



# Welfare Payments and Crime

## Citation

Foley, C. Fritz. "Welfare Payments and Crime." Review of Economics and Statistics 93, no. 1 (February 2011): 97–112.[url: [http://www.mitpressjournals.org/doi/abs/10.1162/REST\\_a\\_00068#.WRN22xPytE5](http://www.mitpressjournals.org/doi/abs/10.1162/REST_a_00068#.WRN22xPytE5) dataverse: <https://dataverse.harvard.edu/dataset.xhtml?persistentId=hdl:1902.1/18646>]

## Published Version

[http://www.mitpressjournals.org/doi/10.1162/REST\\_a\\_00068](http://www.mitpressjournals.org/doi/10.1162/REST_a_00068)

## Permanent link

<http://nrs.harvard.edu/urn-3:HUL.InstRepos:32969786>

## Terms of Use

This article was downloaded from Harvard University's DASH repository, and is made available under the terms and conditions applicable to Open Access Policy Articles, as set forth at <http://nrs.harvard.edu/urn-3:HUL.InstRepos:dash.current.terms-of-use#OAP>

# Share Your Story

The Harvard community has made this article openly available.  
Please share how this access benefits you. [Submit a story](#).

[Accessibility](#)

# WELFARE PAYMENTS AND CRIME

C. Fritz Foley\*

*Abstract*—Analysis of daily reported incidents of major crimes in twelve U.S. cities reveals an increase in crime over the course of monthly welfare payment cycles. This increase reflects an increase in crimes that are likely to have a direct financial motivation as opposed to other kinds of crime. Temporal patterns in crime are observed in jurisdictions in which disbursements are focused at the beginning of monthly welfare payment cycles and not in jurisdictions in which disbursements are relatively more staggered. These findings indicate that welfare beneficiaries consume welfare-related income quickly and then attempt to supplement it with criminal income.

## I. Introduction

CONSIDER an individual who receives support from monthly welfare payments that are distributed at the beginning of the month. These payments may be made directly to this individual or to someone who provides for the individual or transacts with the individual. Welfare payments are disbursed on a monthly basis, and a series of studies indicate that the typical recipient of cash assistance increases consumption immediately following the receipt of payments and exhausts these payments quickly. Poor individuals are also unlikely to have access to savings or credit that might help cover temporary cash shortfalls and often have weak earnings prospects in legitimate economic activity. Consequently, this hypothetical individual might deplete welfare-related income quickly and turn to crime to supplement this income. This paper tests if income-generating criminal activity is increasing in the amount of time that has passed since welfare payments occurred.

The analysis exploits plausibly exogenous variation in the timing of payments across cities and differences in the likely motivation of different kinds of crime. The three welfare programs that provide the largest share of income maintenance benefits to the poor are considered: the Food Stamp Program, the Temporary Assistance for Needy Families (TANF) Program, and the Supplemental Security Income (SSI) Program. The sample of reported incidents of crime covers twelve cities in which more than 10% of the population receives payments from the most inclusive welfare program, the Food Stamp Program. If patterns in crime are influenced by the timing of welfare payments, then increases in crime over the course of monthly payment cycles should be most pronounced in cities in which such payments are focused at the beginning of these cycles. If

criminal income is used to supplement welfare income, then any increase in crime should be reflected in Type I Uniform Crime Report (UCR) or Group A National Incident Based Reporting System (NIBRS) crimes with a direct financial motivation (burglary, larceny-theft, motor vehicle theft, and robbery) and not other Type I UCR or Group A NIBRS crimes (arson, assault offenses, forcible sex offenses, and homicide).

Two approaches yield results indicating that crime rates in fact increase in the amount of time that has passed since welfare payments occurred. The first approach tests if levels of criminal activity are different in the first ten calendar days of the month; this time frame corresponds to the period over which food stamp payments occur in cities where they are focused at the beginning of the month. Rates of crime and counts of reported incidents are higher after the first ten days of the month in jurisdictions where welfare payments are focused at the beginning of the month but not in other jurisdictions. The second approach employs an index that reflects the number of days since welfare payments occurred in a city. This index takes into account payments related to not only food stamps but also TANF and SSI. Higher values of the index are associated with more crime.

Both approaches also reveal that increases in crime over the course of monthly welfare payment cycles are observed only for crimes that are likely to have a financial motivation and not for other Type I UCR or Group A NIBRS crimes. These findings are inconsistent with explanations for temporal patterns in crime that are unrelated to the timing of welfare payments, like explanations related to police officer deployment or incentives to report crimes as having occurred at certain times.

The findings in this paper make a number of contributions. First, they indicate a role for behavioral considerations in economic explanations of criminal activity. Becker (1968) provides a framework for analyzing criminal behavior in which criminals rationally weigh the costs and benefits of illegal activity and are more likely to turn to crime when they are likely to earn less from legitimate activities. This framework has received ample empirical support.<sup>1</sup> Recent work showing that cash assistance recipients typically spend their payments too quickly implies a channel by which a particular behavioral bias, short-run impatience, affects the decision to engage in criminal activity. Shapiro (2005) documents that food stamp recipients experience a

Received for publication November 24, 2008. Revision accepted for publication October 14, 2009.

\* Harvard Business School and NBER.

I thank Jeff Cronin, Linnea Meyer, and Janelle Prevost for excellent research assistance and police departments in twelve cities for providing data. Seminar participants at the American Law and Economics Association Annual Meeting, Harvard University, the NBER Law and Economics Program Meeting, Wesleyan University, Yale Law School, an anonymous referee, and numerous others provided very helpful comments. The Division of Research at Harvard Business School provided generous funding.

<sup>1</sup> Numerous studies including Donohue and Levitt (2001), Raphael and Winter-Ember (2001), and earlier work summarized in Freeman (1995) have found a significant but small effect of unemployment on property crimes. Machin and Meghir (2004) and Gould, Weinberg, and Mustard (2002) find that changes in earnings of low wage and unskilled workers in particular affect crime.

decline in caloric intake and an increase in the marginal utility of consumption in between food stamp payments. Stephens (2003) finds that households that depend primarily on social security for income increase spending on goods that reflect instantaneous consumption in the first few days following the receipt of their check. Stephens and Unayama (2008) show that more frequent retirement payments smooth consumption among retired Japanese pension recipients. Dobkin and Puller (2007) find that welfare recipients increase their consumption of illegal drugs when their checks arrive at the beginning of the month, spurring an increase in hospitalizations and deaths. These studies provide evidence of short-run impatience and violations of the permanent income hypothesis.<sup>2</sup> My results indicate that this type of consumption behavior is associated with an increase in financially motivated criminal activity later in monthly welfare payment cycles. These types of behavioral effects call for distinctive public policy responses, as noted by Jolls (2007) and Bertrand, Mullainathan, and Shafir (2004).

Second, the paper illustrates an effect of the design of welfare programs on crime. A large literature, parts of which are reviewed in Moffitt (1992) and Blank (2002), considers the effects of welfare programs on employment, poverty, family structure, and other factors. Some studies analyze the effects of welfare payments on criminal activity using cross-sectional data. DeFranzo (1996, 1997) and Hannon and DeFranzo (1998a, 1998b) present evidence that welfare payments reduce major crimes. However, Burek (2005) finds that welfare payments are associated with higher levels of less severe crimes. These studies typically face challenges controlling for all the characteristics of jurisdictions that are likely to affect both the use of welfare programs and criminal activity.

The findings in my paper point out that the timing and frequency of welfare payments have effects that carry policy implications. Staggered, frequent payments would smooth levels of crime. The leveling of criminal activity would make communities safer because police departments would not become overwhelmed by cyclical spikes. If, as shown in previous work, welfare beneficiaries exhibit short-run impatience and follow a quasi-hyperbolic model of intertemporal choice, more frequent payments would reduce the extent to which they overconsume soon after payments arrive. Beneficiaries would be less likely to experience increased marginal utility of consumption and dire circumstances at the end of monthly payment cycles. As a consequence, they

would not have such strong incentives to turn to crime to augment their income, and crime rates could be lower.

This paper also adds to the burgeoning literature on household finance. Campbell (2006) explores this field. Only a small part of the work in this field specifically considers the personal finances of low-income individuals. Duflo et al. (2006) and Beverly, Schneider, and Tufano (2006) argue that low-income individuals in particular do not save enough. Low savings levels can have detrimental consequences for the poor, who face severe credit constraints, as documented in Adams, Einav, and Levin (2009), Barr (2004), and elsewhere. My analysis indicates that individuals who exhaust their legitimate income rapidly and do not have access to savings or credit attempt to increase their income through criminal activity.<sup>3</sup>

The remainder of the paper is organized as follows. The next section explains the hypotheses in more detail, and section III describes the data and the main tests. Section IV presents the results, and the last section concludes.

## II. Hypotheses

Welfare payments are distributed on a monthly basis according to payment schedules that vary across programs and states. In many jurisdictions, payments from all the major programs to all recipients occur during a short period within each month, typically the beginning of the month. Studies of the consumption of cash assistance recipients, including Shapiro (2005), Stephens (2003), and Stephens and Unayama (2008), reveal that recipients of infrequent payments do not smooth their consumption but instead exhibit short-run impatience. These recipients typically do not have access to savings or credit.

Shapiro (2005) shows that the consumption behavior of food stamp recipients is consistent with their following a quasi-hyperbolic model, not an exponential model, of intertemporal choice. In the data he analyzes and uses to calibrate this model, levels of caloric intake fall, and the marginal utility of consumption appears to increase over the course of monthly welfare payment cycles. Recipients report missing meals because they have exhausted their food stamp payments. In the quasi-hyperbolic model, recipients would be better off and less likely to face dire circumstances at the end of the month if they were somehow forced to smooth their consumption.

Short-run impatience generates circumstances that are likely to cause crime rates to increase as time passes in monthly welfare payment cycles. In jurisdictions where all welfare payments occur at the beginning of the month, individuals who are welfare recipients or who transact with or receive support from a recipient are likely to have sufficient resources at the start of the month for their consumption needs and for engaging in activities that incapacitate them

<sup>2</sup> Phelps and Pollak (1968) develop a simple framework of short-run impatience, and this framework is employed by Laibson (1997), O'Donoghue and Rabin (1999, 2001), and Angeletos et al. (2001) to consider a variety of economic applications. A number of papers provide evidence on the validity of the permanent income hypothesis by studying the immediate consumption response to changes in income. Recent work includes Shapiro and Slemrod (2003), Hsieh (2003), Johnson, Parker, and Souleles (2006), and Stephens (2008). Lee and McCrary (2005) present evidence that criminals typically have high discount rates or hyperbolic time preferences.

