Local Crime and Local Business Cycles

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I. ABSTRACT

Crime is a community attribute that, in part, determines the attractiveness of a region and, as such, a region's crime rate is often considered a factor in its economic success. Given the importance of crime in determining a region's economic progress, numerous academic studies have explored the relationship between deterrence and crime and between economic conditions and crime. The basic hypothesis of the deterrence effect is that greater police resources targeted toward a specific crime increase the likelihood of arrest for that crime, thereby lowering the rate at which the specific crime is committed. Regarding economic conditions, the literature suggests that worsening economic conditions increase the attractiveness of criminal activity because the opportunity cost of committing a crime (forgoing wages, employment, etc.) is reduced. The hypothesis is that improving economic conditions will result in less crime.

Previous studies have used numerous empirical methodologies to estimate the relationship between economic conditions and crime and between deterrence and crime. Cross-sectional studies have looked at differences across cities, counties or states at a specific point in time. The majority of time-series studies have explored the long-run relationship between crime, arrests and economic conditions—that is, whether long-run trends in these variables are evidence of any causal relationship between the variables. Not surprisingly, the many economic models of crime have not produced a definitive conclusion on the effects of economic conditions and deterrence on crime.

This report contributes to the literature on crime by exploring the short-run relationship between economic conditions and crime and between deterrence and crime for a sample of 23 cities in the United States from, roughly, the early 1980s to the early 2000s. The report also looks at crime statistics for the Eighth Federal Reserve District cities of St. Louis, Little Rock, Louisville and Memphis.

Rather than focusing on the relationship between long-run trends, the main objective of this study is to see whether month-to-month changes in a city's economic conditions and arrests influence month-to-month changes in crime. We also explore the hypothesis that arrests increase in response to an increase in crime—that police resources are adjusted in response to an increase in crime. We consider seven crimes in our analysis: murder, rape, assault, robbery, burglary, larceny and motor vehicle theft. In accordance with previous studies, we use the city's unemployment rate and the real minimum wage as measures of economic conditions. As discussed in the report, this methodology has several advantages over previous works.

We find that changes in economic conditions and deterrence affect property crimes more than they affect violent crimes. However, the evidence suggests that for many cities in our sample, there is no statistically significant relationship between short-run changes in economic conditions and crime and between deterrence and crime. For those cities in which a significant relationship is found, there is no evidence that suggests either economic conditions or deterrence have a stronger impact on crime. This suggests that a determination of the effects of economic conditions and deterrence must be made on a city-by-city basis, rather than generalizing from results generated from more aggregated analyses. We also find evidence that an increase in arrests follows an increase in crime, especially for the more visible crimes of robbery and motor vehicle theft. This suggests that local officials respond quickly to deter crimes that are most likely to result in a negative city image and impede economic development.

Some of our results are consistent with previous works that have explored a long-run relationship between economic conditions and crime and between crime and deterrence. Other results are quite different and provide a contrast in the conclusions reached from models of crime that consider the short run versus the long run. In addition to revealing intercity differences on the effects that economic conditions and deterrence have on various categories of criminal activity, our results are suggestive of intercity differences in the allocation of law enforcement resources and in the effectiveness of law enforcement, as well as possible economic development incentives facing city officials to reduce certain crimes but not others. ■

II. INTRODUCTION

Crime is a community attribute—along with educational quality, infrastructure and employment opportunity—that, in part, determines the attractiveness of a city or region. Local governments and economic development officials, especially those in urban areas, are aware that increasing crime rates will adversely affect residential and business immigration to their communities. A city's crime rate is, thus, considered a factor in the city's economic success. There has been much academic research on the effects of crime on the general economic growth of local areas (Burnham et al., 2004; Greenbaum and Tita, 2004; Mauro and Carmeci, 2007). This research generally finds that areas with higher crime rates experience lower rates of economic growth and development.

Economists explain an individual's propensity to commit a crime by examining the expected costs and benefits from criminal activity (Becker, 1968). Empirical research on crime has modeled the direct cost to an individual as the probability of arrest and/or incarceration and the direct benefit as the value of the illegally acquired goods (Ehrlich, 1996; Levitt, 1997). Much work has been done to estimate the effect of deterrence measures on crime, but the mixed results from these studies do not allow a definitive conclusion (Grogger, 1991; Levitt, 1997, 1998; Cover and Thistle, 1988; Cornwall and Trumbull, 1994; Lee and McCrary, 2005). In addition, the literature suggests that it is not that arrests influence crime, but rather that arrests follow an increase in crime (Decker and Kohfeld, 1985).

Criminal behavior also depends upon other cost comparisons, such as forgone wages and employment opportunities (Gould et al., 2002; Mocan and Bali, 2005; Corman and Mocan, 2000, 2005). The reasoning is that higher wages and employment opportunities decrease the attractiveness (by increasing the opportunity cost) of acquiring assets through criminal activity.

There has been much research on the effects of unemployment on crime.[1] Lee and Holoviak (2006) find evidence of a positive, long-run relationship between crime and unemployment in three Asian-Pacific countries. Corman and Mocan (2000, 2005), using time-series data for New York City, illustrate that property crimes increase in response to an increase in the unemployment rate and decrease in response to greater police presence. They show that deterrence (measured by arrests) is more important than economic conditions in explaining crime. For example, the authors find that a 10 percent increase in burglary arrest rates results in a 3.2 percent reduction in the growth of burglaries, whereas a 10 percent increase in unemployment growth increases burglary growth by 1.6 percent. Mocan and Bali (2005), using a panel of data for U.S. states, also find a direct relationship between unemployment and crime. Raphael and Winter-Ember (2001) show a direct relationship between unemployment and property crimes, and a weaker direct relationship between unemployment and violent crimes, in their panel data analysis of U.S. states. The authors find that declining unemployment between 1992 and 1997 explained more than 40 percent of the decline in property crimes. A relationship between unemployment and crime is less evident in a study by Imrohoroglu et al. (2004), who analyze trends in property crimes in the United States. Finally, Carmichael and Ward (2000), in their analysis of crime in England, find no evidence of a relationship between unemployment and robbery, burglary and property crimes.

Several studies have also considered the effect of wages on criminal activity. Grogger (1998) uses individual-level data from the National Longitudinal Survey of Youth to explore the relationship between property crimes and wages. He finds evidence that falling wages partially explain rising youth crime during the 1970s and 1980s. Gould et al. (2002), using a sample of 705 U.S. counties over the period 1979 to 1997, find that both unemployment and wages are related to crime, but the effect of wages is greater than that of unemployment. The authors show that over 50 percent of the variation in property crime and violent crime is explained by wages. Finally, Corman and Mocan (2005) find that changes in criminal activity are inversely related to changes in real wages in New York City. Specifically, they estimate that a 10 percent increase in the growth rate of wages reduced the growth rate of various crimes by 4 percent to 6 percent.

Although some general patterns emerge regarding the relationship between crime and economic activity (and between crime and deterrence, to some degree), it is fair to say that the results of past

studies do not provide conclusive evidence on the relationship.[2] Certainly, the different units of observations, time periods and empirical methodologies used in each study contribute to the difference in results. In addition, the likely simultaneous relationship between crime and deterrence and between crime and economic conditions (Cullen and Levitt, 1996) and the various methods authors have used to control this simultaneity may also explain the divergent results.

Much of the time-series modeling of crime has focused on the long-run relationships (e.g., 10- or 20-year trends) between crime and deterrence and between crime and economic activity rather than on any short-run relationship, say month-to-month or quarter-to-quarter. In this report, we explore whether monthly city-level crime varies with monthly changes in local economic conditions and deterrence.

For 20 large cities in the United States, as well as the Eighth Federal Reserve District cities of St. Louis, Louisville and Little Rock (Memphis is included in the top 20), we use monthly time-series data to explore whether changes in seven separate criminal offenses can be explained by changes in unemployment and real wages, as well as changes in deterrence. In addition, we empirically test the hypothesis that arrests follow an increase in crime.[3]

Because we examine month-to-month changes in crime, economic conditions and deterrence rather than trends, our study is an analysis of the shorter-run impact of arrests and economic conditions on crime. The empirical framework we use is similar to that of Corman and Mocan (2000, 2005), who used monthly time-series data to estimate a model of crime for New York City.

