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WELFARE PAYMENTS AND CRIME

C. Fritz Foley

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ABSTRACT

This paper tests the hypothesis that the timing of welfare payments affects criminal activity. 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 like burglary, larceny-theft, motor vehicle theft, and robbery, as opposed to other kinds of crime like arson, assault, homicide, and rape. 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.

C. Fritz Foley
Harvard Business School
Soldiers Field
Boston, MA 02163
and NBER
ffoley@hbs.edu

1. 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 the hypothesis that 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; these are 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 12 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 do 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 timeframe 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 only observed 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 suggest a role for behavioral considerations in economic explanations for 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.[1] Recent work that shows that cash assistance recipients typically spend their payments too quickly suggests one mechanism by which a particular behavioral bias, short-run impatience, could affect the decision to engage in criminal activity. Shapiro (2005) documents that food stamp recipients experience a decline in caloric intake and an increase in the marginal utility of consumption in between food stamp payments. Stephens (2003) finds that households that primarily depend on social security for income increase spending on goods that reflect instantaneous consumption in the first few days following the receipt of their check. 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 behavior that suggests short-run impatience and violations of the permanent income hypothesis.[2] My results suggest that this type of consumption behavior is associated with increased criminal

[1] 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.

[2] Phelps and Pollak (1968) develop a simple framework of short-run impatience, and this framework is employed by Laibson (1997), O'Donohue and Rabin (1999), O'Donohue and Rabin (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), and Johnson, Parker, and Souleles (2006). Lee and McCrary (2005) present evidence that criminals typically have low discount rates or hyperbolic time preferences.

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. Police forces might therefore have an easier time fighting crime because they would be less likely to be overwhelmed during particular periods. If welfare beneficiaries do exhibit short run impatience when making consumption decisions, as indicated in the literature, frequent payments would smooth their consumption and reduce the extent to which they face dire circumstances because they consumed welfare related income too quickly. Levels of crime would be lower as a consequence.

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, Gale, Liebman, Orszag, and Saez (2006) and Beverly, Shneider, 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 (forthcoming), Barr (2004) and elsewhere. My analysis does not study the income, savings, and consumption behaviors of poor individuals directly, but it does suggest 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.[3]

The remainder of the paper is organized as follows. The next section explains the hypotheses in more detail, and Section 3 describes the data and the main tests. Section 4 presents the results, and the last section concludes.

2. 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. Payment schedules are set at the state and federal level, not the city level, and they have not changed substantially over the last decade. Conversations with state policy makers suggest that the distribution schedule for payments was set on the basis of administrative considerations rather than considerations related to patterns in consumption or criminal activity.

[3] Garmaise and Moskowitz (2006) show that weak credit conditions increase crime more generally.

Studies of the consumption of cash assistance recipients, including Shapiro (2005), and Stephens (2003), reveal that recipients do not smooth their consumption but instead exhibit short run impatience. They appear to spend their monthly payments too quickly and to experience increasing marginal utility of consumption over monthly payment cycles. This increase in the marginal utility of consumption in part reflects that the poor do not have access to savings or credit, as documented in Adamds, Einav, and Levin (forthcoming), Duflo, Gale, Liebman, Orszag, and Saez (2006), Beverly, Shneider, and Tufano (2006), and Barr (2004).

As a consequence, 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 might not have the resources to satisfy their needs later in the monthly payment cycle. Such individuals may turn to crime to augment their welfare related income later in payment cycles. Frameworks that account for short-run impatience, like the one developed in O'Dononhue and Rabin (1999), suggest 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.

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, 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. These potential effects tend to work against the predictions described above. 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. Alternatively, potential victims of crime might respond to changes in the demand for criminal income by taking additional 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. Therefore, the timing of disbursement is unlikely to have a large effect on the supply of potential victims.

3. 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 the distribution of welfare payments by jurisdiction and detailed crime data.

3.1 Data on Welfare Programs

The three primary welfare programs that provide income maintenance benefits are the Food Stamps program, the TANF program, and the SSI program. 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 of these 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 disabled adults and children who have limited means. SSI payments are distributed by check, which is mailed to recipients once a month. 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 selected 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 received 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 those jurisdictions in which at least 10% of the population participates in the Food Stamp program. This screen yields a sample of 15 cities including Baltimore, MD; Detroit, MI; El Paso, TX; Fresno, CA; McAllen-Edinburg-Mission, TX; Memphis, TN; Miami, FL; Milwaukee, WI; New Orleans, LA; New York, NY; Newark, NJ; Philadelphia, PA; Providence, RI; St. Louis, MO; and Washington, DC. As explained below, data on reported incidents of crime are not available for Memphis, New York, and McAllen-Edinburg-Mission, so the final sample includes 12 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 which are drawn from Fellowes and Berube (2005), the data on TANF and SSI programs cover the year 1999.[4] 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 payments and SSI program payments often exceed the value of food stamp payments, implying higher payments per recipient. However, relative to TANF and SSI, Food Stamps have become a more significant source of income over the 1999-2005 period. Appendix Table 1 provides information on the value of all three programs from 1999 through 2005. Averaged across

[4] 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*.

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. In most jurisdictions, each of the three programs makes payments to recipients once a month.[5] In some jurisdictions, Food Stamp and TANF payments occur during 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.

3.2 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 in which welfare is widely used are not available in NIBRS; NIBRS only covers 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 that is classified as a Part I UCR offense or a Group A NIBRS offense. These categories of crime include arson, assault offenses, burglary, forcible sex offenses, homicide, larceny-theft, motor vehicle theft, and robbery. For each incident, I requested information about the type, the date and time, and the location of the incident.

[5] 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.

12 of the 15 jurisdictions identified above provided useable data.[6] Table 2 provides a description of the crime data obtained from each of the cities included 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 only available for portions of this time frame, as indicated in the last column of Table 2.[7]

3.3 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. 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 10 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

[6] 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 is a collection of three cities so I excluded it.