<sup>3</sup> Garmaise and Moskowitz (2006) show that weak credit conditions increase crime more generally.

from committing crimes. However, such individuals may not have sufficient resources later in the monthly payment cycle and may turn to crime to augment their welfare-related income. Frameworks that account for short-run impatience, like the one developed in O'Donoghue and Rabin (1999), imply that such individuals will delay criminal activity even if they anticipate a cash shortfall at the time of the payment and plan to make up this shortfall with criminal income. This is because criminal activity has immediate costs; it requires effort and potentially results in punishment.

Self-control problems would not affect patterns in consumption or crime if people learned to control them, but there is little evidence that this is the case. DellaVigna and Malmendier (2006) find that gym members frequently renew monthly contracts even though they would pay less per visit if they paid on a daily basis. Choi, Laibson, and Madrian (2005) find positive but small effects of financial education on savings decisions. Self-control problems seem to persist.

Although previous work finds compelling evidence of short-run impatience among welfare recipients, it is noteworthy that even an individual who receives support from welfare payments and does not exhibit short-run impatience may be more likely to engage in criminal activity later during monthly welfare payment cycles. He may have very low income, a high marginal utility of consumption, and no savings or access to credit and face uncertainty about the extent to which he will face a cash shortfall. He may, for example, face unexpected shocks to the prices of the goods he consumes. Given this uncertainty, he would be likely to delay criminal activity until it is necessary.

These considerations imply predictions for temporal patterns in crime in different kinds of cities. In cities where payments from welfare programs are focused at the beginning of the month, criminal activity should increase as the time since payments occurred increases. Increased criminal activity should reflect increases in types of crime that have a financial motivation, not other kinds of crime. In cities where welfare programs make payments to different recipients on different days over longer time periods or where payments to individuals occur more frequently than once a month, there should not be any significant monthly temporal pattern in crime.

This discussion has stressed the effect of the timing of welfare payments on the demand for criminal income. It is worth considering briefly the potential effects of the timing of payments on the supply of victims. If all welfare payments occurred at a particular point in time during the month, this might increase the pool of potential victims and the attractiveness and ease of stealing property. Crime rates could then be higher immediately following payments. However, most welfare payments are distributed onto electronic benefit transfer cards, and the funds on these cards are difficult to steal because recipients must present a valid identification card to use them. Therefore, the timing of dis-

bursement is unlikely to have a large effect on the supply of potential victims.

Potential victims of crime might respond to changes in the demand for criminal income by taking avoidance measures. For example, potential victims of burglary or robbery could remain ensconced in their locked homes during periods when such crimes are expected to be more common. However, most avoidance activities are costly, so any response by potential victims to changes in the demand for criminal income is likely to be incomplete.

### III. Data and Tests

The basic empirical approach is to study differences in criminal activity over the course of monthly welfare payment cycles in cities across which there is variation in the timing of payments. This analysis requires information on welfare payments by jurisdiction and detailed crime data.

#### A. Data on Welfare Programs

The three primary welfare programs that provide income maintenance benefits are the Food Stamp Program, the TANF Program, and the SSI Program.<sup>4</sup> Each of these programs provides assistance to poor households that meet income and resource requirements. The Food Stamp Program provides funds that can be used at most grocery stores, and the TANF Program provides income maintenance payments to needy families. In most states, both programs distribute payments electronically through electronic benefit transfer debit cards, and payments that are not spent in a particular month are carried forward to the next month. SSI pays benefits to adults and children who have limited means and are physically or mentally disabled. These payments are made once a month by check or direct deposit, with each means of distribution comprising half of the total. The Food Stamp Program has the broadest coverage in the sense that TANF and SSI recipients typically meet the eligibility requirements to receive food stamps. Because of its extensive coverage, I select a sample of cities on the basis of participation in the Food Stamp Program.

Quantifiable effects of the timing of welfare payments on crime are more likely to be observed in jurisdictions where a substantial share of the population receives such payments. Fellowes and Berube (2005) compute Food Stamp Program participation rates in major metropolitan areas and counties. On the basis of their study, I select jurisdictions in which at least 10% of the population participates in the Food Stamp Program. This screen yields a sample of fifteen cities: Baltimore, Maryland; Detroit, Michigan; El Paso, Texas; Fresno, California; McAllen-Edinburg-Mission, Texas; Memphis, Tennessee;

<sup>4</sup> There are other smaller programs that provide income maintenance payments to the poor. For example, general assistance programs exist in some jurisdictions in the United States of America but these are not federally funded and at the national level comprise less than 5% of the payments made by the three programs that are considered in my analysis.

TABLE 1.—WELFARE PROGRAM DETAILS BY CITY

<b>A: Population and Share of Population Receiving Welfare Payments</b>				
City	Population	Food Stamps	TANF	SSI
<i>Early payment sample</i>				
Detroit, Michigan	2,061,162	12.2%	6.3%	3.7%
Fresno, California	799,407	10.2%	7.3%	4.5%
Newark, New Jersey	793,633	11.5%	5.1%	3.2%
Philadelphia, Pennsylvania	1,517,550	17.9%	9.3%	5.4%
Providence, Rhode Island	621,602	10.0%	6.6%	3.4%
Washington, DC	572,059	14.3%	8.5%	3.5%
<i>Staggered payment sample</i>				
Baltimore, Maryland	651,154	15.3%	7.5%	5.1%
El Paso, Texas	679,622	16.7%	2.6%	3.1%
Miami, Florida	2,253,362	11.3%	2.7%	4.8%
Milwaukee, Wisconsin	940,164	10.6%	3.2%	3.4%
New Orleans, Louisiana	1,381,652	12.0%	1.7%	2.0%
St. Louis, Missouri	348,189	22.4%	5.6%	5.3%
<b>B: Value of Welfare Payments</b>				
City	Food Stamps	TANF	SSI	
<i>Early payment sample</i>				
Detroit, Michigan	214,368	407,981	394,728	
Fresno, California	81,530	183,609	206,600	
Newark, New Jersey	92,768	94,436	124,160	
Philadelphia, Pennsylvania	264,965	288,589	436,889	
Providence, Rhode Island	43,410	108,703	99,618	
Washington, District of Columbia	81,061	100,401	91,231	
<i>Staggered payment sample</i>				
Baltimore, Maryland	103,252	139,554	162,470	
El Paso, Texas	100,659	30,488	75,551	
Miami, Florida	208,965	143,462	502,810	
Milwaukee, Wisconsin	71,092	165,946	204,177	
New Orleans, Louisiana	161,504	27,150	89,401	
St. Louis, Missouri	70,183	67,542	89,401	
<b>C: Delivery Dates of Welfare Payments</b>				
City	Food Stamps	TANF	SSI	
<i>Early payment sample</i>				
Detroit, Michigan	1st–9th	Twice a month, staggered	1st	
Fresno, California	1st–10th	1st	1st	
Newark, New Jersey	1st–5th	1st	1st	
Philadelphia, Pennsylvania	1st–10th	Twice a month, staggered	1st	
Providence, Rhode Island	1st	1st and 16th	1st	
Washington, District of Columbia	1st–10th	1st	1st	
<i>Staggered payment sample</i>				
Baltimore, Maryland	6th–15th	1st–15th	1st	
El Paso, Texas	1st–15th	1st–15th	1st	
Miami, Florida	1st–15th	1st–15th	1st	
Milwaukee, Wisconsin	2nd–15th	1st	1st	
New Orleans, Louisiana	5th–14th	1st–5th	1st	
St. Louis, Missouri	1st–22nd	1st–4th	1st	

This table provides details about welfare programs in the twelve cities in the sample. Panel A lists city populations and the percent of the population receiving food stamps, TANF payments, and SSI payments. Panel B provides data on the value of payments in thousands of dollars for each of these programs, and panel C lists the dates in the month on which these payments are distributed. Population data and data on the number of recipients and the value of payments are all for the year 1999, except that the number of SSI recipients in Miami and El Paso are for the year 1995. Data from Detroit cover Wayne County; Fresno, Fresno County; Newark, Essex County; Philadelphia, Philadelphia County; Providence, Providence County; Washington, District of Columbia County; Baltimore, Baltimore City County; El Paso, El Paso MSA; Miami, Miami MSA; Milwaukee, Milwaukee County; New Orleans, Orleans Parish; and St. Louis, St. Louis County.

Miami, Florida; Milwaukee, Wisconsin; New Orleans, Louisiana; New York, New York; Newark, New Jersey; Philadelphia, Pennsylvania; Providence, Rhode Island; St. Louis, Missouri; and Washington, DC. Data on reported incidents of crime are not available for Memphis, New York, and McAllen-Edinburg-Mission, so the final sample contains twelve cities.

Panels A and B of table 1 provide information on the use of the three main welfare programs in each city in the sample. For comparability with the data on the Food Stamp Program, drawn from Fellowes and Berube (2005), the data on

TANF and SSI Programs cover the year 1999.<sup>5</sup> On average across cities, the Food Stamp Program serves about twice as many people as TANF programs and more than three times as many people as SSI. The value of TANF Program

<sup>5</sup> Data on the value of family assistance and SSI Program payments are taken from the Bureau of Economic Analysis Local Area Personal Income Database. Numbers of family assistance recipients are obtained from the offices of state TANF directors. Data on the number of SSI recipients for counties are from *SSI Recipients by State and County*, and for MSAs they are drawn from the *State and Metropolitan Area Databook 1997–1998*.

payments and SSI Program payments often exceeds the value of food stamp payments, implying higher payments per recipient. However, relative to TANF and SSI, food stamps became a more significant source of income over the 1999–2005 period. Foley (2008) reports that, averaged across cities, the compound annual growth rate in the value of food stamps over this period is 8.2%, while the rates for TANF and SSI are  $-0.7\%$  and  $2.3\%$ , respectively.