Our time-series study of multiple cities has several advantages over past works. The high-frequency time-series data we use allows us to avoid (or at least better minimize) the complex simultaneity problem between crime and deterrence and between crime and economic conditions that has plagued studies using cross-sectional or panel data. Our study also has the advantage that an identical empirical framework is used for each of the 23 cities, thus providing a more accurate comparison of results across cities. As noted by Levitt (2001), inferences made from aggregate time-series analysis regarding the unemployment and crime relationship may be misleading. In addition, a comparison of results across cities should prove interesting, as Topel (1994) and Glaeser and Sacerdote (1999) have shown that crime rates and labor market conditions vary significantly across regions. Also, research has shown that large differences in crime exist between urban and rural areas (Smith, 1980; Weisheit et al., 1994). Thus, unlike our city-level time-series analysis, the results from a county- or state-level analysis may mask the greater crime rates and variability in economic conditions that occur in urban areas relative to rural areas.

III. DATA AND METHODOLOGY

Data

Our city-level crime data are from the FBI's *Uniform Crime Reports* (UCR).[4] We obtained the monthly number of offenses and arrests for seven categories of crime: murder, rape, assault, robbery, burglary, larceny and motor vehicle theft.[5] Although the UCR is the most widely used source of crime data, the fact that these data are self-reported by cities raises some possible problems (Ehrlich, 1996). These include under-reporting of crime by local police departments and differences in the collecting and reporting of criminal activity across cities. Because we are estimating crime models for each city and each crime, there is no concern of cross-city variation in reporting methods contaminating our individual city results. Similarly, bias due to under-reporting of crime would be minimized in our time-series analysis if the under-reporting was consistent over the sample period.

Crime data were obtained from the largest 20 cities in the United States based on 1990 population for which sufficient crime data were available.[6] Data also were obtained for the Eighth Federal Reserve District cities of St. Louis, Louisville and Little Rock. Our sample period for the majority of cities covers December 1983 to December 2004. The failure of cities to report crime data for several months or several years early or late in the sample period has shortened the sample for several cities. For some cities, the absence of offense statistics for certain crimes over an extended period of time mid-sample led us to omit the crime from the list of seven crime equations estimated. In addition, appropriate steps were taken to handle the occasional monthly missing observation in order to preserve the sample for estimation purposes (Maltz, 1999, p. 28).[7] Table 1

Table 1: CITIES, Sample Periods and Data Notes			
City	**Sample Period**	**Sample Size**	**Data Notes***
Baltimore	1983:12 to 1998:12	181	The August 1997 missing value for murders was replaced with the August 1996 value.
Boston	1989:5 to 2004:12	188	———
Cleveland	1983:12 to 1998:9	178	———
Columbus	1983:12 to 2002:12	229	The October 1991 and 1998 missing values for rape arrests were replaced with the October 1990 and October 1997 values, respectively. The October 1998 missing value for robbery arrests was replaced with the October 1997 value.
Dallas	1983:12 to 2004:12	253	The August 1997 missing value for murders was replaced with the August 1996 value.
Detroit	1983:12 to 2004:12	253	The August 1997 missing value for murders was replaced with the August 1996 value.
El Paso	1983:12 to 2004:12	253	———
Houston	1983:12 to 2004:12	253	The August 1997 missing value for murders was replaced with the August 1996 value.
Indianapolis	1996:1 to 2004:12	108	———
Little Rock	1983:12 to 2004:12	253	The November and December 1989 missing values for arrests for all crimes were replaced with the November and December 1988 values. The April 1984 missing value for vehicle theft arrests was replaced with the April 1983 value.
Los Angeles	1983:12 to 2004:12	253	The August 1997 missing value for murders was replaced with the August 1996 value.
Louisville	1993:1 to 2002:12	120	———
Memphis	1985:1 to 2004:12	240	The December 1994 missing values for arrests for all crimes were replaced with December 1993 values.
Milwaukee	1983:12 to 2004:12	253	The August 1997 missing value for murders was replaced with the August 1996 value. The March 1986 missing values for all arrests were replaced with March 1985 values. The July 2002 missing value for rape arrests was replaced with the July 2001 value.
New Orleans	1983:12 to 2004:12	253	The August 1997 missing value for murders was replaced with the August 1996 value.
Philadelphia	1983:12 to 2004:12	253	The August 1997 missing value for murders was replaced with the August 1996 value. The November 1988 missing values for arrests for all crimes were replaced with the November 1987 values.
Phoenix	1983:12 to 2004:11	252	———
St. Louis	1983:12 to 2004:12	253	———
San Antonio	1983:12 to 2004:12	253	———
San Diego	1983:12 to 2004:12	253	———
San Francisco	1983:12 to 2004:12	253	———
San Jose	1983:12 to 2001:8	213	———
Seattle	1983:12 to 1997:12	169	The May 1986 and June 1992 missing values for arrests for all crimes were replaced with the May 1985 and June 1991 values, respectively.
* The method used to impute missing UCR crime and arrest data for individual jurisdictions is based on Maltz (1999, p. 28).			

lists the cities used in the analysis, the sample period for each city and notes on data editing.

Our models of crime assume that criminal activity is a function of deterrence and economic conditions. As in many previous studies, we use the number of crime-specific arrests as our measure of deterrence.[8] Changes in economic conditions are captured by the city-level unemployment rate (seasonally adjusted) and changes in the real minimum wage (Gould et al., 2002; Corman and Mocan, 2005).[9] While the unemployment rate captures the employment situation for the average city resident, the minimum wage is more likely to capture the financial situation of young, single men, as this group generally constitutes the greatest percentage of all minimum-wage workers.[10] This demographic group is also the most likely to commit property-related crimes (Grogger, 1998).

Model and Hypotheses

Our objective is to explore whether changes in deterrence and economic conditions influence monthly changes in crime. We estimate the following crime equation for each of seven crimes for each of the 23 cities:

(1)

$$C_t = \alpha + \sum_{1}^{r} \beta_r C_r + \sum_{1}^{r} \delta_r AR_r + \sum_{0}^{r} \phi_r UN_r + \sum_{0}^{r} \gamma_r MW_r + \sum \tau S + \varepsilon_t$$

The number of criminal offenses is denoted by C and the number of arrests for the respective crime is denoted by AR. UN and MW denote the city unemployment rate and the city real minimum wage, respectively. Because we are interested in month-to-month changes, all variables are transformed into percent changes. We also include monthly dummy variables (S) to account for any seasonality in crime.

Because the effects of deterrence and economic conditions on crime may extend over several months, we include lags (r)of arrests, unemployment and the minimum wage. The number of lags captures the degree to which each variable's effect on crime persists. As in Corman and Mocan (2005), in order to minimize any simultaneity between arrests and crime, this study does not include the contemporaneous (i.e., lag length = 0) value of arrests in the empirical models. The model does include a contemporaneous value for both economic variables.[11]

The total effect of each variable on changes in crime is determined by summing the lagged coefficients for each variable. We assess the magnitude of each variable's effect on crime by calculating an elasticity using the sum of the coefficients (contemporaneous and lagged) and the means of the respective variables. The elasticities are interpreted as the effect of a percentage change in the growth rate of the independent variable on the percentage change in the growth rate of the crime. As a specific example, if the arrest elasticity for larceny is estimated to be –0.50, this is interpreted to mean that a 1 percent increase (decrease) in the growth rate of arrests for larceny results in a 0.5 percent decrease (increase) in the growth rate of larcenies.

Several points regarding the elasticity estimates are worth mentioning. It is important to note when comparing elasticities across cities that the elasticities may reflect different time spans, depending upon lag length of each variable. In addition, the size of an elasticity estimate is not only dependent on the sum of the coefficients (and, thus, the number of lags), but also on the magnitude of the respective variables' means. Because we are looking at percentage changes in growth rates rather than the changes in the levels of each variable (the former is a much smaller number than the latter), small changes in growth rates can translate into large percentage changes (i.e., large elasticity estimates).