[7] In several jurisdictions, changes to computer systems prevented departments from providing me with data for the full sample period. Certain kinds of crime are 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.

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 one in the first 10 days of the month and otherwise equal to zero as well as an interaction between this dummy and a dummy that is equal to one for the Staggered Payment Sample and zero 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 any 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 payments are received on the 1st 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 1st of the month in Milwaukee, which is 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 this 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 day of the month, on the fourth day of the month this average will be 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.[8] The weighted average is divided by 30 to create an index that takes on values between zero and one. If all welfare recipients received a payment from each program on the 1st of the month, the index would be zero on that day, and if no additional payments occurred over the course of the month, the index would be equal to one 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 Stamps and SSI payments occur only once a month on the 1st of the month, and TANF payments occur twice a month on the first and 16th. Therefore, the index for Providence is zero on the 1st of the month. It increases over the course of the month and drops down on the 16th to reflect the fact that TANF recipients receive a payment at that time. In St. Louis, SSI payments occur on the 1st of the month, but Food Stamp and TANF payments are distributed over the first 22 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 declines over the first 22 days of the month before increasing. One benefit of using this index in specifications that identify patterns in

[8] Similar indices and results are obtained if the values of program payments are used as weights.

criminal activity is that it allows for the use of fixed effects for each calendar day of the month.

By identifying 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 that 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 non-financially motivated or other crimes, and they include arson, assault offenses, forcible sex offenses, and homicide.[9]

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

[9] 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 non-financially motivated 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 occurs most frequently soon after the distribution of government transfer payments, when drug users have the resources to increase their consumption.

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 the 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 below 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.[10] Days that are U.S. federal holiday are identified as holidays. Table 3 provides descriptive statistics for the variables used in the analysis.

4. 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

[10] 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.

period average number of reported incidents in the city.[11] 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%. Panel B and C respectively show crime rates for financially motivated crimes and non-financially motivated crimes. In cities in the Early Payment Sample, there are pronounced monthly cycles 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 dotted 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 1 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. Patterns in crime observed in the Early Payment Sample do not appear to be a consequence of factors that are also operative in the Staggered Payment Sample.

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 1-4 is the crime rate, which is defined as the number of reported incidents in a city on a particular date divided by average daily reported

[11] Jacob, Lefgren, and Morretti (2007) use a similar approach to measure weekly crime rates.

incidents in the city. Each specification in Table 4 includes two kinds of fixed effects.[12] City*Month*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*Day of Week fixed effects control for differences in criminal activity across days of the week in individual cities. Standard errors that allow for clustering within each city/month pair appear in parentheses.[13]

The coefficients on Dummy for 1^{st}-10^{th} 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 in the beginning of the month. The coefficients on the Staggered Payment Dummy interacted with the Dummy for 1^{st}-10^{th} are positive and significant and of slightly smaller magnitude than the coefficients on the Dummy for 1^{st}-10^{th}. An F-test reveals that the sum of the coefficients on Dummy for 1^{st}-10^{th} and on the interaction terms for each specification is not statistically distinguishable from zero. These results indicate that there are no discernable increases 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.

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[12] The results in Table 4 and the remainder of the analysis do not appear to depend on the inclusion of these fixed effects. Using only city fixed effects to control for constant city characteristics yields estimates of the effects of the timing of welfare payments on crime that are similar.

[13] In order to consider the possible effect of serial correlation on the magnitude of the standard errors, I have also computed these for the OLS specifications using a block bootstrap technique. This approach yields very similar estimates that do not materially change the significance of the results.

The specifications in column 2 include controls for weather and a dummy that is equal to one on holidays and zero 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 they 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 0.1079 coefficient on the Time Since Payment Index in column 4 implies that, if all welfare payments occurred on the 1st of the month, crime rates would be 10.8% higher on the 31st of the month relative to the 1st of the month.

Columns 5-8 of Table 4 contain results of negative binomial specifications that analyze counts of reported incidents as opposed to crime rates. The results in the specifications are qualitatively and quantitatively very similar to those in columns 1-4. These findings are consistent with the hypothesis that criminal income supplements welfare income at the end of monthly welfare payment cycles.

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 1-4 and the count of reported incidents of financially motivated crime in columns 5-8. As in Table 4, the coefficients on the Dummy for 1^{st}-10^{th} are negative and significant, and the coefficients on this dummy interacted with the Staggered Payment Dummy are positive and significant. These results indicate that there are 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 analyzed in Table 4. The -0.0378 coefficient on the Dummy for 1^{st}-10^{th} 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) below average in the first 10 days of the month than it is over the rest of the month. The 0.1254 coefficient on Day of the Month in column 4 indicates that if all welfare payments occurred on the 1^{st} of the month, the financially motivated crime rate would be 12.5% (as opposed to 10.8% for all crimes) higher on the 31^{st} of the month relative to the 1^{st}.

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 non-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 non-financially motivated crimes. These specifications are the same as those presented in Tables 4 and 5, but the dependent variables considered are the non-financially motivated crime rate in columns 1-4 and the count of reported incidents of non-financially motivated crime in columns 5-8. The results do not indicate any statistically significant relations between the timing of welfare payments and non-financially motivated crimes. The coefficients on the Dummy for 1st-10th are positive, but 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 Time Since Payment Index are also insignificant, and they are very small in magnitude in 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 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 columns 1 and 2, larcenies 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, and these coefficients are significant for all types of crime except burglary. The insignificant coefficient on burglary 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.[14] Therefore, this type of crime may be less motivated by short run liquidity needs than other kinds of financially motivated crimes. The implied effect of the timing of welfare payments is particularly pronounced for robbery. The 0.2224 coefficient on the Time Since Payment Index in column 8 implies

[14] Weisel (2002) and Clarke (2002) provide descriptive information about burglary.

that robbery rates are 22% higher on the 31st of the month relative to the 1st of the month in a jurisdiction where all welfare payments occur on the 1st of the month. This result might reflect the fact that individuals who have exhausted their welfare related income need liquid assets, and robbery is more likely to yield cash than other financially motivated crimes.