Panel C of table 1 provides information about the timing of payments for each program in each city. Payment schedules are set at the state and federal levels, not the city level, and they have not changed substantially over the past decade. In most jurisdictions, each of the three programs makes payments to recipients once a month.<sup>6</sup> In some jurisdictions, food stamp and TANF payments occur during certain time periods. For example, in Fresno, food stamps are paid over the first ten days of the month, with the date of distribution depending on the last digit of the recipient's case number. TANF payments occur twice per month in three of the cities in the sample.

Interviews with welfare program managers suggest several common considerations were important in setting payment schedules.<sup>7</sup> Legal requirements, historical precedent, and budget processes played a role in decisions to make a single monthly payment early in the month. Federal law requires that food stamp payments and SSI payments occur in monthly allotments. Historically, payments occurred by mail in the form of a check. This method entailed delivery costs that were not insignificant, creating an incentive to make TANF payments only once a month as well. Managers of many programs seem to have somewhat arbitrarily decided to provide recipients with payments for each calendar month at the beginning of the month. Some managers explain that such a payment schedule was simply carried over when methods of payment changed. The timing of payments to recipients was also often set to follow monthly budget and funding practices. Welfare program budgets are often set on a monthly basis. Some managers asserted that the most straightforward way of matching expenses to funding levels is to make payments intended to cover the next month once a month at the beginning of the month.

Managers of programs that make payments twice a month or stagger payments across recipients say that such schedules were selected because of a desire to help recipients manage their money, requests from retailers, and considerations related to information technology systems and

program support services. Bimonthly payments were in part designed to help recipients manage their resources. In some cases, retailers, especially grocers, asked that payments be staggered across a set of delivery dates in order to reduce monthly fluctuations in demand. These motivations for smoothing payouts indicate that some program managers are aware of the consumption behavior of welfare recipients documented in the literature. Managers also stagger payments in some cases in order to facilitate the administration of certain aspects of their programs. They can better respond to recipient queries if payments are staggered because payments trigger queries, and these are easier to handle if they do not all occur around the same time. Some information technology systems can also process claims more efficiently if these claims are not all handled at once.

Thus, welfare payment schedules do not seem to have been set in a way that might misconstrue the impact of consumption patterns and liquidity constraints on crime. None of the program managers interviewed cited scheduling motivations that would correlate with crime other than concerns about how recipient manage their money.

#### *B. Data on Criminal Activity*

Conducting tests on the effects of the timing of welfare payments on crime across jurisdictions also requires detailed data on reported incidents of crime. Unfortunately, comprehensive incident data for the cities with large welfare populations are not available in NIBRS; NIBRS covers only jurisdictions that have agreed to provide data, and very few large cities have done so. Therefore, obtaining these data required directly contacting police departments. In order to ensure the comparability of data across jurisdictions, I attempted to obtain data covering the 2004–2006 period on each incident classified as a Part I UCR offense or a Group A NIBRS offense. These categories of crime are arson, assault offenses, burglary, forcible sex offenses, homicide, larceny-theft, motor vehicle theft, and robbery. I requested information about the type, date, time, and the location of each incident.

Twelve of the fifteen jurisdictions identified above provided usable data.<sup>8</sup> Table 2 identifies the crime data obtained from each city in the sample. All of the cities except Detroit used the UCR reporting system. Although I attempted to obtain complete data covering the 2004–2006 period from each jurisdiction, detailed data from some cities are available for only portions of this time frame, as indicated in table 2.<sup>9</sup>

<sup>6</sup> Cole and Lee (2005) identify the dates on which food stamp disbursements occur. I confirmed these dates and obtained data on the timing of TANF payments from the divisions of state and local governments that oversee this program. The Social Security Administration provided information on the timing of SSI payments.

<sup>7</sup> Information on how payment schedules were set was gathered by interviewing approximately fifteen program managers. For many programs in many jurisdictions, decisions regarding payment schedules are long-standing, and there is no documentation on how decisions were made. Therefore it is difficult to pinpoint rationales, but the interviews suggest several common considerations were important.

<sup>8</sup> The three cities that did not provide data are Memphis, New York, and the McAllen-Edinburg-Mission MSA. Police officers in Memphis and New York denied my requests for data and rejected my appeals of their denials. McAllen-Edinburg-Mission is not a single city but a collection of three cities, so I excluded it.

<sup>9</sup> In several jurisdictions, changes to computer systems prevented departments from providing me with data for the full sample period. Certain kinds of crime are also not included in the data for some cities. For example, arson is not covered in the sample for six cities. In some jurisdictions, this type of crime is collected and aggregated by the fire department and not the police department.

TABLE 2.—CRIME DATA COVERAGE FOR CITIES IN THE SAMPLE

City	Type of Crimes Covered	Sample Period
Detroit, Michigan	All Group A NIBRS crimes	2005–2006
Fresno, California	All Part I UCR crimes	2004–2006
Newark, New Jersey	All Part I UCR crimes except rape and arson	2005–2006
Philadelphia, Pennsylvania	All Part I UCR crimes except arson	2004–2006
Providence, Rhode Island	All Part I UCR crimes except arson	2004–2006
Washington, DC	All Part I UCR crimes	Aug. 1, 2004–Sept. 30, 2005; 2006
Baltimore, Maryland	All Part I UCR crimes except arson and homicide	2006
Milwaukee, Wisconsin	All Part I UCR crimes	2005–2006
St. Louis, Missouri	All Part I UCR crimes	2004–2006
Miami, Florida	All Part I UCR crimes	2004, Aug. 1, 2005–Dec. 31, 2006
New Orleans, Louisiana	All Part I UCR crimes except arson, homicide, and rape	2006
El Paso, Texas	Robbery, burglary, theft, motor vehicle theft	July 7, 2005–Dec. 31, 2006

### C. The Tests

The empirical tests consider two measures of crime: crime rates and counts of reported incidents of crime. Crime rates are computed by taking the number of reported incidents of crime on a particular day in a particular city and dividing that number by the sample period average number of daily reported incidents in the city.<sup>10</sup> OLS specifications are used to analyze crime rates, and negative binomial specifications are used to analyze counts of reported incidents.

Variation in the timing of payments allows me to conduct two kinds of tests. The first is transparent but somewhat crude. It distinguishes between cities in which food stamp payments are distributed in the first ten days of the month and those in which payments are more staggered. Food stamp payments occur early in the month in Detroit, Fresno, Newark, Philadelphia, Providence, and Washington, and I refer to this sample as the early payment sample. Food stamp payments are more staggered in the month in Baltimore, El Paso, Miami, Milwaukee, New Orleans, and St. Louis, and I refer to this sample as the staggered payment sample. Tests explaining levels of crime include a dummy that is equal to 1 in the first ten days of the month and otherwise equal to 0, as well as an interaction between this dummy and a dummy that is equal to 1 for the staggered payment sample and 0 for the early payment sample. The coefficient on the time-specific dummy reveals if criminal activity is lower in the early part of the month in cities where welfare payments are focused at the start of the month, and the coefficient on this variable interacted with the staggered payment dummy reveals if temporal patterns in crime are different in cities where payments are more staggered.

Information on the magnitude and timing of TANF payments and SSI payments raises a concern about distinguishing among cities on the basis of the timing of food stamp payments alone. As indicated in panel C of table 1, SSI pay-

ments occur on the first of the month in all jurisdictions. TANF programs make payments twice a month in Detroit, Philadelphia, and Providence, which are all in the early payment sample, and these payments are made on the first of the month in Milwaukee, classified as part of the staggered payment sample. In robustness checks, I remove observations from Detroit, Philadelphia, Providence, and Milwaukee from the data, leaving a set of cities for which the classification based on the timing of food stamp payments is less subject to concern.

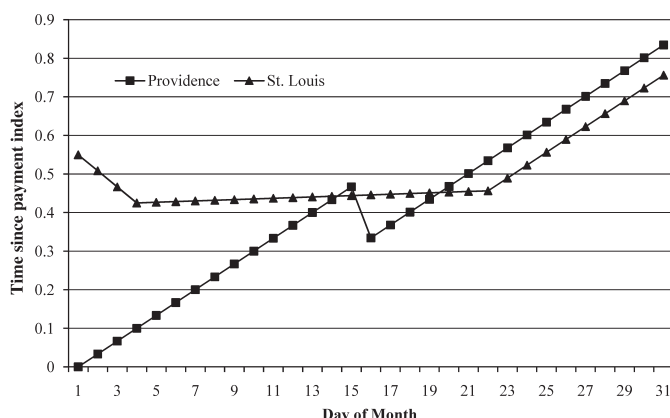
The second type of test employs an index that reflects the number of days that have passed since recipients received their last welfare payment in a particular city. It is computed using the information on the number of welfare recipients and the dates of payments. All three of the major welfare programs are taken into account. For programs that make payments over a period of days within a month, I assume that an equal number of recipients receive payments on each of the days within the period. For each program on each calendar day, I compute the average number of days that have passed since recipients received their last payment. For example, if food stamp payments occur on the first and second days of the month, on the fourth day of the month this average is two and a half days. I then take a weighted average of these program-specific measures where weights are set equal to the number of total recipients in each program.<sup>11</sup> The weighted average is divided by 30 to create an index that takes on values between 0 and 1. In the extreme case that all welfare recipients received a payment from each program on the first of the month, the index would be 0 on that day, and if no additional payments occurred over the course of the month, the index would be equal to 1 on the last day of months with 31 days.

To provide further intuition for this index, figure 1 displays values of the index by the day of the month for Providence and St. Louis. In Providence, food stamp and SSI payments occur only once a month on the first of the month,

<sup>10</sup> Jacob et al. (2007) use a similar approach to measure weekly crime rates.

<sup>11</sup> Similar indices and results are obtained if the values of program payments are used as weights.