It is useful to discuss, based on previous research, the possible effects that arrests, unemployment and wages might have on crime. First, consider changes in arrests. A positive relationship between arrests and crime would lend support for the deterrence model of crime. Although some authors (Levitt, 1998) strongly argue that deterrence is a significant factor in explaining crime, there are several reasons why we might find no significant relationship between arrests and crime.

First, it is possible that the causality is from crime to arrests, rather than from arrests to crime. The idea is that an increase in crime causes a reallocation of police resources to combat the increase in crime. In their study of homicide, robbery and burglary in St. Louis, Decker and Kohfeld (1985) find evidence that arrests follow crimes. Second, one would expect deterrence to be effective only if potential criminals were aware that their probability of being arrested had significantly increased. Wilson and Herrnstein (1985) and Lee and McCrary (2005) suggest that potential offenders are quite myopic when considering the consequences of their activities. This may be especially true in the short run.

We expect unemployment to have a positive effect on crime and wages to have a negative effect on crime. However, these effects are likely dependent on specific crimes. For example, it seems much more reasonable that crimes involving the taking of property would occur more frequently during economic slowdowns than violent crimes, such as murder and rape. Thus, we might expect more significant relationships between economic conditions and property crimes (robbery, burglary, larceny and vehicle theft) than for the most violent crimes. Finally, it is also possible that initial or temporary changes in an individual's employment situation are not as likely to induce criminal behavior as would an unfavorable long-term unemployment situation. This would suggest no short-run relationship between unemployment rates and crime, as individuals may resort to crime only after an extended period of economic distress.

A negative relationship between changes in the minimum wage and crime is expected as the opportunity cost of committing a crime (forgone wage) increases as the real minimum wage increases. What about the relative importance of unemployment versus wages in explaining crime? Gould et al. (2002) find evidence that wages played a greater role in county crime trends than did the unemployment rate over the period 1979 to 1997. The reasonable argument made by the authors is that unemployment is a temporary situation, whereas low or stagnant wages is more of a long-term situation, and it is the latter that creates a greater incentive for individuals to commit crimes.

Because we are looking at changes in wages and unemployment, it is less clear that we would expect to find changes in wages to have a greater effect on crime than a change in unemployment. However, using monthly crime data for New York City, Corman and Mocan (2005) did find that the wage elasticities for certain crimes were greater than unemployment elasticities.

IV. EMPIRICAL RESULTS

The empirical results are presented in tables 2 through 8, with each table containing the elasticities of arrests, unemployment and wages on the respective crime for each of the 23 cities. The elasticities are computed using the sum of the coefficients from equation (1) and the means for each particular pair of variables.[12] Recall that the elasticities are interpreted as the effect of a percentage change in the growth rate of the independent variable (arrests, unemployment or wages) on the percentage change in the growth rate of the crime. Missing values in a table indicate a lack of available crime data for the city.

For the most violent crimes of murder and rape (Tables 2 and 3), there is evidence that changes in deterrence and economic conditions have a significant influence on changes in the number of murders and rapes in only a few cities. In New Orleans, the arrest elasticity for murder is –5.5, suggesting that a 10 percent increase in the growth of murder arrests resulted in a 55 percent decrease in the growth of murders. Real minimum wage growth resulted in lower growth in the number of rapes in New Orleans and San Diego. Growth in unemployment resulted in an increase in rapes in Cleveland. In general, there is little evidence that short-run changes in arrests and economic conditions influence the number of murders and rapes in our sample of cities.

As with murder and rape, the regression results for assault (Table 4) reveal few significant relationships between economic conditions and crime and between arrests and crime. In addition, about half of the significant elasticities are of the wrong sign. For those elasticities having the correct sign, the unemployment elasticities for assault are generally larger in absolute value than the minimum wage elasticities for assault.

The elasticities for robberies are shown in Table 5. Unlike for the crimes of murder and rape, changes in arrests and economic conditions are found to significantly influence the growth in robberies in a larger number of U.S. cities. The arrest elasticities for robbery range from –0.04 in New Orleans to –8.86 in St. Louis.[13] Unemployment growth causes an increase in robberies in Baltimore, Houston, Indianapolis, Milwaukee, St. Louis and San Diego, with elasticities ranging from roughly 0.10 in Milwaukee to 1.87 in Indianapolis. Real minimum wage growth results in lower growth in the number of robberies for four cities: Baltimore, Cleveland, Columbus and San Diego. In the cities of Baltimore and San Diego, robbery growth is influenced by both changes in the unemployment rate and wage growth. A visual comparison suggests that the unemployment elasticities for robbery are slightly

Table 2: MURDER—Deterrence and Business Cycle Elasticities for U.S. Cities

	Arrests			Unemployment			Wages		
	Elasticity	St. Error	Lags	Elasticity	St. Error	Lags	Elasticity	St. Error	Lags
Baltimore	0.199	0.271	1-2	0.038	0.051	0-1	−0.159	0.151	0-1
Boston	—	—	—	—	—	—	—	—	—
Cleveland	—	—	—	—	—	—	—	—	—
Columbus	—	—	—	—	—	—	—	—	—
Dallas	−0.039	0.225	1-3	0.541	1.109	0-1	0.387	0.860	0
Detroit	−0.267	0.380	1	−0.208	0.188	0	−0.753	1.391	0
El Paso	—	—	—	—	—	—	—	—	—
Houston	−0.449	0.598	1-4	0.061	0.101	0	0.398	0.802	0-7
Indianapolis	—	—	—	—	—	—	—	—	—
Little Rock	—	—	—	—	—	—	—	—	—
Los Angeles	−0.006	0.106	1-2	0.039	0.152	0-1	−0.142	0.121	0-1
Louisville	—	—	—	—	—	—	—	—	—
Memphis	—	—	—	—	—	—	—	—	—
Milwaukee	0.002	0.007	1	0.000	0.037	0	−0.045	0.176	0
New Orleans	**−5.502****	1.538	1–7	**−4.176***	1.965	0–4	1.240	1.288	0
Philadelphia	0.006	0.060	1	−0.221	0.210	0	1.087	1.164	0-2
Phoenix	—	—	—	—	—	—	—	—	—
St. Louis	—	—	—	—	—	—	—	—	—
San Antonio	—	—	—	—	—	—	—	—	—
San Diego	—	—	—	—	—	—	—	—	—
San Francisco	—	—	—	—	—	—	—	—	—
San Jose	—	—	—	—	—	—	—	—	—
Seattle	—	—	—	—	—	—	—	—	—

Note: Elasticities are calculated from the sum of coefficients in equation (1). * denotes significance at 5 percent and ** at 1 percent. Missing values indicate zero–value observations for respective city. Elasticities reveal the percentage change in the growth rate of murders resulting from a percentage increase in the growth rate of murder arrests, unemployment and the real minimum wage.

higher in absolute value, on average, than the minimum wage elasticities for robbery.

The results for burglary, larceny and motor vehicle theft reveal substantially more significant elasticities (all of the correct sign) than the more violent crimes of robbery, murder, rape and assault.

Consider the burglary results shown in Table 6. The arrest elasticity for burglary is negative and significant for six cities and ranges from – 0.03 (Los Angeles) to – 0.55 (Louisville). Growth in unemployment increases the growth in burglaries in six cities, with elasticities ranging from 0.04 (Los Angeles) to 0.23 (Boston). Minimum wage growth reduces the growth of burglaries in four cities: El Paso, Los Angeles, Milwaukee and Seattle. The minimum wage elasticities for burglary are slightly higher in absolute value than the unemployment elasticities for burglary.