The results indicate effects of the timing of welfare payments on measures of crime at the city level. 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. Exploring this possibility would require detailed information on the sources of income of the perpetrators of crimes. However, such data are not available. 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.[15]

Even though 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 to determine if it seems plausible that they are behind any temporal patterns in financially motivated crime. Harlow (1998 and 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. Therefore, the income profile of criminals is similar to the income profile of welfare recipients.[16]

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[15] See *Crime in the United States*, published by the Federal Bureau of Investigation.

[16] There are some indications of gender differences between welfare recipients and criminals. During the sample period, 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

As mentioned in Section II, the distinction between the Early Payment Sample and the Staggered Payment Sample used in the tests that include the dummy that is equal to one for the first ten days of the month is subject to some concerns. This distinction is based on the timing of Food Stamp payments. Although this form of welfare is the largest in terms of the number of recipients, TANF programs are larger in value terms in many jurisdictions, and the timing of TANF payments differs from the timing of Food Stamp payments. In order to confirm that results 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.[17]

The results of some of the specifications presented in Tables 5 and 6, run using the reduced sample, appear in Appendix Table 2. The results indicate that using the more strictly defined sample yields estimates suggesting larger effects of the timing of welfare payments on financially motivated crimes in the Early Payment Sample. Using the more refined sample, there are, as before, no significant temporal patterns in non-financially motivated crimes in either the strictly defined Early Payment Sample or Staggered Payment Sample.

Appendix Table 3 presents results of two other robustness checks. First, measurement error or reporting biases could give rise to an excessive number of reported

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large fraction of the males who received TANF benefits were young children. These patterns suggest that individuals committing crimes are not solely the direct recipients of payments and include indirect beneficiaries as well.

[17] In this robustness check, I do not drop New Orleans. Food Stamp payments occur during the 5th-14th period and TANF payments occur from the 1st-5th. This payment schedule is consistent with including this city in the Staggered Payment Sample. Removing it does not qualitatively or quantitatively change the results in a significant way.

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 from the sample. As a second additional robustness check, New Orleans is dropped from the sample. The New Orleans data only cover 2006 and conflating factors related to the aftermath of hurricane Katrina could affect patterns of crime in the city. The results indicate that removing New Orleans from the sample does not substantively change the results.

5. Conclusion

Analysis of patterns in crime in 12 large U.S. cities where more than 10% of the population receive Food Stamps indicates that the timing of welfare payments affects criminal activity. More crime takes place when more time 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 findings are consistent with the hypothesis 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 results suggest a role for behavioral considerations in economic explanations of crime. Existing research indicates that welfare recipients exhibit short-run impatience and do not smooth their consumption of welfare income. My results suggest this type of consumption behavior is associated with 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. Smooth levels of criminal activity might make crime easier to combat because police departments would be unlikely to be overwhelmed. If welfare beneficiaries do exhibit short-run impatience, frequent payments would smooth their consumption and reduce the extent to which they face dire circumstances because they consumed welfare related income too quickly. As a result, more frequent payments would also lower crime rates. Nearly all jurisdictions now distribute Food Stamp and TANF payments on electronic benefit transfer cards, so the costs of more frequent payments would be likely to be low. Shaprio (2005), Wilde and Ranney (2000), and Ohls, Fraker, Martini, and Ponza (1992) also present arguments in favor of more frequent payments.

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 40 hours a week. As a consequence, it might be 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.

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Figure 1: This figure displays the values of the Time Since Payment Index for Providence and St. Louis for each day of the month. The Time Since Payment Index is an index between zero and one 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.