FIGURE 1.—THE VALUES OF THE TIME-SINCE-PAYMENT INDEX FOR PROVIDENCE AND ST. LOUIS



The time-since-payment index is an index between 0 and 1 that reflects the average number of days that have passed since welfare recipients received their last payment. It accounts for payments related to food stamps, TANF, and SSI. If a program makes payments over a range of dates, it is assumed that an equal number of recipients receives payment on each day in the range. The total number of recipients in each program is used to weight the payment schedules of each program.

and TANF payments occur twice a month, on the first and the sixteenth. Therefore, the index for Providence is 0 on the first of the month. It increases over the course of the month and drops down on the sixteenth to reflect the fact that TANF recipients receive a payment at that time. In St. Louis, SSI payments occur on the first of the month, but food stamp payments are distributed over the first 22 days of the month, and TANF payments are distributed over the first 4 days of the month, with different recipients receiving payment on different days. As a consequence, there is less variation in the index for St. Louis than there is for Providence, and it is fairly level over the first 22 days of the month before increasing. One benefit of using this index in specifications that identify patterns in criminal activity is that it allows the use of fixed effects for each calendar day of the month.

By identifying the effects of the timing of welfare program payments off of differences in payment schedules across cities, the tests rule out explanations for temporal patterns in crime that are unrelated to welfare payments but are related to factors that are likely to be operative in all the cities in the sample. For example, rents are typically due at the start of the month, and these payments could induce criminal activity at the end of the month. Paychecks from legitimate employment are also often issued once or twice a month. Differences in temporal patterns of crime across cities where the timing of welfare payments differs are not consistent with alternative explanations for an increase in crime throughout the month based on these kinds of considerations.

The tests are performed for different types of crime. The main hypothesis makes predictions about the timing of crimes in which perpetrators are likely to have a direct financial motivation. I refer to burglary, larceny-theft, motor vehicle theft, and robbery as financially motivated crimes. I refer to other Type I or Group A crimes as other

crimes, and they include arson, assault offenses, forcible sex offenses, and homicide.<sup>12</sup>

Some factors would give rise to the same temporal patterns for both types of crime. Police officers may have an incentive to document incidents as occurring at a particular time, perhaps the beginning or end of the month. If the deployment of law enforcement resources varies through the month, criminals of all types might time their activity so as to minimize the chances of arrest. Criminals might also benefit from conspiring to commit more of all types of crimes at a particular point in time because limited enforcement resources could be more easily evaded. Under each of these scenarios, financially motivated crimes and other types of crime would exhibit similar temporal patterns. However, if patterns in crime reflect the timing of welfare payments, then only financially motivated crimes should become more prevalent over the course of welfare payment cycles in jurisdictions where payments are focused at the beginning of these cycles.

In keeping with the analysis of patterns in crime presented in papers like Jacob, Lefgren, and Morretti (2007) and Jacob and Lefgren (2003), the analysis here controls for the effects of weather and holidays on crime. Daily data on the average temperature in degrees Fahrenheit, inches of precipitation, and inches of snowfall are obtained from the National Climatic Data Center.<sup>13</sup> Days that are U.S. federal holidays are identified as holidays. Table 3 provides descriptive statistics for the variables used in the analysis.

The nature of the data and tests raises two issues regarding the calculation of standard errors in regression analysis. First, there could be serial correlation across observations for a city over the course of each month. In order to address this possibility, the tables present standard errors that are computed using a block bootstrap technique in which city-month blocks are used for resampling. Second, it is also conceivable that observed patterns in crime within a city are similar over the course of the month for different months. To consider the potential impact of this issue, unreported analysis collapses the data to the city level and compares average crime rates in the first ten days of the month and the remainder of the month across cities in the early payment sample and the staggered payment sample. The results of this analysis and the statistical significance of

<sup>12</sup> This distinction is not perfect. For some incidents, a criminal commits more than one offense, and these incidents are typically classified according to the most serious offense in the data according to a hierarchy established by the Federal Bureau of Investigation. For example, if a criminal robs and then kills his victim, this incident is typically classified as a homicide. Therefore, some incidents that are classified as other crimes may have financial motivations. It is noteworthy that the crime data do not cover the possession and sale of illegal drugs. Evidence presented in Dobkin and Puller (2007) suggests that this kind of activity most frequently occurs soon after the distribution of government transfer payments, when drug users have the resources to increase their consumption.

<sup>13</sup> For each city, weather measurements are taken from the airport station nearest to the city, and missing data are augmented with data from other nearby stations.

TABLE 3.—DESCRIPTIVE STATISTICS

	Mean	Median	Standard Deviation
Crime rate—All crimes	1.0000	0.9987	0.1814
Count of reported incidents—All crimes	107.75	96.000	65.975
Crime rate—Financially motivated crimes	1.0000	0.9955	0.2146
Count of reported incidents—Financially motivated crimes	91.633	75.000	60.017
Crime rate—Other crimes	1.0000	0.9465	0.5386
Count of reported incidents—Other crimes	15.673	12.000	12.118
Count of reported incidents—Burglary	16.904	13.000	14.679
Count of reported incidents—Larceny-theft	45.478	42.000	29.708
Count of reported incidents—Motor vehicle theft	20.001	16.000	14.657
Count of reported incidents—Robbery	9.2505	6.0000	9.5026
Dummy for 1st–10th	0.3286	0.0000	0.4697
Time-since-payment index	0.4698	0.4457	0.1788
Average temperature	59.802	62.000	17.930
Precipitation	0.1083	0.0000	0.3418
Snowfall	0.0506	0.0000	0.5040
Holiday dummy	0.0321	0.0000	0.1763

The crime data include reported incidents of all crimes that are classified as Type I crimes in the UCR reporting system and Group A crimes in the NIBRS reporting system. Financially motivated crimes include reported incidents of crimes in which the perpetrator is likely to have a direct financial motivation, specifically burglary, larceny-theft, motor vehicle theft, and robbery. Other crimes include arson, assault offenses, forcible sex offenses, and homicide. Crime rates for each city on each day are computed by taking incident counts and dividing by the sample period average number of daily reported incidents in the city. Dummy for 1st–10th is a dummy that is equal to 1 in the first ten days of the month and 0 otherwise. Time-since-payment Index is an index between 0 and 1 that reflects the average number of days that have passed since welfare recipients received their last payment. Average temperature is the average temperature in degrees Fahrenheit. Precipitation and snowfall are measured in inches. The holiday dummy is equal to 1 on U.S. federal holidays and 0 otherwise.

these results are not substantially different from the results presented in tables 4 to 6.<sup>14</sup>

#### IV. Results

Figure 2 presents crime rates, averaged over three-day intervals, for the early payment sample and the staggered payment sample. Daily crime rates are computed for each city and type of crime by dividing the count of reported incidents by the sample period average number of reported incidents in the city. Panel A displays rates for all crimes. The solid line with diamond markers indicates how rates change over the course of the month in cities in the early payment sample. In the cities in this sample, the overall crime rate is above average in the middle of the month, and it falls at the beginning of the month. It reaches its lowest point, 0.97, at the start of the month and then increases to about 1.01 over the next two weeks, implying an increase of about 4%. Panels B and C, respectively, show crime rates for financially motivated crimes and other crimes. In cities in the early payment sample, there is a pronounced monthly cycle in the rate of financially motivated crimes but no discernable trend in other crimes. Financially motivated crime rates increase from around 0.96 at the beginning of the month to more than 1.02, indicating an increase of about 6%.

The dashed lines with square markers indicate how crime rates change over the course of the month for cities in the staggered payment sample. In this sample, there is no apparent trend in overall crime, financially motivated crime, or other crime over the course of the month. These patterns in figure 2 are consistent with the theory that welfare beneficiaries exhaust their welfare-related income soon after receiving it and then attempt to augment their income with income from criminal activity later in the month.

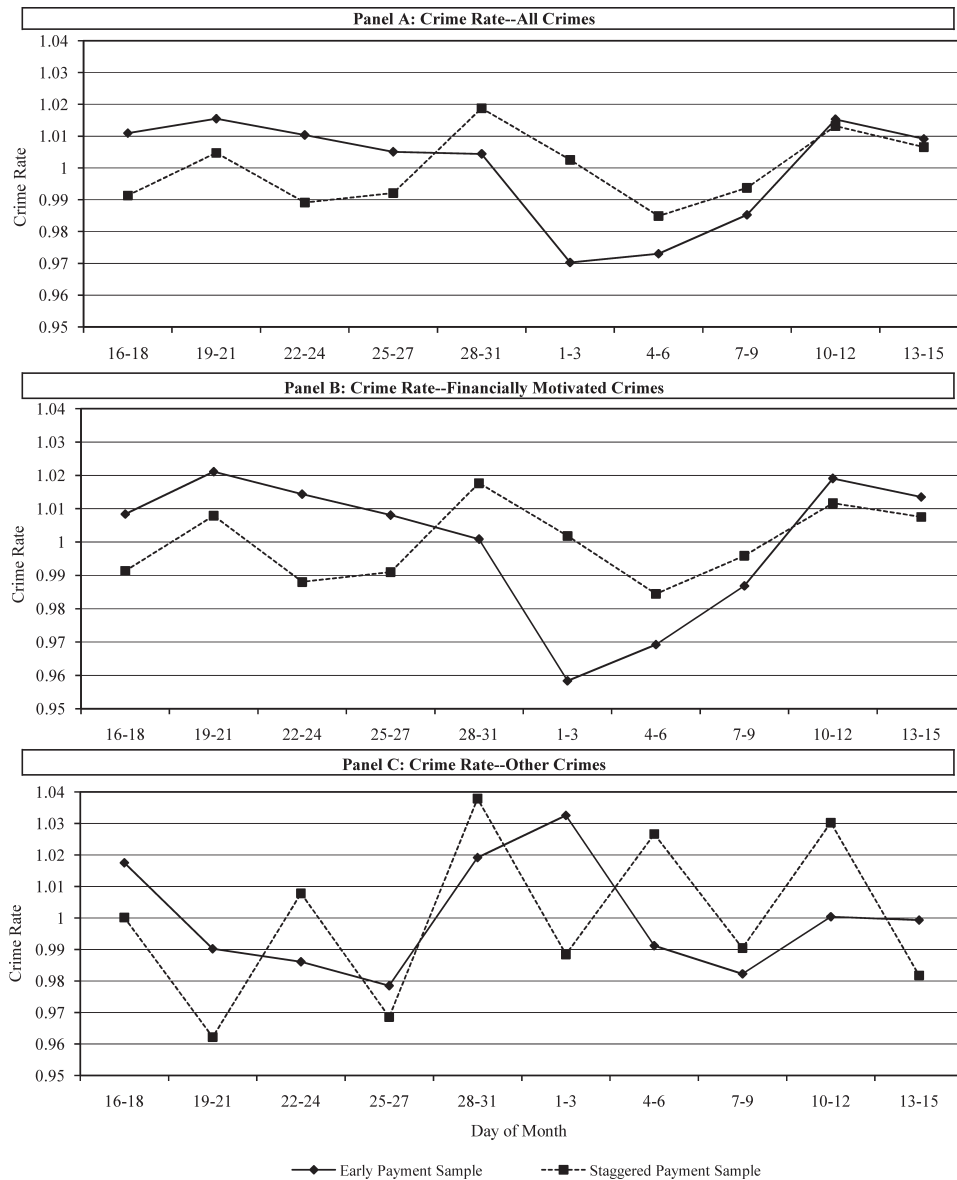
Table 4 presents the results of specifications that analyze patterns in total reported incidents of Type I or Group A crimes. The dependent variable studied in the OLS specifications in columns 1 to 4 is the crime rate, defined as the number of reported incidents in a city on a particular date divided by average daily reported incidents in the city. Each specification in table 4 includes two kinds of fixed effects. City  $\times$  Month  $\times$  Year fixed effects control for differences across cities even if these vary month to month. For example, these fixed effects control for local election cycles that have been shown by Levitt (1997) to affect the size of police forces. City  $\times$  Day of week fixed effects control for differences in criminal activity across days of the week in individual cities. Standard errors appear in parentheses, and they are computed using a block bootstrap technique in which city-month blocks are used for sampling.