The larceny elasticities are presented in Table 7. The arrest elasticity for larceny is negative and significant for eight cities. These elasticities are, on average, slightly higher than those for robbery, ranging from –0.07 (Baltimore) to –2.65 (Milwaukee). The unemployment elasticity for larceny is positive and significant for four cities (range of 0.02 to 0.14), and each are of similar value to the unemployment elasticity for burglary shown in Table 6, although for a different set of cities. The minimum wage elasticity for larceny is negative and significant for six cities (range of –0.19 to –3.57), and the elasticities are generally larger than the minimum wage elasticities for burglary shown in Table 6.

Table 3: RAPE—Deterrence and Business Cycle Elasticities for U.S. Cities

	Arrests			Unemployment			Wages		
	Elasticity	St. Error	Lags	Elasticity	St. Error	Lags	Elasticity	St. Error	Lags
Baltimore	0.543	0.345	1-2	0.041	0.048	0-1	0.009	0.123	0
Boston	0.002	0.036	1	0.000	0.102	0	0.161	0.106	0
Cleveland	−1.577	1.118	1-7	**3.885+**	2.119	0-2	0.255	0.201	0
Columbus	−0.040	0.072	1	0.113	0.179	0	−0.046	0.234	0
Dallas	0.010	0.017	1	0.102	0.258	0	0.356	0.268	0
Detroit	—	—	—	—	—	—	—	—	—
El Paso	0.002	0.104	1	−0.370	0.902	0	0.693	1.942	0
Houston	0.643	0.559	1	0.277	0.789	0-3	−0.678	1.29	0
Indianapolis	−0.167	0.145	1	−0.143	0.622	0	0.188	0.290	0-9
Little Rock	—	—	—	—	—	—	—	—	—
Los Angeles	0.003	0.005	1	0.058	0.048	0	0.006	0.023	0
Louisville	—	—	—	—	—	—	—	—	—
Memphis	0.002	0.015	1-9	0.010	0.187	0-3	−0.080	0.346	0
Milwaukee	−0.085	0.089	1	0.143	0.295	0-3	1.017	1.128	0
New Orleans	−0.018	0.016	1-2	−0.002	0.224	0	**−0.849***	0.350	0-2
Philadelphia	−0.006	0.014	1	0.190	0.323	0-6	−2.849	2.266	0-4
Phoenix	0.055	1.322	1-5	0.239	0.152	0-1	4.804	3.553	0-1
St. Louis	—	—	—	—	—	—	—	—	—
San Antonio	—	—	—	—	—	—	—	—	—
San Diego	0.192	0.569	1	2.452	5.177	0-4	**−2.307****	0.795	0-1
San Francisco	—	—	—	—	—	—	—	—	—
San Jose	−0.061	0.073	1-2	0.054	0.165	0-6	0.316	0.210	0-9
Seattle	0.022	0.119	1-2	−0.383	0.459	0	−0.008	0.039	0

Note: Elasticities are calculated from the sum of coefficients in equation (1). + denotes significance at 10 percent, * at 5 percent and ** at 1 percent. Missing values indicate zero-value observations for respective city. Elasticities reveal the percentage change in the growth rate of rape resulting from a percentage increase in the growth rate of rape arrests, unemployment and the real minimum wage.

The results for motor vehicle theft are shown in Table 8. Changes in arrests are found to have a negative influence on motor vehicle thefts in four cities, with the elasticities ranging from – 0.04 to – 0.34. The unemployment elasticity for motor vehicle theft is positive and significant for eight cities, thus suggesting that short-run downturns in the employment situation of these cities result in greater motor vehicle thefts. Increases in the real minimum wage lead to lower motor vehicle thefts in five cities. Changes in both the unemployment rate and the real minimum wage influence motor vehicle thefts in Milwaukee and Detroit. As for many of the other crimes, no clear difference emerges regarding the effects of changes in unemployment and wages on crime.

Given the volume of empirical results presented, a brief summary is warranted. There was no significant short-run relationship between arrests and crime and between economic conditions and crime for many of the cities.

There are some interesting insights for cities that had statistical relationships. No consistent difference in the magnitude of the elasticities appears across crimes or cities, a likely result of the very different labor market conditions across regions (Topel, 1994; Glaeser and Sacerdote, 1999) as well as differences in the allocation of police resources (Benson et al., 1994). This suggests that determining whether crime is more influenced by changes in economic conditions or by changes in deterrence must be made on a city-by-city basis. Finally, changes in eco-

Table 4: ASSAULT—Deterrence and Business Cycle Elasticities for U.S. Cities									
	Arrests			Unemployment			Wages		
	Elasticity	St. Error	Lags	Elasticity	St. Error	Lags	Elasticity	St. Error	Lags
Baltimore	−0.017	0.010	1	−0.009	0.008	0-1	−0.007	0.025	0
Boston	0.000	0.007	1	0.050	0.090	0	0.053	0.110	0-3
Cleveland	−0.214	0.203	1	0.041	0.036	0	0.012	0.009	0
Columbus	0.004	0.008	1-3	**−0.234+**	0.138	0-8	−0.014	0.058	0
Dallas	**0.766***	0.321	1-11	**0.053+**	0.029	0	0.027	0.020	0-2
Detroit	**0.994***	0.406	1-5	−0.014	0.009	0	**0.624***	0.299	0-4
El Paso	0.0921	0.066	1	−0.013	0.025	0	−0.067	0.112	0-3
Houston	−0.050	0.048	1	**0.020+**	0.012	0-1	−0.042	0.043	0-1
Indianapolis	0.422	0.461	1-3	0.070	0.275	0	**0.088+**	0.049	0-1
Little Rock	−0.029	0.026	1-2	−0.050	0.033	0	0.015	0.035	0
Los Angeles	0.074	0.009	1	0.146	0.131	0-1	−0.005	0.034	0-1
Louisville	−0.069	0.152	1	0.015	0.014	0	0.020	0.028	0
Memphis	**−0.368+**	0.205	1-9	−0.002	0.017	0	0.066	0.051	0
Milwaukee	0.364	0.334	1-2	0.039	0.089	0-3	−0.009	0.234	0
New Orleans	−0.017	0.096	1	0.181	0.279	0	−0.082	0.198	0
Philadelphia	0.004	0.005	1	−0.003	0.052	0-2	0.922	0.590	0-8
Phoenix	−0.138	0.103	1	0.003	0.008	0-4	0.006	0.184	0-9
St. Louis	−0.042	0.360	1-11	0.065	0.161	0-1	−0.256	0.631	0-6
San Antonio	−0.005	0.008	1	0.000	0.000	0	0.130	0.079	0
San Diego	0.026	0.023	1	0.090	0.178	0-12	**−0.039****	0.014	0
San Francisco	**−0.871***	0.377	1-4	0.091	0.061	0-1	−0.049	0.056	0
San Jose	**−0.161***	0.071	1-2	−0.018	0.052	0-5	**−0.136****	0.034	0-3
Seattle	0.014	0.010	1	**−0.907***	0.446	0-1	**0.145****	0.049	0-3

Note: Elasticities are calculated from the sum of coefficients in equation (1). + denotes significance at 10 percent, * at 5 percent and ** at 1 percent. Elasticities reveal the percentage change in the growth rate of assault resulting from a percentage increase in the growth rate of assault arrests, unemployment and the real minimum wage.

nomic conditions matter much more for nonviolent crimes such as larceny, burglary and motor vehicle theft than for the more violent crimes of murder and rape. This is not too surprising, since nonviolent crimes are more likely to result in financial gain.

V. DO ARRESTS FOLLOW CRIME?

The previous analysis explored the effect of deterrence, as measured by arrests, on criminal activity. The hypothesis is that criminals adjust their activity in response to increases or decreases in the likelihood of arrest. A causal relationship from arrests to crime, however, depends upon two key factors. The first is that arrests are a suitable measure of deterrence, and the second is that criminals have perfect, or at least semiperfect, knowledge of increased police activity to deter crime.