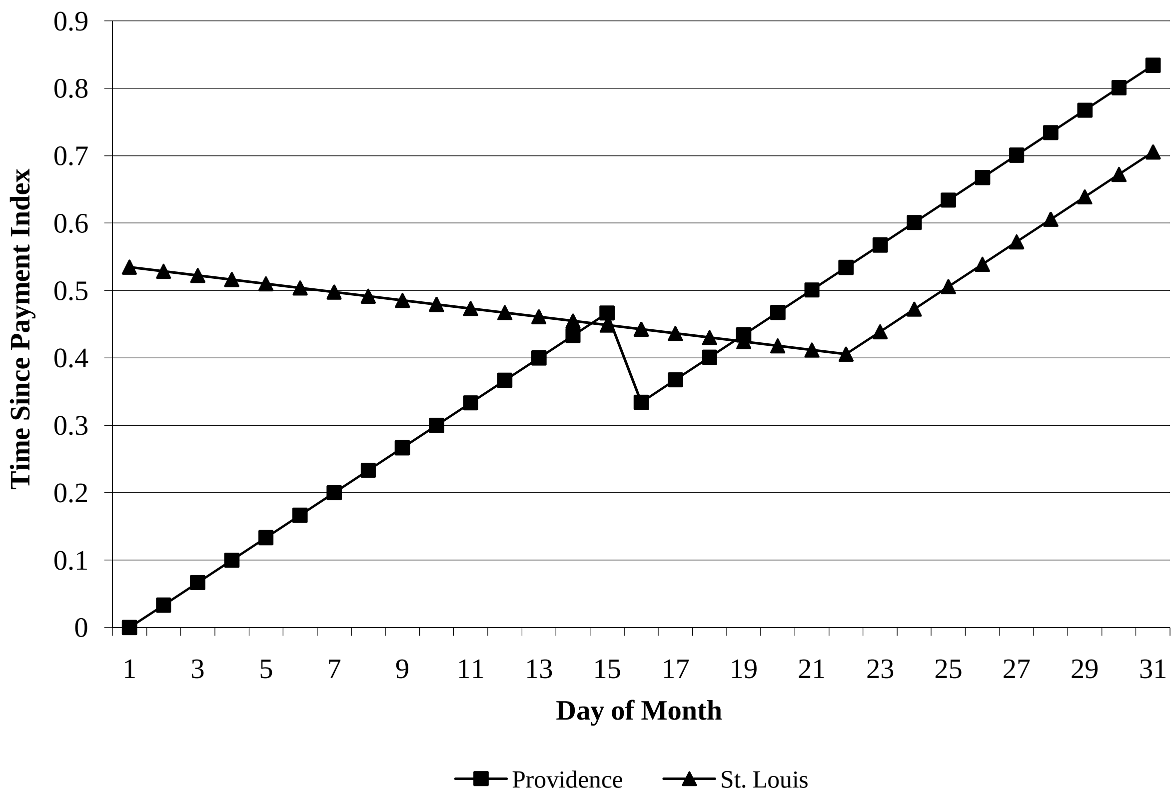

Figure 2. This figure displays crime rates over the course of the month. Panel A displays rates for all crimes that are classified as Type I crimes in the UCR reporting system and Group A crimes in the NIBRS reporting system. Panel B display rates for crimes in which the perpetrator is likely to have 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 displayed 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 and cities in which these payments are more staggered. 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.

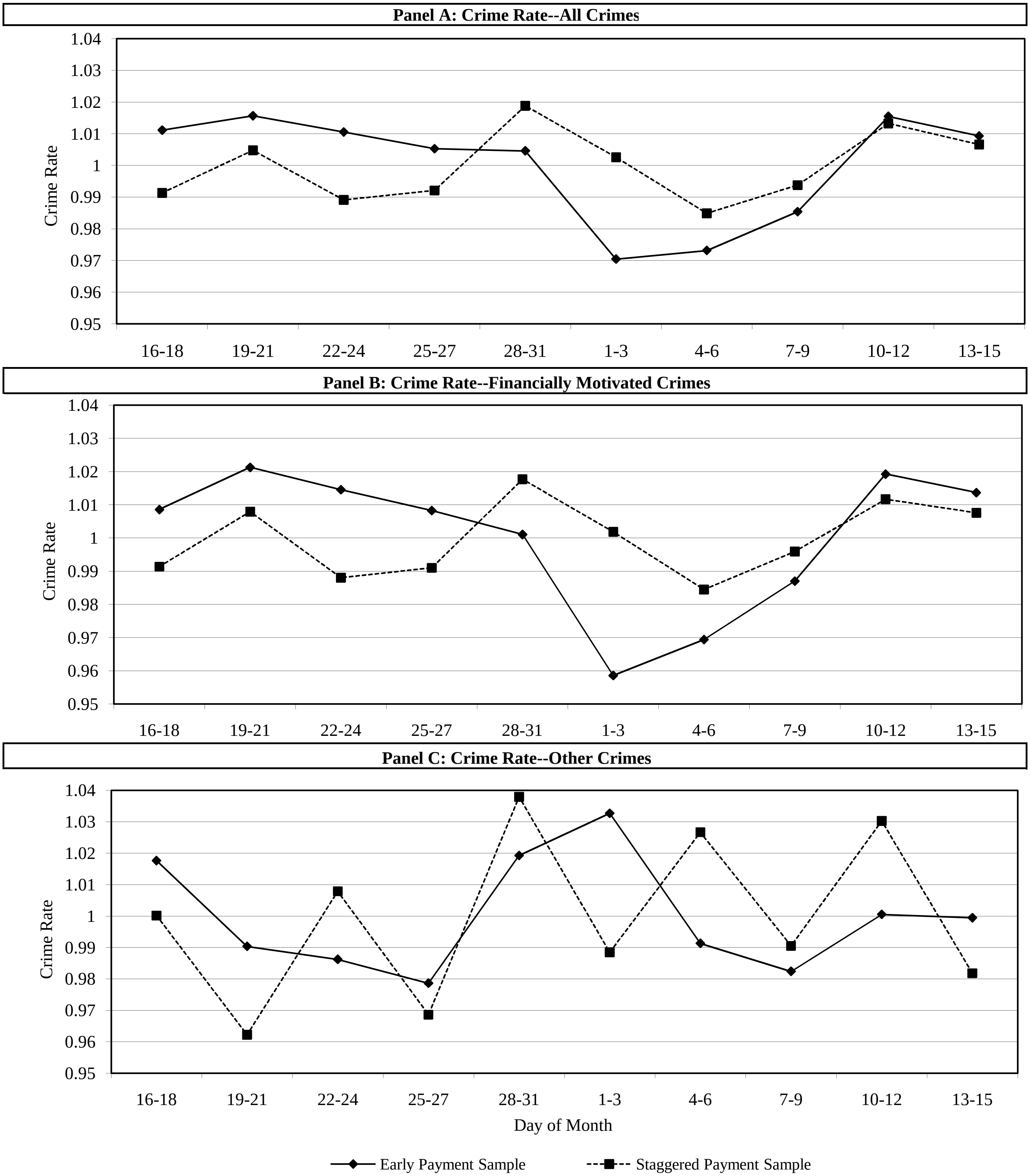

Table 1

Welfare Program Details by City

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 Supplemental Security Income. 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 the number of SSI recipients in Miami, FL and El Paso, TX are for the year 1995. Data from Detroit, MI cover Wayne County, Fresno, CA Fresno County, Newark, NJ Essex County, Philadelphia, PA Philadelphia County, Providence, RI Providence County, Washington, DC District of Columbia County, Baltimore, MD Baltimore City, El Paso, TX El Paso MSA, Miami, FL Miami MSA, Milwaukee, WI Milwaukee County, New Orleans, LA Orleans Parish, St. Louis, MO St. Louis County.