The coefficients on dummy for the first to the tenth of the month are negative and significant in columns 1 and 2. The  $-0.0318$  coefficient in column 2 implies that the crime rate is 3.2% below average during the first ten days of the month in cities where welfare payments are focused at the beginning of the month. The coefficients on the staggered payment dummy interacted with the dummy for the first to the tenth of the month are positive and significant and of slightly smaller magnitude than the coefficients on the dummy for the first to the tenth. A Wald test reveals that the sum of the coefficients on the dummy for the first to the tenth of the month and on the interaction terms for each specification is not statistically distinguishable from 0, implying no discernable monthly patterns in reported incidents of crime in cities in the staggered payment sample. Factors that are operative in both the early payment sample and the staggered payment sample do not explain increases in crime in the early payment sample.

The specification in column 2 includes controls for weather and a dummy that is equal to 1 on holidays and 0

<sup>14</sup> Results are available from the author on request.

FIGURE 2.—CRIME RATES OVER THE COURSE OF THE MONTH



Panel A displays rates for all crimes that are classified as Type I crimes in the UCR reporting system and Group A crimes in the NIBRS reporting system. Panel B displays rates for crimes in which the perpetrator is likely to have a direct financial motivation, specifically burglary, larceny-theft, motor vehicle theft, and robbery. Panel C displays rates for other crimes, specifically arson, assault offenses, forcible sex offenses, and homicide. The data points are calculated by taking average crime rates across three-day periods for cities in which food stamp payments are focused at the beginning of the month (the early payment sample) and cities in which these payments are more staggered (the staggered payment sample). Crime rates for each city on each day are computed by taking incident counts and dividing by the sample period average number of daily reported incidents in the city.

otherwise. Consistent with previous work, crime appears to increase as temperatures rise and decrease with precipitation and snowfall. Crime rates are also lower on holidays.

The specifications presented in columns 3 and 4 are similar to those in columns 1 and 2, but they use the time-since-payment index to identify the effects of the timing of welfare payments and also include a fixed effect for each calendar day of the month. These specifications identify the effect of the timing of payments off of differences in how the index changes over the course of the month across cities. The results indicate that crime rates increase with the amount of time that has passed since welfare payments occurred. The 0.1201 coefficient on the time-since-payment

index in column 4 implies that, in the extreme case in which all welfare payments occurred on the first of the month, crime rates would be 12.0% higher on the thirty-first of the month relative to the first of the month. A 1 standard deviation increase in the time-since-payment index is associated with a 2.2% increase in the overall crime rate.<sup>15</sup> Columns 5 to 8 of table 4 contain results of negative binomial speci-

<sup>15</sup> If increases in criminal activity were focused among welfare beneficiaries and these beneficiaries committed only a fraction of crimes, then increases in crime among this population would be larger than the aggregate results indicate.

TABLE 4.—THE EFFECTS OF THE TIMING OF WELFARE PAYMENTS ON CRIME

<i>Dependent Variable</i>	Crime Rate				Count of Reported Incidents			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.9976 (0.0153)	0.8703 (0.0233)	0.9005 (0.0303)	0.7732 (0.0421)	5.2373 (0.2168)	5.4441 (0.2427)	5.1876 (0.2400)	5.4294 (0.2850)
Dummy for 1st–10th	–0.0292 (0.0061)	–0.0318 (0.0055)			–0.0226 (0.0054)	–0.0254 (0.0048)		
Staggered payment dummy*	0.0255 (0.0097)	0.0266 (0.0090)			0.0143 (0.0081)	0.0153 (0.0074)		
Dummy for 1st–10th								
Time-since-payment index			0.1165 (0.0260)	0.1201 (0.0325)			0.0863 (0.0221)	0.0858 (0.0242)
Average temperature		0.0026 (0.0003)		0.0026 (0.0003)		0.0030 (0.0003)		0.0029 (0.0003)
Precipitation		–0.0175 (0.0043)		–0.0169 (0.0037)		–0.0189 (0.0040)		–0.0180 (0.0051)
Snowfall		–0.0303 (0.0031)		–0.0310 (0.0027)		–0.0381 (0.0049)		–0.0387 (0.0045)
Holiday dummy		–0.0977 (0.0107)		–0.1014 (0.0115)		–0.1148 (0.0100)		–0.1165 (0.0085)
City × Month × Year fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City × Day of the week fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of month fixed effects?	No	No	Yes	Yes	No	No	Yes	Yes
Number of observations	9,496	9,496	9,496	9,496	9,496	9,496	9,496	9,496
R <sup>2</sup>	0.1434	0.1794	0.1590	0.1951				
Log likelihood					–35,413	–35,091	–35,336	–35,018

The crime data include reported incidents of all crimes that are classified as Type I crimes in the UCR reporting system and Group A crimes in the NIBRS reporting system. Crime rates for each city on each day are computed by taking incident counts and dividing by the sample period average number of daily reported incidents in the city. The specifications presented in columns 1–4 are OLS specifications, and those in columns 5–8 are negative binomial specifications. Each specification includes fixed effects for each city/month/year combination and each city/day of the week pair, and the specifications in columns 3, 4, 7, and 8 also include fixed effects for each day of the month. Dummy for 1st–10th is a dummy that is equal to 1 in the first ten days of the month and 0 otherwise. Staggered payment dummy is equal to 1 for cities where food stamp payments are not exclusively made during the first ten days of the month. Time-since-payment index is an index between 0 and 1 that reflects the average number of days since welfare recipients received their last payment. Average temperature is measured in degrees Fahrenheit. Precipitation and snowfall are measured in inches. The holiday dummy is equal to 1 on U.S. federal holidays and 0 otherwise. Standard errors appear in parentheses, and they are computed using a block bootstrap technique in which city-month blocks are used for sampling.

cations that analyze counts of reported incidents as opposed to crime rates. The results in the specifications are very similar to those in columns 1 to 4.

The timing of welfare payments is hypothesized to affect crimes in which perpetrators have a direct financial motivation and not necessarily other kinds of crime. The specifications in table 5 analyze crimes that are likely to have financial motives. The specifications in this table are the same as those presented in table 4 except the dependent variables analyzed are the rate of financially motivated crime in columns 1 to 4 and the count of reported incidents of financially motivated crime in columns 5 to 8. As in table 4, the coefficients on the dummy for the first to the tenth of the month are negative and significant, and the coefficients on this dummy interacted with the staggered payment dummy are positive and significant. These results indicate increases in financially motivated crimes in cities where welfare payments are focused at the beginning of the month. In cities where welfare payments are more staggered, increases are less pronounced and do not differ statistically from the null of there being no temporal trend. The coefficients on the time-since-payment index are also positive and significant.

The effects of the timing of welfare payments on financially motivated crimes appear to be more pronounced than its effects on total crime. The –0.0377 coefficient on the dummy for the first to the tenth in column 2 implies that in the early payment sample, the financially motivated crime rate is 3.8% (as opposed to 3.2% for all crimes) lower in the first ten days of the month than it is over the rest of the

month. The 0.1408 coefficient on the time-since-payment index in column 4 indicates that in the extreme case, all welfare payments occurred on the first of the month, the financially motivated crime rate would be 14.1% (as opposed to 12.0% for all crimes) higher on the thirty-first of the month relative to the first.