While there has been debate in the literature regarding the degree to which arrests are a suitable measure of deterrence (Fisher and Nagin, 1978), most research, including the present study, has measured deterrence through arrests, given the lack of a more reasonable alternative. However, the notion that criminals do not possess good information on increased police activity seems reasonable. Combined with evidence that suggests that criminals are quite myopic when considering the costs and benefits of criminal activity (Wilson and Herrnstein, 1985; and Lee and McCrary, 2005), it questions any significant linkage from arrests to criminal activity, especially in the short run.

Table 5: ROBBERY—Deterrence and Business Cycle Elasticities for U.S. Cities									
	Arrests			Unemployment			Wages		
	Elasticity	St. Error	Lags	Elasticity	St. Error	Lags	Elasticity	St. Error	Lags
Baltimore	0.001	0.111	1	**0.180***	0.086	0-5	**−0.560***	0.266	0-3
Boston	−0.004	0.070	1	0.059	0.117	0	0.088	0.097	0
Cleveland	−0.446	0.336	1-6	0.261	0.181	0	**−0.328+**	0.188	0-9
Columbus	−0.170	0.170	1-3	0.250	0.227	0	**−0.582+**	0.304	0
Dallas	**−0.113****	0.039	1	0.159	0.136	0	−0.477	0.495	0-7
Detroit	0.017	0.034	1	−0.012	0.012	0	0.063	0.059	0
El Paso	**−0.762****	0.247	1-6	−0.203	0.163	0-1	0.000	0.270	0
Houston	−0.041	0.031	1	**0.230****	0.075	0	−0.175	0.195	0
Indianapolis	−0.171	0.206	1	**1.869+**	1.008	0-7	0.019	0.082	0-2
Little Rock	7.318	4.502	1-3	6.587	8.813	0	−1.718	11.295	0-1
Los Angeles	−0.366	0.235	1-9	0.179	0.122	0-6	−0.003	0.029	0
Louisville	−3.838	2.984	1	0.343	0.831	0	2.486	5.635	0
Memphis	−0.026	0.060	1	−0.348	0.280	0	−1.171	0.967	0
Milwaukee	−0.020	0.084	1-2	**0.096+**	0.057	0	**1.343****	0.280	0
New Orleans	**−0.041***	0.017	1-2	−0.020	0.104	0	−0.139	0.111	0
Philadelphia	**−0.379***	0.192	1	−0.109	0.338	0-2	−0.190	1.187	0-1
Phoenix	0.004	0.031	1-2	0.002	0.007	0	0.101	0.089	0
St. Louis	**−8.864****	2.931	1-6	**1.487+**	0.798	0-2	−2.428	2.968	0-6
San Antonio	0.048	0.076	1-2	0.001	0.001	0	−0.014	0.542	0
San Diego	−0.011	0.237	1-7	**0.430+**	0.129	0	**−0.084****	0.034	0
San Francisco	0.003	0.030	1	0.027	0.052	0	−0.091	0.075	0-9
San Jose	0.010	0.007	1-2	0.070	0.043	0-1	−0.007	0.047	0
Seattle	−0.063	0.056	1	−6.930	8.393	0-1	−0.403	0.570	0

Note: Elasticities are calculated from the sum of coefficients in equation (1). + denotes significance at 10 percent, * at 5 percent and ** at 1 percent. Elasticities reveal the percentage change in the growth rate of robbery resulting from a percentage increase in the growth rate of robbery arrests, unemployment and the real minimum wage.

Decker and Kohfeld (1985) argue that, for the aforementioned reasons, one should not expect arrests to cause crime, but rather crime is more likely to cause arrests, thus suggesting an increase in crime causes an increase in arrests for that crime. The idea is that police resources are adjusted in response to increases in criminal activity. In this section, we test the hypothesis that arrests follow crime using our sample of 23 cities. We estimate the following regression for each of the seven crimes for the 23 cities in our sample:

(2) $$AR_t = \alpha + \sum_1^r \beta_r C_r + \sum_1^r \delta_r AR_r + \sum \tau S + \varepsilon_t$$

As in equation (1), the number of criminal offenses (lagged) is denoted by C, the number of arrests for the respective crime is denoted by AR, and monthly dummy variables (S) account for any seasonality in crime. Lags of crime are included to assess the degree to which the effect of crime on arrests persists.[14] We assess the magnitude of crime's effect on own arrests by calculating an elasticity using the sum of the lagged crime coefficients and the means of the respective variables. So, for example, if the elasticity for larceny arrests is estimated to be 0.50, this can be interpreted to mean that a 1 percent increase (decrease) in the growth rate of larcenies results in a 0.5 percent increase (decrease) in the growth rate of larceny arrests.

The elasticities shown in Table 9 provide evidence for the hypothesis that arrests follow crime. Unlike earlier tests of the deterrence hypothesis, which

Table 6: BURGLARY—Deterrence and Business Cycle Elasticities for U.S. Cities

	Arrests			Unemployment			Wages		
	Elasticity	St. Error	Lags	Elasticity	St. Error	Lags	Elasticity	St. Error	Lags
Baltimore	0.040	0.077	1	0.089	0.061	0-1	0.079	0.105	0
Boston	−0.039	0.033	1	**0.234****	0.064	0	0.098	0.063	0-1
Cleveland	−0.013	0.025	1	−0.218	0.183	0-1	0.0023	0.022	0
Columbus	0.395	0.433	1-10	0.138	0.139	0	−0.443	0.309	0-1
Dallas	**−0.229+**	0.123	1	0.105	0.192	0	−0.039	0.277	0
Detroit	0.007	0.090	1-3	−0.003	0.012	0-1	−0.071	0.121	0-1
El Paso	−0.005	0.012	1-3	0.020	0.032	0	**−0.106***	0.042	0
Houston	**−0.185***	0.081	1-2	**0.092***	0.043	0-1	−0.027	0.102	0
Indianapolis	0.203	0.682	1-8	0.015	0.247	0	0.011	0.018	0
Little Rock	−0.004	0.003	1	0.643	0.933	0-5	0.397	0.278	0
Los Angeles	**−0.029+**	0.016	1	**0.041+**	0.022	0	**−0.024****	0.009	0-1
Louisville	**−0.549+**	0.332	1-2	−0.013	0.076	0-1	0.015	0.388	0-4
Memphis	−0.008	0.020	1	**0.190+**	0.111	0	−0.545	0.467	0-1
Milwaukee	0.005	0.036	1	0.044	0.033	0	**−0.464***	0.209	0
New Orleans	−0.034	0.023	1-3	0.038	0.080	0	0.037	0.062	0
Philadelphia	−0.030	0.047	1	−0.085	0.086	0-5	0.289	0.322	0-5
Phoenix	**−0.432****	0.155	1-3	0.001	0.014	0	0.109	0.144	0-1
St. Louis	−0.267	0.312	1-4	0.143	0.113	0-1	–0.018	0.126	0
San Antonio	0.006	0.040	1-6	0.000	0.000	0	−0.527	0.954	0-7
San Diego	−0.011	0.023	1	0.114	0.085	0	−0.032	0.027	0
San Francisco	**−0.039+**	0.021	1	**0.098***	0.049	0-1	0.009	0.027	0
San Jose	0.003	0.009	1-4	**0.059***	0.026	0-1	0.018	0.015	0
Seattle	−0.026	0.028	1	−0.398	0.254	0	**−0.114****	0.039	0-2

Note: Elasticities are calculated from the sum of coefficients in equation (1). + denotes significance at 10 percent, * at 5 percent and ** at 1 percent. Elasticities reveal the percentage change in the growth rate of burglary resulting from a percentage increase in the growth rate of burglary arrests, unemployment and the real minimum wage.

revealed relatively little statistical evidence that arrests influence crime, the effect of crime on arrests is found to be positive and statistically significant for a greater number of cities and crimes.

Of the seven crime categories, an increase in the less violent crimes leads to greater arrests for these crimes, especially robbery and motor vehicle theft. A positive and significant relationship from robbery to robbery arrests was found for 17 of the 23 cities, and a positive and significant relationship from motor vehicle theft to motor vehicle theft arrests was found for 12 of the 23 cities. This is an interesting finding in that it may reflect the reasonable idea that law enforcement makes a greater effort to reduce an increase in crimes that are more visible to city residents, as well as to businesses and tourists.