Panel A: Population and Share of Population Receiving Welfare Payments

City	Population	Food Stamps	TANF	SSI
Early Payment Sample				
Detroit, MI	2,061,162	12.2%	6.3%	3.7%
Fresno, CA	799,407	10.2%	7.3%	4.5%
Newark, NJ	793,633	11.5%	5.1%	3.2%
Philadelphia, PA	1,517,550	17.9%	9.3%	5.4%
Providence, RI	621,602	10.0%	6.6%	3.4%
Washington, DC	572,059	14.3%	8.5%	3.5%
Staggered Payment Sample				
Baltimore, MD	651,154	15.3%	7.5%	5.1%
El Paso, TX	679,622	16.7%	2.6%	3.1%
Miami, FL	2,253,362	11.3%	2.7%	4.8%
Milwaukee, WI	940,164	10.6%	3.2%	3.4%
New Orleans, LA	1,381,652	12.0%	1.7%	2.0%
St. Louis, MO	348,189	22.4%	5.6%	5.3%

Panel B: Value of Welfare Payments

City	Food Stamps	TANF	SSI
Early Payment Sample			
Detroit, MI	214,368	407,981	394,728
Fresno, CA	81,530	183,609	206,600
Newark, NJ	92,768	94,436	124,160
Philadelphia, PA	264,965	288,589	436,889
Providence, RI	43,410	108,703	99,618
Washington, DC	81,061	100,401	91,231
Staggered Payment Sample			
Baltimore, MD	103,252	139,554	162,470
El Paso, TX	100,659	30,488	75,551
Miami, FL	208,965	143,462	502,810
Milwaukee, WI	71,092	165,946	204,177
New Orleans, LA	161,504	27,150	89,401
St. Louis, MO	70,183	67,542	89,401

Panel C: Delivery Dates of Welfare Payments

City	Food Stamps	TANF	SSI
Early Payment Sample			
Detroit, MI	1st - 9th	Twice a month, staggered	1st
Fresno, CA	1st - 10th	1st	1st
Newark, NJ	1st - 5th	1st	1st
Philadelphia, PA	1st-10th	Twice a month, staggered	1st
Providence, RI	1st	1st and 16th	1st
Washington, DC	1st - 10th	1st	1st
Staggered Payment Sample			
Baltimore, MD	6th-15th	1st-15th	1st
El Paso, TX	1st-15th	1st-15th	1st
Miami, FL	1st - 15th	1st - 15th	1st
Milwaukee, WI	2nd-15th	1st	1st
New Orleans, LA	5th - 14th	1st-5th	1st
St. Louis, MO	1st - 22nd	1st - 22nd	1st

Table 2

Crime Data Coverage

This table displays information about the crime data obtained from each city in the sample.

City	Type of Crimes Covered	Sample Period
Detroit, MI	All Group A NIBRS Crimes	2005-2006
Fresno, CA	All Part I UCR Crimes	2004-2006
Newark, NJ	All Part I UCR Crimes except Rape and Arson	2005-2006
Philadelphia, PA	All Part I UCR Crimes except Arson	2004-2006
Providence, RI	All Part I UCR Crimes except Arson	2004-2006
Washington, DC	All Part I UCR Crimes	08/01/2004-09/30/2005, 2006
Baltimore, MD	All Part I UCR Crimes except Arson and Homicide	2006
Milwaukee, WI	All Part I UCR Crimes	2005-2006
St. Louis, MO	All Part I UCR Crimes	2004-2006
Miami, FL	All Part I UCR Crimes	2004, 08/01/2005-12/31/2006
New Orleans, LA	All Part I UCR Crimes except Arson, Homicide, and Rape	2006
El Paso, TX	Robbery, Burglary, Theft, Motor Vehicle Theft	07/01/05-12/31/06

Table 3

Descriptive Statistics

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 one in the first ten days of the month and zero otherwise. Time Since Payment Index is an index between zero and one 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 one on U.S. federal holidays and zero otherwise.

	Mean	Median	Standard Deviation
Crime Rate--All Crimes	1.000	0.999	0.181
Count of Reported Incidents--All Crimes	107.747	96.000	65.975
Crime Rate--Financially Motivated Crimes	1.000	0.996	0.215
Count of Reported Incidents--Financially Motivated Crimes	91.633	75.000	60.017
Crime Rate--Other Crimes	1.000	0.947	0.539
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	45.478	42.000	29.708
Count of Reported Incidents--Motor Vehicle Theft	20.001	16.000	14.657
Count of Reported Incidents--Robbery	9.251	6.000	9.503
Dummy for 1st-10th	0.329	0.000	0.470
Time Since Payment Index	0.470	0.455	0.178
Average Temperature	59.802	62.000	17.930
Precipitation	0.108	0.000	0.342
Snowfall	0.051	0.000	0.504
Holiday Dummy	0.032	0.000	0.176

Table 4

The Effects of the Timing of Welfare Payments on Crime

The dependent variable in columns 1-4 is the crime rate, and for columns 5-8 it is a count of the total reported incidents of crime. 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 one in the first ten days of the month and zero otherwise. Staggered Payment Dummy is equal to one 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 zero and one 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 one on U.S. federal holidays and zero otherwise. Heteroskedasticity consistent standard errors that allow for clustering within each city-month appear in parentheses.