If patterns in crime were attributable to reporting biases or effects of police deployment that are similar across different types of crime, then the data would indicate an increase in crimes other than financially motivated crimes over the course of welfare payment cycles as well. The hypothesis that patterns in crime reflect income needs that arise during welfare payment cycles does not make this prediction. Table 6 presents results of specifications that test for temporal trends in other crimes. The results do not indicate any statistically significant relations between the timing of welfare payments and other crimes. The coefficients on the dummy for first through the tenth are positive, and they are insignificant and of much smaller magnitude than the coefficients on this variable in the specifications that explain financially motivated crimes presented in table 5. The coefficients on the dummy are statistically significantly lower in specifications explaining financially motivated crimes than in specifications explaining other crimes. This implies that in the early payment sample, crime rates for financially motivated crimes are significantly lower in the first ten days of the month than crime rates for other crimes. The coefficients on the time-since-payment index are all also insignificant, and they are very small in magnitude in

TABLE 5.—THE EFFECTS OF THE TIMING OF WELFARE PAYMENTS ON CRIME—FINANCIALLY MOTIVATED CRIMES

<i>Dependent Variable</i>	Crime Rate				Count of Reported Incidents			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	1.0045 (0.0214)	0.9253 (0.0276)	0.8785 (0.0309)	0.7991 (0.0417)	4.8847 (0.2732)	5.1146 (0.2306)	4.8154 (0.2232)	5.0771 (0.1913)
Dummy for 1st–10th	–0.0353 (0.0062)	–0.0377 (0.0068)			–0.0289 (0.0050)	–0.0316 (0.0054)		
Staggered payment dummy*	0.0313 (0.0100)	0.0324 (0.0089)			0.0214 (0.0075)	0.0224 (0.0093)		
Dummy for 1st–10th								
Time-since-payment index			0.1379 (0.0311)	0.1408 (0.0291)			0.1107 (0.0256)	0.1103 (0.0232)
Average temperature		0.0019 (0.0004)		0.0019 (0.0004)		0.0022 (0.0003)		0.0022 (0.0003)
Precipitation		–0.0082 (0.0058)		–0.0075 (0.0058)		–0.0106 (0.0044)		–0.0096 (0.0053)
Snowfall		–0.0321 (0.0027)		–0.0329 (0.0031)		–0.0400 (0.0043)		–0.0406 (0.0042)
Holiday dummy		–0.1373 (0.0121)		–0.1411 (0.0111)		–0.1550 (0.0121)		–0.1564 (0.0120)
City × Month × Year fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City × Day of the week fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of month fixed effects?	No	No	Yes	Yes	No	No	Yes	Yes
Number of observations	9,496	9,496	9,496	9,496	9,496	9,496	9,496	9,496
R <sup>2</sup>	0.1823	0.2148	0.1958	0.2284				
Log likelihood					–34,581	–34,280	–34,509	–34,211

The crime data include reported incidents of crimes in which the perpetrator is likely to have a direct financial motivation, specifically burglary, larceny-theft, motor vehicle theft, and robbery. Crime rates for each city on each day are computed by taking incident counts and dividing by the sample period average number of daily reported incidents in the city. The specifications presented in columns 1–4 are OLS specifications, and those in columns 5–8 are negative binomial specifications. Each specification includes fixed effects for each city/month/year combination and each city/day of the week pair, and the specifications in columns 3, 4, 7, and 8 also include fixed effects for each day of the month. Dummy for 1st–10th is a dummy that is equal to 1 in the first ten days of the month and 0 otherwise. Staggered payment dummy is equal to 1 for cities where food stamp payments are not exclusively made during the first ten days of the month. Time-since-payment index is an index between 0 and 1 that reflects the average number of days since welfare recipients received their last payment. Average temperature is the average temperature in degrees Fahrenheit. Precipitation and snowfall are measured in inches. The holiday dummy is equal to 1 on U.S. federal holidays and 0 otherwise. Standard errors appear in parentheses, and they are computed using a block bootstrap technique in which city-month blocks are used for sampling.

TABLE 6.—THE EFFECTS OF THE TIMING OF WELFARE PAYMENTS ON CRIME—OTHER CRIMES

<i>Dependent Variable</i>	Crime Rate				Count of Reported Incidents			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.9249 (0.0366)	0.4702 (0.0412)	0.9389 (0.0804)	0.4254 (0.0870)	4.5437 (2.8284)	4.5530 (0.4375)	4.6775 (0.3521)	4.6483 (0.3862)
Dummy for 1st–10th	0.0065 (0.0197)	0.0027 (0.0190)			0.0070 (0.0099)	0.0058 (0.0088)		
Staggered payment dummy*	0.0030 (0.0261)	0.0047 (0.0216)			–0.0112 (0.0173)	–0.0111 (0.0147)		
Dummy for 1st–10th								
Time-since-payment index			0.0787 (0.0743)	0.0905 (0.0751)			–0.0015 (0.0489)	0.0062 (0.0517)
Average temperature		0.0080 (0.0005)		0.0079 (0.0009)		0.0071 (0.0006)		0.0070 (0.0006)
Precipitation		–0.0833 (0.0138)		–0.0824 (0.0131)		–0.0748 (0.0108)		–0.0739 (0.0090)
Snowfall		–0.0199 (0.0092)		–0.0200 (0.0102)		–0.0229 (0.0079)		–0.0233 (0.0083)
Holiday dummy		0.1574 (0.0270)		0.1493 (0.0326)		0.1297 (0.0222)		0.1238 (0.0201)
City × Month × Year fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City × Day of the week fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of month fixed effects?	No	No	Yes	Yes	No	No	Yes	Yes
Number of observations	8,947	8,947	8,947	8,947	8,947	8,947	8,947	8,947
R <sup>2</sup>	0.0680	0.0932	0.0728	0.0963				
Log likelihood					–23,051	–22,872	–23,022	–22,853

The crime data include reported incidents of arson, assault offenses, forcible sex offenses, and homicide. Crime rates for each city on each day are computed by taking incident counts and dividing by the sample period average number of daily reported incidents in the city. The specifications presented in columns 1–4 are OLS specifications, and those in columns 5–8 are negative binomial specifications. Each specification includes fixed effects for each city/month/year combination and each city/day of the week pair, and the specifications in columns 3, 4, 7, and 8 also include fixed effects for each day of the month. Dummy for 1st–10th is a dummy that is equal to 1 in the first ten days of the month and 0 otherwise. Staggered payment dummy is equal to 1 for cities where food stamp payments are not exclusively made during the first ten days of the month. Time-since-payment index is an index between 0 and 1 that reflects the average number of days that have passed since welfare recipients received their last payment. Average temperature is the average temperature in degrees Fahrenheit. Precipitation and snowfall are measured in inches. The holiday dummy is equal to 1 on U.S. federal holidays and 0 otherwise. Standard errors appear in parentheses, and they are computed using a block bootstrap technique in which city-month blocks are used for sampling.

columns 7 and 8. These results suggest that explanations for patterns in crime over monthly welfare payment cycles that do not differentiate between financially motivated and other crimes are incomplete.

Table 7 displays an analysis of financially motivated crimes by type of crime. The specifications are the same as those presented in columns 7 and 8 of table 5, but the dependent variable is the count of reported burglaries in

TABLE 7.—THE EFFECTS OF THE TIMING OF WELFARE PAYMENTS BY TYPE OF FINANCIALLY MOTIVATED CRIME

<i>Dependent Variable</i>	<i>Count of Reported Incidents</i>							
	<i>Burglary</i>		<i>Larceny-Theft</i>		<i>Motor Vehicle Theft</i>		<i>Robbery</i>	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	3.6781 (0.3607)	3.6426 (0.4205)	4.3150 (0.2959)	4.4937 (0.1998)	4.0290 (0.3103)	4.0644 (0.2821)	3.4936 (0.2704)	3.4055 (0.3200)
Time-since-payment index	0.0865 (0.0401)	0.0910 (0.0504)	0.0926 (0.0285)	0.0913 (0.0305)	0.1354 (0.0490)	0.1363 (0.0473)	0.2484 (0.0750)	0.2512 (0.0662)
Average temperature		0.0033 (0.0005)		0.0023 (0.0004)		0.0007 (0.0005)		0.0029 (0.0006)
Precipitation		0.0184 (0.0084)		−0.0293 (0.0078)		0.0110 (0.0096)		−0.0122 (0.0116)
Snowfall		−0.0439 (0.0085)		−0.0470 (0.0060)		−0.0244 (0.0050)		−0.0360 (0.0093)
Holiday dummy		−0.1415 (0.0163)		−0.2080 (0.0122)		−0.0725 (0.0232)		−0.1304 (0.0223)
City × Month × Year fixed effects?	Y	Y	Y	Y	Y	Y	Y	Y
City × Day of the week fixed effects?	Y	Y	Y	Y	Y	Y	Y	Y
Day of month fixed effects?	Y	Y	Y	Y	Y	Y	Y	Y
Number of observations	9,496	9,496	9,496	9,496	9,496	9,496	9,496	9,496
Log likelihood	−24,933	−24,849	−30,621	−30,367	−26,469	−26,448	−20,856	−20,816

The specifications are negative binomial specifications, and each specification includes fixed effects for each city/month/year combination, each city/day of the week pair, and each day of the month. Time-since-payment index is an index between 0 and 1 that reflects the average number of days since welfare recipients received their last payment. Average temperature is the average temperature in degrees Fahrenheit. Precipitation and snowfall are measured in inches. The holiday dummy is equal to 1 on U.S. federal holidays and 0 otherwise. Standard errors appear in parentheses, and they are computed using a block bootstrap technique in which city-month blocks are used for sampling.

columns 1 and 2, larceny-thefts in columns 3 and 4, motor vehicle thefts in columns 5 and 6, and robberies in columns 7 and 8. The time-since-payment index attracts a positive coefficient in each specification. These coefficients are insignificant in the burglary specification that includes controls. This could reflect the fact that burglars often study potential targets before deciding to enter them and typically attempt to commit their crimes when properties are unoccupied.<sup>16</sup> Therefore, this type of crime may be less motivated by short-run liquidity needs than other kinds of financially motivated crimes.

The coefficients on the time-since-payment index in the specifications explaining patterns in larceny-theft are similar in magnitude to those estimated in the specifications explaining patterns in burglary, but they are more precisely estimated. These coefficients, and those on the index in the specifications that analyze the incidence of motor vehicle theft and robbery, are all statistically significant. The implied effect of the timing of welfare payments is particularly pronounced for robbery. The 0.2512 coefficient on the time-since-payment index in column 8 implies that robbery rates are 25.1% higher on the thirty-first of the month relative to the first of the month in the extreme case of a jurisdiction where all welfare payments occurred on the first of the month. Individuals who have exhausted their welfare-related income need liquid assets, and robbery is more likely to yield cash than burglary, larceny-theft, and motor vehicle theft, each of which typically involves stealing other types of property.

The specifications presented in tables 4 to 7 test for a linear relation between crime rates and the time-since-payment index. However, the patterns in figure 2 suggest that the increase in criminal activity in the early payment sample primarily occurs early in the month and that criminal activity recedes at the end of the month. Less parametric tests that include indicators set equal to 1 for 0.1 increments of the time-since-payment-index shed additional light on the exact timing of the estimated effects. Table 8 presents the results of tests that are similar to those presented in columns 7 and 8 of tables 5 and 6, replacing the index with indicators. The indicator for values of the time-since-payment index between 0 and 0.1 is omitted from the specifications, so the other indicators measure the incidence of crime relative to periods that have these low index values.