There appears to be no consistent difference in the magnitude of crime elasticities across crimes or cities. Although many of the elasticities are less than one, some of the elasticities are large by conventional standards. For example the larceny elasticity for Phoenix is 66.7. It is important to keep in mind that the elasticities are capturing percentage changes in growth rates and not levels, with the former being much smaller numbers than the latter.[15] In addition, the size of the elasticity is a function of the sum of coefficients (longer lag length generally equates to a greater sum of coefficients) and the relative size of the variable means. An inspection of the raw data and regression results reveals that the large elasticities are a result of (1) a very small average monthly arrest growth rate compared to the average monthly crime growth rate

Table 7: LARCENY—Deterrence and Business Cycle Elasticities for U.S. Cities									
	Arrests			Unemployment			Wages		
	Elasticity	St. Error	Lags	Elasticity	St. Error	Lags	Elasticity	St. Error	Lags
Baltimore	**−0.070****	0.022	1-2	**0.023+**	0.012	0-1	**−0.194+**	0.100	0
Boston	−0.038	0.098	1-2	0.121	0.099	0-2	0.008	0.097	0
Cleveland	0.435	0.327	1	−0.379	0.420	0	0.036	0.128	0
Columbus	−0.038	0.044	1-8	**−1.050****	0.387	0-9	−0.232	0.808	0-3
Dallas	**−0.497****	0.159	1-2	0.003	0.197	0	−0.127	0.202	0
Detroit	**0.799***	0.395	1-6	−0.006	0.013	0-1	−0.072	0.141	0-1
El Paso	**−0.116+**	0.067	1-3	−0.329	0.287	0	−0.967	0.876	0
Houston	0.006	0.077	1-3	0.075	0.080	0	**−0.426****	0.132	0
Indianapolis	0.557	0.767	1-11	0.213	0.176	0-2	0.000	0.050	0-2
Little Rock	−0.007	0.393	1-2	−1.356	5.394	0	−6.097	5.629	0
Los Angeles	−0.895	0.580	1-11	**0.125+**	0.074	0-1	−0.030	0.024	0-1
Louisville	−0.061	0.063	1	0.064	0.073	0	**−0.673****	0.143	0
Memphis	**−0.129****	0.020	1	0.008	0.023	0	**−0.657+**	0.337	0-10
Milwaukee	**−2.645****	0.782	1	−0.491	0.540	0	2.980	2.878	0
New Orleans	−0.012	0.028	1	−0.107	0.138	0-1	−0.098	0.090	0
Philadelphia	2.273	2.65	1-4	**−1.830****	0.683	0-4	**−3.574***	1.82	0-1
Phoenix	**−0.079****	0.028	1-2	**0.018+**	0.010	0	0.129	0.170	0-1
St. Louis	**−2.196****	1.339	1-13	0.094	0.252	0	**−0.986+**	1.425	0-5
San Antonio	0.015	0.036	1	0.000	0.000	0	−0.290	0.262	0-2
San Diego	0.759	1.05	1-8	−0.558	0.430	0-5	−0.042	0.060	0
San Francisco	−0.007	0.089	1	**0.139+**	0.081	0-3	−0.017	0.037	0-1
San Jose	**−0.245***	0.105	1-4	0.034	0.022	0-1	0.027	0.017	0
Seattle	0.066	0.175	1	−0.851	0.856	0	−0.053	0.093	0

Note: Elasticities are calculated from the sum of coefficients in equation (1). + denotes significance at 10 percent, * at 5 percent and ** at 1 percent. Elasticities reveal the percentage change in the growth rate of larceny resulting from a percentage increase in the growth rate of larceny arrests, unemployment and the real minimum wage.

and (2) a larger sum of coefficients due to longer lag length than those variables with smaller elasticities.[16]

VI. CRIME IN EIGHTH FEDERAL RESERVE DISTRICT CITIES

Some general observations (from Tables 2 through 8) can be made on the effects of economic conditions and deterrence on crime in the Eighth District cities of St. Louis, Memphis, Little Rock and Louisville.

First, as with the other cities in the analysis, changes in economic conditions and arrests appear to have no significant influence on murder or rapes in Eighth District cities. Arrests for assault in Memphis are found to reduce the growth in the number of assaults: A 10 percent increase in the growth rate for assault arrests reduces the growth in assaults by 3.7 percent. The growth in burglaries is negatively related to burglary arrests in Louisville (a 5.5 percent reduction for a 10 percent increase in arrest growth rate), and an increase in the unemployment rate in Memphis causes an increase in burglaries in Memphis (a 1.9 percent increase in the growth rate for a 10 percent increase in unemployment rate growth).

Of all seven crime categories, larceny and motor vehicle theft appear to be most influenced by arrests and unemployment growth in the cities of Memphis and St. Louis. The growth in larceny is negatively related to larceny arrests in both Memphis and St. Louis, with a 10 percent increase in the growth rate of larceny arrests leading to a 1.3 percent and a

Table 8: VEHICLE THEFT—Deterrence and Business Cycle Elasticities for U.S. Cities									
	Arrests			Unemployment			Wages		
	Elasticity	St. Error	Lags	Elasticity	St. Error	Lags	Elasticity	St. Error	Lags
Baltimore	−0.060	0.052	1	**0.061***	0.028	0-2	−0.108	0.116	0-4
Boston	−0.035	0.098	1-4	0.022	0.097	0	0.118	0.080	0
Cleveland	−0.018	0.023	1	−0.028	0.099	0	−0.045	0.031	0
Columbus	−0.006	0.047	1-3	0.013	0.030	0	**−0.244****	0.094	0-3
Dallas	−0.012	0.012	1	0.047	0.070	0	−0.120	0.132	0
Detroit	**−0.177****	0.038	1-4	**0.020****	0.006	0	**−0.238+**	0.143	0-4
El Paso	−0.018	0.025	1	**1.332+**	0.689	0-2	−0.625	0.586	0
Houston	**−0.340****	0.123	1-3	0.005	0.022	0	−0.037	0.146	0-1
Indianapolis	−0.082	0.078	1-11	0.276	0.353	0	0.003	0.091	0-5
Little Rock	−0.062	0.038	1	**2.359+**	1.219	0	−0.277	2.489	0-1
Los Angeles	0.022	0.027	1	**0.155****	0.050	0	−0.034	0.061	0-1
Louisville	−0.250	0.225	1	0.022	0.036	0	−0.023	0.259	0
Memphis	**−0.039+**	0.022	1	**0.236+**	0.129	0-2	−0.390	0.419	0-1
Milwaukee	0.078	0.200	1	**0.614****	0.072	0	**−8.272****	1.406	0
New Orleans	−0.131	0.121	1	1.445	1.454	0	−1.408	2.067	0
Philadelphia	−0.038	0.130	1-9	−0.120	0.092	0	−0.338	0.526	0
Phoenix	**0.043***	0.021	1	0.004	0.004	0	**−0.167****	0.060	0-1
St. Louis	**−0.036+**	0.021	1-7	**0.586+**	0.302	0-3	−0.338	0.367	0
San Antonio	−0.000	0.019	1	0.000	0.000	0	−0.194	0.274	0-1
San Diego	1.148	1.230	1-13	−0.649	0.456	0-4	**−0.374***	0.179	0-5
San Francisco	0.035	0.033	1	0.012	0.080	0-2	−0.026	0.034	0
San Jose	−0.175	0.189	1	−0.559	0.832	0	−1.903	1.813	0-2
Seattle	0.046	0.037	1	0.065	0.135	0	−0.005	0.008	0

Note: Elasticities are calculated from the sum of coefficients in equation (1). + denotes significance at 10 percent, * at 5 percent and ** at 1 percent. Elasticities reveal the percentage change in the growth rate of motor vehicle theft resulting from a percentage increase in the growth rate of motor vehicle arrests, unemployment and the real minimum wage.