Dependent Variable:	Crime Rate				Count of Reported Incidents			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.9921	0.8744	0.9231	0.7699	3.3180	4.5112	3.6260	4.4797
	(0.0038)	(0.0185)	(0.0253)	(0.0314)	(0.0265)	(0.0145)	(0.0353)	(0.0311)
Dummy for 1st-10th	-0.0292	-0.0318			-0.0234	-0.0256		
	(0.0063)	(0.0061)			(0.0053)	(0.0051)		
Staggered Payment Dummy *	0.0255	0.0266			0.0170	0.0176		
Dummy for 1st-10th	(0.0092)	(0.0089)			(0.0083)	(0.0079)		
Time Since Payment Index			0.1044	0.1079			0.0802	0.0819
			(0.0266)	(0.0262)			(0.0247)	(0.0240)
Average Temperature		0.0026		0.0026		0.0028		0.0027
		(0.0003)		(0.0003)		(0.0003)		(0.0003)
Precipitation		-0.0175		-0.0169		-0.0182		-0.0175
		(0.0046)		(0.0046)		(0.0041)		(0.0042)
Snowfall		-0.0303		-0.0310		-0.0368		-0.0375
		(0.0029)		(0.0030)		(0.0042)		(0.0042)
Holiday Dummy		-0.0977		-0.1014		-0.1074		-0.1111
		(0.0112)		(0.0110)		(0.0107)		(0.0102)
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?	N	N	Y	Y	N	N	Y	Y
No. of Obs.	9,496	9,496	9,496	9,496	9,496	9,496	9,496	9,496
R-Squared	0.3853	0.4111	0.3962	0.4221				
Log Likelihood					-37,061	-36,767	-36,975	-36,677

Table 5

The Effects of the Timing of Welfare Payments on Crime--Financially Motivated Crimes

The dependent variable in columns 1-4 is the crime rate, and for columns 5-8 it is a count of the total reported incidents of crime. 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 one in the first ten days of the month and zero otherwise. Staggered Payment Dummy is equal to one 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 zero and one 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 one on U.S. federal holidays and zero otherwise. Heteroskedasticity consistent standard errors that allow for clustering within each city-month appear in parentheses.

Dependent Variable:	Crime Rate				Count of Reported Incidents			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	1.0022	0.9425	0.9062	0.8202	3.2596	4.4191	3.5594	4.3752
	(0.0043)	(0.0208)	(0.0269)	(0.0347)	(0.0286)	(0.0146)	(0.0377)	(0.0324)
Dummy for 1st-10th	-0.0353	-0.0378			-0.0300	-0.0322		
	(0.0066)	(0.0064)			(0.0054)	(0.0051)		
Staggered Payment Dummy * Dummy	0.0313	0.0325			0.0239	0.0248		
for 1st-10th	(0.0098)	(0.0095)			(0.0088)	(0.0083)		
Time Since Payment			0.1226	0.1254			0.0984	0.0998
			(0.0285)	(0.0281)			(0.0259)	(0.0253)
Average Temperature		0.0019		0.0019		0.0021		0.0020
		(0.0003)		(0.0003)		(0.0003)		(0.0003)
Precipitation		-0.0082		-0.0075		-0.0098		-0.0091
		(0.0056)		(0.0056)		(0.0046)		(0.0047)
Snowfall		-0.0321		-0.0329		-0.0393		-0.0400
		(0.0025)		(0.0026)		(0.0044)		(0.0044)
Holiday Dummy		-0.1374		-0.1411		-0.1459		-0.1496
		(0.0126)		(0.0126)		(0.0119)		(0.0115)
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?	N	N	Y	Y	N	N	Y	Y
No. of Obs.	9,496	9,496	9,496	9,496	9,496	9,496	9,496	9,496
R-Squared	0.4715	0.4925	0.4799	0.5010				
Log Likelihood					-36,191	-35,916	-36,115	-35,836

Table 6

The Effects of the Timing of Welfare Payments on Crime--Other Crimes

The dependent variable in columns 1-4 is the crime rate, and for columns 5-8 it is a count of the total reported incidents of crime. 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 one in the first ten days of the month and zero otherwise. Staggered Payment Dummy is equal to one 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 zero and one 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 one on U.S. federal holidays and zero otherwise. Heteroskedasticity consistent standard errors that allow for clustering within each city-month appear in parentheses.

Dependent Variable:	Crime Rate				Count of Reported Incidents			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.9199	0.4595	0.8867	0.4062	2.5700	0.5670	0.5531	0.6120
	(0.0112)	(0.0459)	(0.0616)	(0.0764)	(0.0460)	(0.1054)	(0.1067)	(0.1131)
Dummy for 1st-10th	0.0065	0.0027			0.0135	0.0111		
	(0.0199)	(0.0200)			(0.0145)	(0.0141)		
Staggered Payment Dummy *	0.0030	0.0047			-0.0142	-0.0138		
Dummy for 1st-10th	(0.0258)	(0.0253)			(0.0197)	(0.0192)		
Time Since Payment Index			0.0763	0.0872			0.0155	0.0236
			(0.0662)	(0.0645)			(0.0453)	(0.0432)
Average Temperature		0.0080		0.0079		0.0074		0.0072
		(0.0007)		(0.0008)		(0.0005)		(0.0005)
Precipitation		-0.0833		-0.0824		-0.0770		-0.0763
		(0.0130)		(0.0131)		(0.0124)		(0.0125)
Snowfall		-0.0199		-0.0200		-0.0228		-0.0234
		(0.0094)		(0.0096)		(0.0066)		(0.0067)
Holiday Dummy		0.1575		0.1494		0.1306		0.1234
		(0.0282)		(0.0277)		(0.0208)		(0.0210)
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?	N	N	Y	Y	N	N	Y	Y
No. of Obs.	8,947	8,947	8,947	8,947	8,947	8,947	8,947	8,947
R-Squared	0.4194	0.4351	0.4224	0.4371				
Log Likelihood					-24,312	-24,119	-24,280	-24,100

Table 7

The Effects of the Timing of Welfare Payments by Type of Financially Motivated Crime

The dependent variable is the country of reported incidents of burglary in columns 1 and 2, larceny in columns 3 and 4, motor vehicle theft in columns 5 and 6, and robbery in columns 7 and 8. 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 zero and one 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 one on U.S. federal holidays and zero otherwise. Heteroskedasticity consistent standard errors that allow for clustering within each city-month appear in parentheses.