The specifications in the first two columns explain the count of financially motivated crimes. In column 2, the coefficient on the indicator for values of the time-since-payment index that are larger than 0.1 and less than or equal to 0.2 is equal to 0.0716 and is statistically significant, suggesting an increase in the crime rate soon after payments occur. The coefficients on the indicators increase as the index increases, reaching a value of 0.1254 for index values between 0.7 and 0.8. *F*-tests reveal that this coefficient is statistically different from each of the coefficients on the indicators for values of the index less than or equal to 0.5. Therefore, financially motivated crime is increasing for a fairly large range of index values, suggesting that the raw patterns in figure 2 are a bit misleading.

The results in columns 1 and 2 also indicate that financially motivated crime recedes for very high values of the time-since-payment index. In column 2, the coefficient on the indicator for values of the index that are greater than 0.9

<sup>16</sup> Weisel (2002) and Clarke (2002) provide descriptive information about burglary.

TABLE 8.—NONPARAMETRIC SPECIFICATIONS

<i>Dependent Variable</i> <i>Type of Crime</i>	Count of Reported Incidents			
	Financially Motivated Crimes		Other Crimes	
	(1)	(2)	(3)	(4)
Constant	4.7912 (0.2138)	5.0510 (0.1877)	4.6498 (0.2450)	4.6113 (0.3971)
Time-since-payment index $>.1$ and $\leq .2$	0.0710 (0.0239)	0.0716 (0.0244)	0.0402 (0.0511)	0.0407 (0.0455)
Time-since-payment index $>.2$ and $\leq .3$	0.0867 (0.0232)	0.0863 (0.0229)	0.0395 (0.0483)	0.0455 (0.0415)
Time-since-payment index $>.3$ and $\leq .4$	0.0951 (0.0242)	0.0958 (0.0222)	0.0282 (0.0435)	0.0335 (0.0381)
Time-since-payment index $>.4$ and $\leq .5$	0.0968 (0.0237)	0.0983 (0.0231)	0.0350 (0.0446)	0.0425 (0.0401)
Time-since-payment index $>.5$ and $\leq .6$	0.1078 (0.0234)	0.1090 (0.0243)	0.0276 (0.0447)	0.0364 (0.0376)
Time-since-payment index $>.6$ and $\leq .7$	0.1259 (0.0242)	0.1239 (0.0267)	0.0340 (0.0486)	0.0377 (0.0415)
Time-since-payment index $>.7$ and $\leq .8$	0.1276 (0.0265)	0.1254 (0.0282)	0.0466 (0.0506)	0.0476 (0.0419)
Time-since-payment index $>.8$ and $\leq .9$	0.1181 (0.0281)	0.1167 (0.0346)	0.0182 (0.0562)	0.0250 (0.0452)
Time-since-payment index $>.9$ and $\leq 1$	0.0723 (0.0428)	0.0733 (0.0396)	−0.0257 (0.0808)	−0.0038 (0.0522)
Average temperature		0.0022 (0.0003)		0.0070 (0.0006)
Precipitation		−0.0096 (0.0051)		−0.0740 (0.0086)
Snowfall		−0.0405 (0.0052)		−0.0232 (0.0082)
Holiday dummy		−0.1561 (0.0127)		0.1240 (0.0232)
City $\times$ Month $\times$ Year fixed effects?	Yes	Yes	Yes	Yes
City $\times$ Day of the week fixed effects?	Yes	Yes	Yes	Yes
Day of month fixed effects?	Yes	Yes	Yes	Yes
Number of observations	9,496	9,496	8,947	8,947
Log likelihood	−34,499	−34,203	−23,019	−22,850

The specifications are negative binomial specifications. Each specification includes fixed effects for each city/month/year combination, each city/day of the week pair, and each day of the month. Time-since-payment index is an index between 0 and 1 that reflects the average number of days that have passed since welfare recipients received their last payment. The specifications include indicators that are equal to 1 for each 0.1 increment of this index and otherwise equal 0, omitting the indicator for values of the index less than or equal to 0.1. Average temperature is the average temperature in degrees Fahrenheit. Precipitation and snowfall are measured in inches. The holiday dummy is equal to 1 on U.S. federal holidays and 0 otherwise. Standard errors appear in parentheses, and they are computed using a block bootstrap technique in which city-month blocks are used for sampling.

and less than or equal to 1 is 0.0733, and on  $F$ -test reveals that this coefficient is smaller than the 0.1254 coefficient for index values between 0.7 and 0.8.<sup>17</sup> A few factors might explain this pattern. First, some programs in some jurisdictions make payments to recipients before the scheduled payment dates if the scheduled payment dates fall on week-ends or holidays. As a consequence, days that I have classified as being at the end of monthly payment cycles could be days when payments occur. Second, it is possible that welfare beneficiaries may be able to delay consumption at the end of the month and hold out until payments arrive. By doing so, they avoid the costs and potential punishment of committing crime. Third, estimates of the coefficient on the dummy that is equal to 1 for values of the time-since-payment index that lie between 0.9 and 1.0 are estimated from only 71 data points, and they have a high standard error. Therefore, the declines observed at the very end of the month are imprecisely estimated.

The tests presented in columns 3 and 4 of table 8 explain the count of reported incidents of other crimes. None of the indicators attracts a significant coefficient, and these coefficients do not tend to increase as the value of the index increases. As seen in the analysis described earlier, the incidence of other crimes does not seem to increase with the amount of time that has passed since welfare payments occurred.

Taken together, the results are consistent with the idea that individuals who receive support from welfare payments consume welfare-related income quickly and then attempt to supplement it with income from criminal activity. Unfortunately, it is not possible to bolster this evidence with analysis of the sources of income of the perpetrators of crimes because of data constraints. According to national data, only approximately 15% of Part I UCR crimes result in an arrest, and detailed income data are not even collected for arrested individuals.<sup>18</sup>

<sup>17</sup> The 0.0733 coefficient does not differ from the coefficients on any of the other index indicators by a statistically significant margin.

<sup>18</sup> See *Crime in the United States*, published by the Federal Bureau of Investigation.

Although detailed income data for perpetrators are not available, it is possible to compare the demographics of arrested individuals with those who receive support from welfare payments, and some considerations suggest it is plausible that they are behind temporal patterns in financially motivated crime. First, the number of individuals directly receiving welfare payments in a month is much higher than the number of crimes committed in a month. In the cities in my sample, there are approximately fifty food stamp recipients for each financially motivated crime in the average month.<sup>19</sup> Put differently, if all financially motivated crimes were committed by recipients of some form of welfare payment, 2% or less of welfare recipients, depending on the overlap of recipients across welfare programs, would commit such crimes in a typical month. This level of criminal activity does not seem implausibly large. Furthermore, unreported results indicate that the timing of welfare payments appears to have more pronounced effects in jurisdictions where a larger share of the population receives food stamp payments.<sup>20</sup> Specifications like those presented in tables 4 to 6 that include not only the time-since-payment index, but also this index interacted with the share of the population receiving food stamps shown in table 1 yields insignificant coefficients on the index itself and positive and significant coefficients on the interaction terms when the dependent variable measures the incidence of all crime or financially motivated crime. These results imply that the time that has passed since welfare payments occurred matters more in cities with larger welfare populations.<sup>21</sup>

The results also seem plausible given that the income profile of criminals is similar to that of welfare recipients. Harlow (1998, 2000) presents the results of surveys of jail inmates and finds that individuals who are in jail for committing financially motivated crimes report very low pre-arrest levels of monthly income and that more than 75% of them qualify for and receive public counsel.

However, there are notable gender and age differences between criminals and direct welfare recipients. During the sample period at the national level, 59% of food stamp recipients, 57% of SSI recipients, and 60% of TANF recipients were female, but only 30% of individuals arrested for financially motivated crimes were female. Furthermore, a large fraction of the males who received TANF benefits were young children. However, Hays (2003), Venkatesh (2006), and others point out that a large fraction of females who receive welfare payments live with and pool their resources with men, often without reporting these relationships to

welfare providers. These studies also point out that welfare recipients are economically embedded in their local communities. Therefore, payments to women are also likely to generate cycles in resources for other low-income individuals who benefit from welfare indirectly.

Additional tests indicate that the results are robust to several concerns.<sup>22</sup> As mentioned in section II, the distinction between the early payment sample and the staggered payment sample is imperfect. This distinction is based on the timing of food stamp payments. In order to confirm that results of tests that use the dummy for the first through the tenth of the month are robust to using a more strictly defined sample, I drop Detroit, Philadelphia, Providence, and Milwaukee from the sample. These are cities in which either food stamp payments are focused at the beginning of the month but TANF payments are more staggered or food stamp payments are staggered but TANF payments are focused at the beginning of the month. The results are not materially different from those presented in the tables.

Two other robustness checks are worth noting. First, measurement error or reporting biases could give rise to an excessive number of reported incidents on the first or last day of the month. For example, if there is a delay between when a crime occurs and when it is discovered or reported, there may be an incentive to report the crime on the first or last day of the month, so it is included in crime statistics for that month. The results are little changed by dropping observations from the first and last day of each month. The results are also robust to dropping New Orleans from the sample. The New Orleans data cover only 2006, and confounding factors related to the aftermath of hurricane Katrina could affect patterns of crime.

## V. Conclusion

Analysis of patterns in crime in twelve large U.S. cities where more than 10% of the population receives food stamps shows that criminal activity is increasing in the amount of time that has passed since welfare payments occurred. The increase reflects an increase in crimes in which the perpetrator is likely to have a financial motivation and not other types of Part I UCR or Group A NIBRS offenses. Temporal patterns in crime are not observed in jurisdictions where welfare payments are relatively more staggered. These results indicate that individuals who receive support from welfare payments consume welfare-related income quickly and then attempt to supplement it with income from criminal activity.

The findings point out a role for behavioral considerations in economic explanations of crime. Existing research shows that welfare recipients exhibit short-run impatience and do not smooth their consumption of welfare income. This type of consumption behavior is associated with

<sup>19</sup> This figure is computed by dividing the number of food stamp recipients in a typical month as measured in table 1, summed across the sample cities, by the monthly average aggregate number of financially motivated crimes in all the sample cities.

<sup>20</sup> These results are available from the author on request.