21.2 percent reduction in the larceny growth rate in the respective cities. The effect of arrests on vehicle theft in Memphis and St. Louis are very similar: A 10 percent increase in the arrest growth rate reduces the growth in motor vehicle thefts by 3.9 percent and 3.6 percent, respectively. An increase in the growth of unemployment is found to increase motor vehicle thefts in St. Louis, Memphis and Little Rock, where the elasticity estimate for Little Rock (2.3) is much larger than that of Memphis (0.24) or St. Louis (0.59).

Evidence also suggests (Table 9) that police departments in Eighth District cities increase arrests in response to increases in certain crimes, especially in Little Rock and Memphis. For example, an increase in the growth rates of assault, robbery and burglary results in an increase in arrests for these crimes. Of these three crimes, changes in the growth rate of assault result in the greatest response in arrests for this crime (elasticity of 1.59). Increases in the growth of assault, robbery and motor vehicle theft in Memphis lead to an increase in the growth rate of arrests for these crimes, with motor vehicle theft having the largest elasticity of 5.51. The growth rate of robbery arrests is quite responsive to the growth in robberies in St. Louis, with the elasticity having an estimate of 14.3. No positive and significant elasticities were found for Louisville.

Eighth District Statistics

Differences in crimes and arrests across Eighth District cities are shown in Table 10, which lists the

Table 9: DO ARRESTS FOLLOW CRIME? Elasticity Estimates

	Murder		Rape		Assault		Robbery		Burglary		Larceny		Vehicle Theft	
City	**Elasticity**	**Lags**	**Elasticity**	**Lags**	**Elasticity**	**Lags**	**Elasticity**	**Lags**	**Elasticity**	**Lags**	**Elasticity**	**Lags**	**Elasticity**	**Lags**
Baltimore	0.009	1-2	**−0.117***	1	0.028	1	**6.262***	1-2	−0.149	1-5	−0.388	1-5	**0.043+**	1
Boston	—	—	−2.338	1	0.328	1	**0.940+**	1-5	**0.187+**	1-2	0.127	1-2	0.127	1
Cleveland	—	—	0.231	1-5	0.128	1	**1.847****	1-7	**0.522****	1-3	0.428	1	**2.676****	1-4
Columbus	—	—	**0.933****	1	**18.229****	1-12	0.210	1	0.291	1	29.486**	1-9	**10.415***	1
Dallas	**0.721****	1-5	0.012	1	**0.504****	1	**13.598****	1-4	0.013	1	0.168**	1-2	**2.829****	1-8
Detroit	0.045	1	—	—	**−2.057****	1-8	**−3.893***	1-4	**−0.452+**	1	−0.505+	1-2	0.140	1
El Paso	—	—	0.212	1-3	**0.269***	1-2	**4.582***	1-2	2.229	1-5	0.052	1	0.024	1
Houston	**25.098****	1-7	**5.443****	1-7	0.132	1	**1.108****	1-7	**0.905****	1-9	0.099+	1	**1.915****	1-4
Indianapolis	—	—	**0.134***	1-2	−0.015	1	0.161	1	0.284	1-2	0.211	1	0.234	1
Little Rock	—	—	—	—	**1.588****	1-4	**0.762****	1-7	**0.169****	1	−0.510	1	0.132	1
Los Angeles	0.066	1	0.905	1-3	**1.014****	1-4	**10.442+**	1-8	0.087	1-3	−0.255	1-3	0.705	1-3
Louisville	—	—	—	—	**−0.798+**	1-5	−0.073	1	−0.021	1	−0.031	1	−0.111	1-12
Memphis	—	—	0.016	1	**0.968****	1	**0.139****	1-2	−0.177	1-4	0.185	1	**5.505****	1-3
Milwaukee	**0.035+**	1	**−0.131+**	1	**0.174+**	1	**0.049+**	1	0.071	1-2	0.001	1	**−0.138+**	1
New Orleans	0.265	1-3	0.030	1	0.179	1	0.142	1-2	0.202	1	−0.048	1	**0.175+**	1
Philadelphia	**4.519****	1-8	0.075	1-4	−3.212	1-4	**0.126****	1-2	**0.184+**	1-2	0.032	1-3	**8.185****	1-4
Phoenix	—	—	−0.004	1	0.154	1	**2.965****	1-9	0.084	1-2	**66.717****	1-4	**2.035+**	1-13
St. Louis	—	—	—	—	−2.309	1-3	**14.332****	1-10	0.031	1	−0.323	1-11	−0.361	1-8
San Antonio	—	—	—	—	−3.804	1	**0.617***	1-4	**0.079***	1	0.520	1	0.035	1
San Diego	—	—	**3.632****	1-8	**0.874****	1-4	**13.511***	1-3	−0.604	1-2	**14.992***	1-4	**0.781***	1-4
San Francisco	—	—	—	—	0.021	1	**0.109***	1	**0.596****	1-3	0.001	1	0.132	1-2
San Jose	—	—	**0.033***	1-5	1.058	1	**0.165+**	1	−0.093	1	0.851	1-5	**0.040****	1-2
Seattle	—	—	0.003	1	6.617	1-3	−0.008	1	**−0.849***	1-3	−0.126	1	**0.094****	1-4

Note: Elasticities are calculated from the sum of coefficients in equation (2). + denotes significance at 10 percent, * at 5 percent and ** at 1 percent. Elasticities reveal the percentage change in the growth rate of arrests resulting from a percentage increase in the (lagged) growth rate of crime.

mean values for each crime, arrests, unemployment and the minimum wage. Mean values are provided for the monthly percentage change of each variable as well as for each variable in levels. The number of crimes per month for each city is graphed in Figures 1 through 7. One point of caution is that the mean of the variables in levels (Table 10) and the data shown in Figures 1 through 7 are not normalized by city population.

The crime and arrest data presented in Table 11 for each of the four Eighth District cities have been adjusted for city population. The sample average (Table 10) for each crime and arrest has been normalized by each city's 1990 population (per 100,000 in population), thus providing an average crime rate and an average arrest rate.

Some differences across cities are worth noting. Of the four cities, St. Louis has the highest average murder rate (3.5 per 100,000), robbery rate (81.2 per 100,000), assault rate (312.1 per 100,000), burglary rate (224.1 per 100,000) and motor vehicle theft rate (170.9 per 100,000). The rate of rapes in Memphis (9.7 per 100,000) is higher than the rate of the other three cities. Little Rock has the highest rate of larceny at 582.8 per 100,000.

Although St. Louis ranks first in five of the seven crimes, it also ranks first in terms of arrests for murders, robberies, assaults and motor vehicle thefts. Rapes are highest in Memphis, which also has the highest arrest rate for rapes. Similarly, Louisville has

(continued on p. 23)

Table 10: EIGHTH DISTRICT CITIES—Descriptive Statistics on Crime and Arrests								
	St. Louis		Louisville		Little Rock		Memphis	
	Mean-Percent Change	Mean Levels	Mean-Percent Change	Mean Levels	Mean-Percent Change	Mean Levels	Mean-Percent Change	Mean Levels
Murder	—	14	—	4	—	3	—	13
Rape	—	22	—	9	—	15	−0.18	60
Robbery	0.04	322	−0.01	110	0.01	76	0.04	391
Assault	0.15	1,238	0.88	275	0.64	505	0.77	1,032
Burglary	−0.29	889	0.18	338	−0.09	391	0.07	1,326
Larceny	0.07	2,138	0.07	687	0.00	1,032	0.22	2,074
Vehicle Theft	0.13	678	0.23	210	0.03	123	−0.10	949
Murder Arrests	—	11	—	2	—	3	—	10
Rape Arrests	—	15	—	3	—	9	−0.15	32
Robbery Arrests	−0.46	81	−0.61	31	0.31	25	−0.12	85
Assault Arrests	0.04	831	1.10	158	0.70	352	0.67	474
Burglary Arrests	−0.60	112	−1.13	66	−0.02	58	0.08	162
Larceny Arrests	−0.31	317	−0.16	126	−0.05	152	0.42	434
Vehicle Theft Arrests	−0.01	82	−1.10	39	−0.05	17	−0.09	89
Unemployment	−0.08	8	0.04	4	−0.13	5	0.06	6
Minimum Wage	−0.24	3	−0.12	3	−0.24	3	−0.19	3

Note: Based on monthly data for the sample period listed in Table 1. The unemployment rate is seasonally adjusted. The minimum wage is the real minimum wage adjusted to 1982-84 dollars. Mean values for levels have been rounded to nearest integer value.

