knife or firearm, "person" crimes include assault, domestic violence, and kidnapping, and "sex offenses" include rape, molestation and indecency with a child. Robust standard errors are clustered on last name group and are shown in parenthesis.
, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table A2: The Effect of Indiana SNAP Receipt on Crime by County

	Any Crime	**Drugs**	**Property**	**Weapon**	**Person**	**Sex Offense**
Panel A. All counties						
Second Week of Month	-0.021	-0.004	0.002	-0.003	-0.000	-0.005
	(0.023)	(0.007)	(0.010)	(0.003)	(0.006)	(0.005)
Third Week of Month	-0.045**	-0.006	-0.022**	0.002	-0.011	0.001
	(0.019)	(0.006)	(0.009)	(0.003)	(0.008)	(0.004)
Fourth Week of Month	-0.015	-0.009	-0.005	0.002	-0.002	0.005
	(0.021)	(0.008)	(0.008)	(0.002)	(0.006)	(0.004)
N	3615300	3615300	3615300	3615300	3615300	3615300
Panel B. High SNAP counties (SNAP Recipients > IN Avg)						
Second Week of Month	-0.022	-0.004	0.002	-0.003	-0.000	-0.006
	(0.023)	(0.007)	(0.010)	(0.003)	(0.006)	(0.005)
Third Week of Month	-0.045**	-0.006	-0.022**	0.002	-0.011	0.001
	(0.019)	(0.006)	(0.009)	(0.003)	(0.008)	(0.004)
Fourth Week of Month	-0.015	-0.009	-0.005	0.002	-0.002	0.005
	(0.021)	(0.008)	(0.008)	(0.002)	(0.006)	(0.004)
N	1793610	1793610	1793610	1793610	1793610	1793610
Panel C. Low SNAP counties (SNAP Recipients < IN Avg)						
Second Week of Month	-0.021	-0.004	0.002	-0.003	-0.000	-0.005
	(0.023)	(0.007)	(0.010)	(0.003)	(0.006)	(0.005)
Third Week of Month	-0.045**	-0.006	-0.023**	0.002	-0.011	0.001
	(0.018)	(0.006)	(0.009)	(0.003)	(0.008)	(0.004)
Fourth Week of Month	-0.015	-0.009	-0.005	0.002	-0.002	0.005
	(0.021)	(0.008)	(0.008)	(0.002)	(0.006)	(0.004)
N	1821690	1821690	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. "Drug" crimes include drug possession and dealing, "property" crimes include buglary, theft, larceny and vandalism, "weapon" crimes include unlawful possession or use of a knife or firearm, "person" crimes include assault, domestic violence, and kidnapping, and "sex offenses" include rape, molestation and indecency with a child. Robust standard errors are clustered on last name group and are shown in parenthesis.
, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table A3: The Effect of Staggering SNAP Benefits on Crime in Census Tracts with Supermarkets

		Day of Month Range		
	Baseline	1st of Month	Days 2-23	Days 24-31
Crime				
SNAP dispersed	-0.0313	0.2344	-0.0580*	0.0151
	(0.0274)	(0.1540)	(0.0302)	(0.0490)
Pre-Period Mean	1.377	1.592	1.373	1.360
Theft				
SNAP dispersed	-0.0292**	0.0617	-0.0388**	-0.0100
	(0.0134)	(0.0775)	(0.0154)	(0.0207)
Pre-Period Mean	0.278	0.370	0.275	0.273
Crime at Grocery				
SNAP dispersed	-0.0135***	0.0013	-0.0152**	-0.0097*
	(0.0048)	(0.0157)	(0.0063)	(0.0055)
Pre-Period Mean	0.016	0.016	0.017	0.016
Theft at Grocery				
SNAP dispersed	-0.0103**	-0.0072	-0.0135**	-0.0014
	(0.0046)	(0.0147)	(0.0063)	(0.0039)
Pre-Period Mean	0.010	0.009	0.011	0.010
N	315589	10374	228228	76987

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 (Column 1) or the ranges listed at the top of each column. Each regression includes month, 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. 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.