<sup>21</sup> It is important to be cautious in interpreting this result because the sample does not include cities in which a small share of the population receives welfare payments. If a larger share of the crimes in such jurisdictions were committed by welfare beneficiaries, temporal patterns in crime could still reflect welfare payment schedules.

<sup>22</sup> The results of these robustness tests appear in Foley (2008).

increased criminal activity later in monthly welfare payment cycles.

The results also carry implications for the design of welfare programs. Increasing the frequency of welfare payments would smooth patterns in crime. The leveling of criminal activity would make communities safer because police departments would not become overwhelmed by cyclical spikes. Under certain assumptions, frequent payments could also lower crime rates. If welfare beneficiaries follow a quasi-hyperbolic model of intertemporal choice, frequent payments would make them better off by forcing them to smooth their consumption. Such payments would reduce the extent to which they face dire circumstances because they consumed welfare-related income too quickly. As a result, circumstances that would be likely to induce criminal activity would be less common. Nearly all jurisdictions now distribute food stamp and TANF payments on electronic benefit transfer debit cards, so the costs of more frequent payments would be likely to be low. Shapiro (2005), Wilde and Ranney (2000), and Ohls et al. (1992) also point out benefits of more frequent payments. Such changes would require legislative action because the law currently requires that food stamp and SSI payments be made in monthly allotments.

Finally, the findings have implications for the deployment of police officers and the labor laws applicable to law enforcement. In jurisdictions where welfare payments are focused at the beginning of the month, increased levels of criminal activity at the end of the month call for increased police protection during this time. However, 1986 amendments to the Fair Labor Standards Act require that law enforcement officers be compensated with overtime pay for working more than forty hours a week. As a consequence, it is costly for departments to shift resources to times when they are particularly needed. More flexible labor laws could help police departments alter deployment schedules to prevent and combat crime.

#### REFERENCES

- Adams, William, Liran Einav, and Jonathan Levin, "Liquidity Constraints and Imperfect Information in Subprime Lending," *American Economic Review* 99 (2009), 49–84.
- Angeletos, George-Marios, David Laibson, Andrea Repetto, Jeremy Tobacman, and Stephen Weinberg, "The Hyperbolic Consumption Model: Calibration, Simulation, and Empirical Evaluation," *Journal of Economic Perspectives* 15 (2001), 47–68.
- Barr, Michael, "Banking the Poor," *Yale Journal of Regulation* 21 (2004), 121–237.
- Blank, Rebecca M., "Evaluating Welfare Reform in the United States," *Journal of Economic Literature* 40 (2002), 1105–1166.
- Becker, Gary S., "Crime and Punishment: An Economic Approach," *Journal of Political Economy* 76 (1968), 169–217.
- Bertrand, Marianne, Sendhil Mullainathan, and Eldar Shafir, "A Behavior Economics View of Poverty," *American Economic Review* 94 (2004), 419–423.
- Beverly, Sondra, Daniel Schneider, and Peter Tufano, "Splitting Tax Refunds and Building Savings: An Empirical Test," *Tax Policy and the Economy* 20 (2006), 111–161.
- Burek, Melissa, "Now Serving Part Two Crimes: Testing the Relationship between Welfare Spending and Property Crimes," *Criminal Justice Policy Review* 16 (2005), 360–384.
- Campbell, John, "Household Finance," *Journal of Finance* 61 (2006), 1553–1604.
- Choi, James J., David Laibson, and Brigitte C. Madrian, "Are Empowerment and Education Enough? Underdiversification in 401(k) Plans," *Brookings Papers on Economic Activity* 2 (2005), 151–213.
- Clarke, Ronald V., "Burglary of Retail Establishments" (Washington, DC: U.S. Department of Justice, Office of Community Oriented Policing Services, 2002).
- Cole, Nancy, and Ellie Lee, "An Analysis of EBT Benefit Redemption Patterns: Methods for Obtaining, Preparing, and Analyzing the Data" (Cambridge, MA: Abt Associates, 2005).
- DeFranzo, James, "Welfare and Burglary," *Crime and Delinquency* 42 (1996), 223–229.
- , "Welfare and Homicide," *Journal of Research in Crime and Delinquency* 34 (1997), 395–406.
- DellaVigna, Stefano, and Ulrike Malmendier, "Paying Not to Go to the Gym," *American Economic Review* 96 (2006), 694–719.
- Dobkin, Carlos, and Stephen Puller, "The Effects of Government Transfers on Monthly Cycles in Drug Abuse, Hospitalization, and Mortality," *Journal of Public Economics* 91 (2007), 2137–2157.
- Donohue, John, and Steven Levitt, "The Impact of Legalized Abortion on Crime," *Quarterly Journal of Economics* 116 (2001), 379–420.
- Duflo, Esther, William Gale, Jeffrey Liebman, Peter Orszag, and Emmanuel Saez, "Saving Incentives for Low- and Middle-Income Families: Evidence from a Field Experiment with H&R Block," *Quarterly Journal of Economics* 121 (2006), 1311–1346.
- Fellowes, Matt, and Alan Berube, "Leaving Money (and Food) on the Table: Food Stamp Participation in Major Metropolitan Areas and Counties" (Washington, DC: Brookings Institution 2005).
- Foley, C. Fritz, "Welfare Payments and Crime," NBER working paper no. 14074 (2008).
- Freeman, Richard, "The Labor Market," in James Q. Wilson and Joan Petersilia (Eds.), *Crime* (San Francisco: ICS Press, 1995).
- Garmaise, Mark, and Tobias Moskowitz, "Bank Mergers and Crime: The Real and Social Effects of Credit Market Competition," *Journal of Finance* 61 (2006), 495–539.
- Gould, Eric D., Bruce A. Weinberg, and David B. Mustard, "Crime Rates and Local Labor Market Opportunities in the United States: 1979–1997," *this REVIEW* 84 (2002), 45–61.
- Hannon, Lance, and James DeFranzo, "Welfare and Property Crime," *Justice Quarterly* 15 (1998a), 273–287.
- , "The Truly Disadvantaged, Public Assistance, and Crime," *Social Problems* 45 (1998b), 432–445.
- Harlow, Caroline Wolf, "Profile of Jail Inmates 1996" (Washington, DC: U.S. Department of Justice, Office of Justice Programs, 1998).
- , "Defense Counsel in Criminal Cases" (Washington, DC: U.S. Department of Justice, Office of Justice Programs, 2000).
- Hays, Sharon, *Flat Broke with Children: Women in the Age of Welfare Reform* (New York: Oxford University Press, 2003).
- Hsieh, Chang-Tai, "Do Consumers Respond to Anticipated Income Changes? Evidence from the Alaska Permanent Fund," *American Economic Review* 93 (2003), 397–405.
- Jacob, Brian, and Lars Lefgren, "Are Idle Hands the Devil's Workshop? Incapacitation, Concentration, and Juvenile Crime," *American Economic Review* 93 (2003), 1560–1577.
- Jacob, Brian, Lars Lefgren, and Enrico Morretti, "The Dynamics of Criminal Behavior: Evidence from Weather Shocks," *Journal of Human Resources* 42 (2007), 489–527.
- Johnson, David S., Jonathan A. Parker, and Nicholas Souleles, "Household Expenditure and the Income Tax Rebates of 2001," *American Economic Review* 96 (2006), 1589–1610.
- Jolls, Christine, "Behavioral Law and Economics," Yale Law School working paper (2007).
- Laibson, David, "Golden Eggs and Hyperbolic Discounting," *Quarterly Journal of Economics* 112 (1997), 443–477.
- Lee, David S., and Justin McCrary, "Crime, Punishment and Myopia," NBER working paper no. 11491 (2005).
- Levitt, Steven D., "Using Electoral Cycles in Police Hiring to Estimate the Effect of Police on Crime," *American Economic Review* 87 (1997), 270–290.

- Machin, Stephen, and Costas Meghir, "Crime and Economic Incentives," *Journal of Human Resources* 39 (2004), 958–979.
- Moffitt, Robert, "Incentive Effects of the U.S. Welfare System," *Journal of Economic Literature* 30 (1992), 1–61.
- O'Donoghue, Ted, and Matthew Rabin, "Doing It Now or Later," *American Economic Review* 89 (1999), 103–124.
- "Choice and Procrastination," *Quarterly Journal of Economics* 116 (2001), 121–160.
- Ohls, James C., Thomas M. Fraker, Alberto P. Martini, and Michael Ponza, "The Effect of Cash-Out on Food Stamp Use by Food Stamp Participants in San Diego" (Princeton, NJ: Mathematica Policy Research, 1992).
- Phelps, E. S., and R. A. Pollak, "On Second-Best National Saving and Game-Equilibrium Growth," *Review of Economic Studies* 35 (1968), 185–199.
- Raphael, Steven, and Rudolf Winter-Ember, "Identifying the Effect of Unemployment on Crime," *Journal of Law and Economics* 44 (2001), 259–283.
- Shapiro, Jesse, "Is There a Daily Discount Rate? Evidence from the Food Stamp Nutrition Cycle," *Journal of Public Economics* 89 (2005), 303–325.
- Shapiro, Matthew, and Joel Slemrod, "Consumer Response to Tax Rebates," *American Economic Review* 93 (2003), 381–396.
- Stephens Jr., Melvin, "'3rd of the Month': Do Social Security Recipients Smooth Consumption between Checks?" *American Economic Review* 93 (2003), 406–422.
- "The Consumption Response to Predictable Changes in Discretionary Income: Evidence from the Repayment of Vehicle Loans," *this REVIEW* 90 (2008), 241–252.
- Stephens Jr., Melvin, and Takashi Unayama, "Can Governments Help Smooth Consumption? Evidence from Japanese Public Pension Benefits," working paper (2008).
- Venkatesh, Sudhir Alladi, *Off the Books: The Underground Economy of the Urban Poor* (Cambridge, MA: Harvard University Press, 2006).
- Weisel, Deborah Lynn, "Burglary of Single-Family Homes" (Washington, DC: U.S. Department of Justice, Office of Community Oriented Policing Services, 2002).
- Wilde, Park E., and Christine K. Ranney, "The Monthly Food Stamp Cycle: Shopping Frequency and Food Intake Decisions in an Endogenous Switching Regression Framework," *American Journal of Agricultural Economics* 82 (2000), 200–213.