Dependent Variable:	Count of Reported Indcidents							
Type of Crime	Burglary		Larceny		Motor Vehichle Theft		Robbery	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	2.4598	2.9474	2.7416	3.6639	1.8927	2.6681	0.4264	1.9019
	(0.0584)	(0.0538)	(0.0523)	(0.0413)	(0.0938)	(0.0518)	(0.0906)	(0.0691)
Time Since Payment Index	0.0655	0.0708	0.0795	0.0806	0.1126	0.1132	0.2222	0.2251
	(0.0477)	(0.0468)	(0.0322)	(0.0316)	(0.0469)	(0.0468)	(0.0622)	(0.0625)
Average Temperature		0.0032		0.0022		0.0004		0.0028
		(0.0005)		(0.0004)		(0.0005)		(0.0007)
Precipitation		0.0197		-0.0281		0.0105		-0.0141
		(0.0098)		(0.0065)		(0.0090)		(0.0111)
Snowfall		-0.0435		-0.0478		-0.0247		-0.0378
		(0.0083)		(0.0061)		(0.0055)		(0.0081)
Holiday Dummy		-0.1357		-0.2013		-0.0623		-0.1267
		(0.0211)		(0.0146)		(0.0212)		(0.0250)
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
No. of Obs.	9,496	9,496	9,496	9,496	9,496	9,496	9,496	9,496
Log Likelihood	-26,183	-26,100	-32,078	-31,831	-27,813	-27,796	-22,007	-21,967

Appendix Table 1

Welfare Program Details by City

This table displays the value of welfare program payments (in thousands of dollars) over the 1999-2005 period. Data from Detroit, MI cover Wayne County, Fresno, CA Fresno County, Newark, NJ Essex County, Philadelphia, PA, Philadelphia County, Providence, RI Providence County, Washington, DC District of Columbia County, Baltimore, MD, Baltimore City, El Paso, TX, El Paso MSA, Miami, FL, Miami MSA, Milwaukee, WI, Milwaukee County, New Orleans, LA, Orleans Parish, St. Louis, MO, St. Louis County.

				Food Stamps			
City	1999	2000	2001	2002	2003	2004	2005
Early Payment Sample							
Detroit, MI	214,368	184,614	198,103	228,424	278,983	313,485	373,735
Fresno, CA	81,530	77,333	77,210	84,075	91,431	107,505	130,202
Newark, NJ	92,768	81,240	75,459	73,506	77,060	85,071	95,870
Philadelphia, PA	264,965	242,318	236,811	244,870	405,520	303,778	337,227
Providence, RI	43,410	44,259	45,302	48,556	53,067	56,693	59,613
Washington, DC	81,061	74,875	70,862	77,074	95,185	96,825	103,176
Staggered Payment Sample							
Baltimore, MD	103,252	94,394	94,263	97,190	108,055	119,352	131,438
El Paso, TX	100,659	95,164	99,027	111,226	140,900	170,434	198,981
Miami, FL	208,965	229,338	230,999	246,204	270,005	371,997	424,516
Milwaukee, WI	71,092	74,277	86,645	102,435	117,257	136,054	157,348
New Orleans, LA	101,959	95,955	104,774	119,186	121,294	133,431	235,945
St. Louis, MO	70,183	71,939	78,095	85,815	96,768	110,754	118,428

				TANF			
	1999	2000	2001	2002	2003	2004	2005
Early Payment Sample							
Detroit, MI	407,981	413,728	353,028	365,952	349,953	340,491	332,969
Fresno, CA	183,609	202,885	195,583	181,232	194,390	203,000	196,871
Newark, NJ	94,436	84,603	105,935	106,050	114,466	109,579	97,639
Philadelphia, PA	288,589	403,194	237,214	247,132	245,940	273,650	283,211
Providence, RI	108,703	110,766	106,010	108,097	101,959	101,527	109,847
Washington, DC	100,401	110,064	118,644	129,304	119,402	118,165	115,150
Staggered Payment Sample							
Baltimore, MD	139,554	149,623	140,844	126,662	105,860	134,910	146,929
El Paso, TX	30,488	32,188	31,760	30,065	34,753	28,565	29,784
Miami, FL	143,462	157,218	163,535	150,467	130,201	125,873	110,398
Milwaukee, WI	165,946	219,813	271,941	280,726	293,403	307,476	287,444
New Orleans, LA	27,150	26,746	30,240	33,358	27,437	23,912	20,869
St. Louis, MO	67,542	70,109	70,747	63,650	37,134	37,839	34,890

	SSI						
	1999	2000	2001	2002	2003	2004	2005
Early Payment Sample							
Detroit, MI	394,728	422,247	421,461	414,186	431,247	443,634	453,732
Fresno, CA	206,600	210,216	218,411	239,892	251,222	260,226	270,260
Newark, NJ	124,160	123,622	127,823	130,081	130,226	135,573	138,055
Philadelphia, PA	436,889	444,756	475,148	504,865	518,179	539,593	559,848
Providence, RI	99,618	105,204	114,169	118,562	121,949	127,133	132,877
Washington, DC	91,231	92,761	97,623	102,153	104,791	109,558	111,897
Staggered Payment Sample							
Baltimore, MD	162,470	162,494	166,061	163,943	161,479	158,818	151,696
El Paso, TX	75,551	78,536	84,434	90,222	92,043	95,113	99,558
Miami, FL	502,810	518,923	540,317	554,838	588,162	602,794	611,416
Milwaukee, WI	204,177	197,271	200,476	207,026	212,753	219,155	220,835
New Orleans, LA	130,870	128,394	131,192	132,440	132,242	136,489	113,814
St. Louis, MO	89,401	89,318	91,174	92,594	92,458	93,109	93,527

Appendix Table 2

The Effects of the Timing of Welfare Payments on Crime: Alternative Sample

The dependent variable in columns 1, 2, 5, and 6 is the crime rate and the specifications in these columns are OLS specifications. The dependent variable in columns 3, 4, 7, and 8 is a count of the total reported incidents of crime, and the specifications in these columns are negative binomial specifications. Columns 1-4 consider crimes in which the perpetrator is likely to have a financial motivation, and columns 5-8 consider other crimes. 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. Each specification includes fixed effects for each city/day of the week pair and each city/month/year combination. Dummy for 1st-10th is a dummy that is equal to one in the first ten days of the month and zero otherwise. Staggered Payment Dummy is equal to one for cities where Food Stamp payments are not exclusively made during the first ten days of the month. Average temperature is the average temperature in degrees Fahrenheit. Precipitation and snowfall are measured in inches. The Holiday Dummy is equal to one on U.S. federal holidays and zero otherwise. Heteroskedasticity consistent standard errors that allow for clustering within each city-month appear in parentheses.

	Financially Motivated Crimes				Other Crimes			
Dependent Variable:	Crime Rate		Count of Reported Incidents		Crime Rate		Count of Reported Incidents	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.9959	0.9213	4.7406	3.5178	0.9294	0.3487	2.6190	2.1234
	(0.0051)	(0.0286)	(0.0162)	(0.0449)	(0.0149)	(0.0749)	(0.0332)	(0.0432)
Dummy for 1st-10th	-0.0466	-0.0483	-0.0426	-0.0441	-0.0155	-0.0174	0.0012	0.0012
	(0.0108)	(0.0107)	(0.0093)	(0.0093)	(0.0285)	(0.0289)	(0.0135)	(0.0139)
Staggered Payment Dummy * Dummy for 1st-10th	0.0486	0.0488	0.0432	0.0433	0.0338	0.0332	0.0092	0.0072
	(0.0132)	(0.0131)	(0.0117)	(0.0116)	(0.0348)	(0.0343)	(0.0221)	(0.0216)
Average Temperature		0.0015		0.0017		0.0092		0.0084
		(0.0004)		(0.0004)		(0.0012)		(0.0007)
Precipitation		-0.0160		-0.0157		-0.0851		-0.0859
		(0.0069)		(0.0061)		(0.0180)		(0.0145)
Snowfall		-0.0336		-0.0510		-0.0210		-0.0643
		(0.0036)		(0.0122)		(0.0215)		(0.0213)
Holiday Dummy		-0.1414		-0.1492		0.1710		0.1271
		(0.0169)		(0.0167)		(0.0409)		(0.0269)
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
No. of Obs.	5,844	5,844	5,844	5,844	5,295	5,295	5,295	5,295
R-Squared	0.5058	0.5224			0.1535	0.1744		
Log Likelihood			-21,775	-21,652			-13,526	-13,406

Appendix Table 3

The Effects of the Timing of Welfare Payments on Crime: Additional Robustness Checks

The dependent variable in columns 1, 2, 5, and 6 is the incident count for crimes in which the perpetrator is likely to have a financial motivation. For columns 3, 4, 7, and 8 it is the count for other crimes. The specifications are negative binomial specifications. The first four specifications remove the first and last day of each month from the sample, and the last four specifications remove New Orleans observations. Each specification includes fixed effects for each city/month/year combination and each city/day of the week pair, and the specifications in columns 2, 4, 6, and 8 also include fixed effects for each day of the month. Dummy for 1st-10th is equal to one in the first ten days of the month and zero otherwise. Staggered Payment Dummy is equal to one 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 zero and one 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 one on U.S. federal holidays and zero otherwise. Heteroskedasticity consistent standard errors that allow for clustering within each city-month appear in parentheses.

	Drop First and Last Day of Month				Drop New Orleans			
Type of Crime:	Financially Motivated		Other		Financially Motivated		Other	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	4.3832	3.0718	0.0354	2.1020	4.4921	4.4140	2.3371	2.1787
	(0.0191)	(0.0377)	(0.1059)	(0.0611)	(0.0171)	(0.0295)	(0.0531)	(0.0440)
Dummy for 1st-10th	-0.0245		0.0133		-0.0428		-0.0136	
	(0.0113)		(0.0281)		(0.0113)		(0.0250)	
Staggered Payment Dummy * Dummy for 1st-10th	0.0168		-0.0091		0.0227		-0.0155	
	(0.0084)		(0.0194)		(0.0083)		(0.0193)	
Time Since Payment Index		0.0913		0.0220		0.0967		0.0189
		(0.0251)		(0.0484)		(0.0257)		(0.0437)
Average Temperature	0.0021	0.0022	0.0068	0.0068	0.0020	0.0021	0.0072	0.0072
	(0.0003)	(0.0003)	(0.0005)	(0.0005)	(0.0003)	(0.0003)	(0.0005)	(0.0005)
Precipitation	-0.0085	-0.0087	-0.0786	-0.0786	-0.0076	-0.0078	-0.0764	-0.0764
	(0.0048)	(0.0047)	(0.0130)	(0.0130)	(0.0048)	(0.0047)	(0.0126)	(0.0126)
Snowfall	-0.0401	-0.0399	-0.0214	-0.0214	-0.0403	-0.0401	-0.0233	-0.0234
	(0.0046)	(0.0046)	(0.0071)	(0.0071)	(0.0044)	(0.0044)	(0.0067)	(0.0067)
Holiday Dummy	-0.1523	-0.1524	0.0902	0.0901	-0.1464	-0.1465	0.1205	0.1205
	(0.0121)	(0.0121)	(0.0222)	(0.0222)	(0.0117)	(0.0116)	(0.0210)	(0.0211)
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?	N	Y	N	Y	N	Y	N	Y
No. of Obs.	8,873	8,873	8,360	8,360	9,132	9,132	8,583	8,583
Log Likelihood	-33,334	-33,324	-22,444	-22,444	-34,627	-34,618	-23,450	-23,451