Table 11: EIGHTH DISTRICT CITIES—Average Crime and Arrest Rates				
	Per 100,000 Population (1990)			
	St. Louis	Louisville	Little Rock	Memphis
Murder	3.53	1.48	1.69	2.10
Rape	5.55	3.34	8.47	9.69
Robbery	81.17	40.77	42.92	63.18
Assault	312.09	101.91	285.17	166.75
Burglary	224.11	125.26	220.80	214.25
Larceny	538.97	254.60	582.77	335.11
Vehicle Theft	170.92	77.82	69.46	153.34
Murder Arrests	2.77	0.74	1.69	1.62
Rape Arrests	3.78	1.11	5.08	5.17
Robbery Arrests	20.42	11.49	14.12	13.73
Assault Arrests	209.49	58.55	198.77	76.59
Burglary Arrests	28.23	24.46	32.75	26.18
Larceny Arrests	79.91	46.69	85.83	70.13
Vehicle Theft Arrests	20.67	14.45	9.6	14.38

Note: The rates shown above were found by normalizing the mean values in Table 10 by the 1990 population (per 100,000) for each city. The 1990 population for each city was: St. Louis, 396,685; Louisville, 269,838; Little Rock, 177,086; Memphis, 618,894.

Figure 1: MURDERS—Eighth District Cities

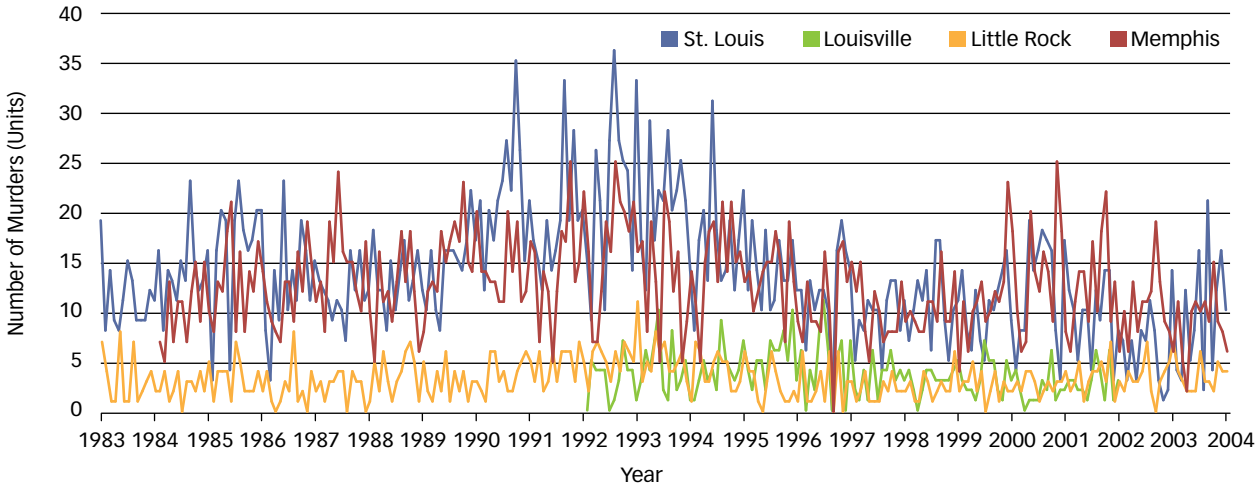


Figure 2: RAPES—Eighth District Cities

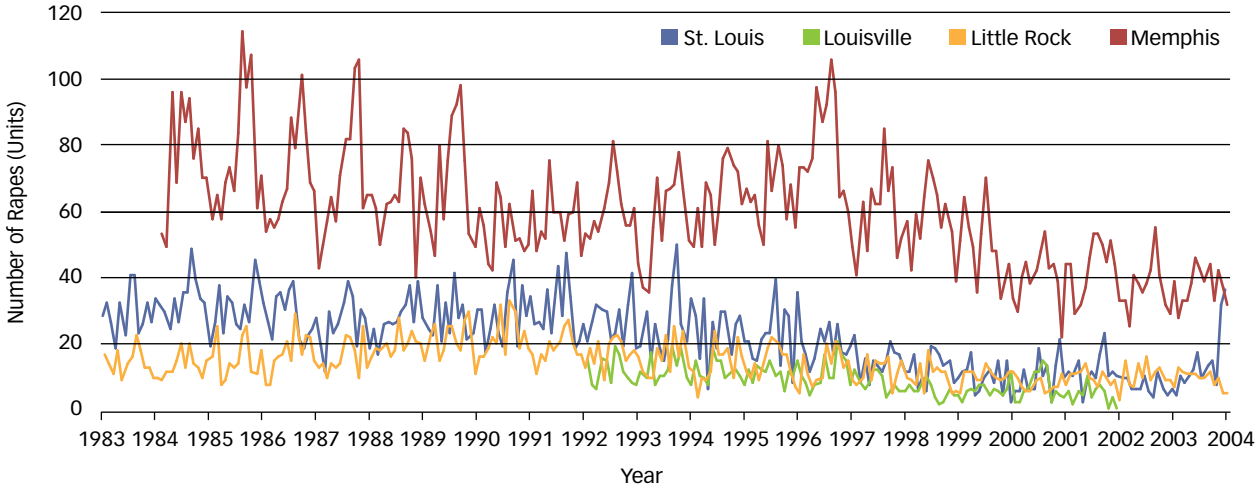


Figure 3: ROBBERIES—Eighth District Cities

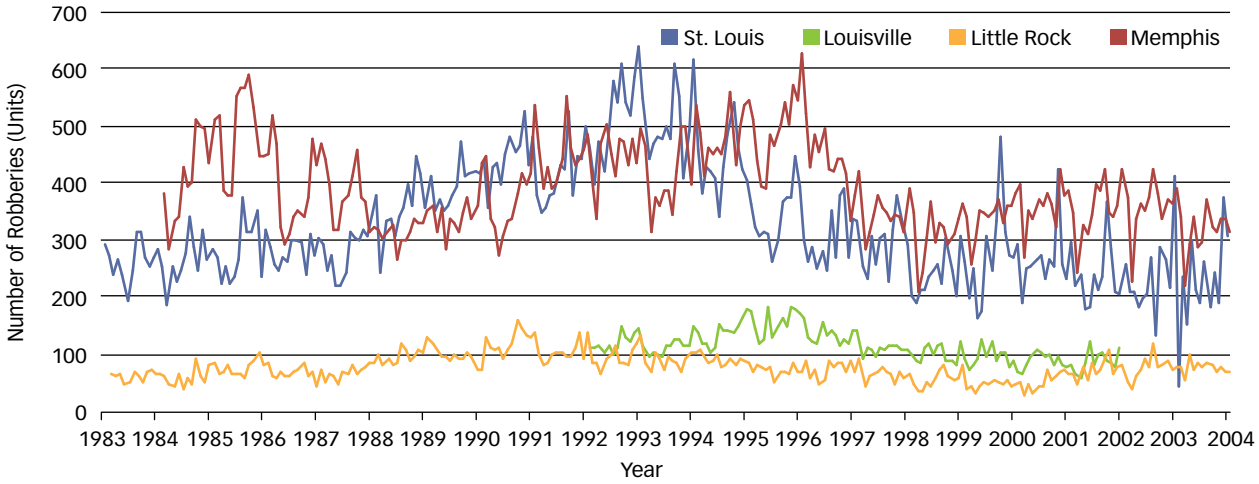


Figure 4: ASSAULTS—Eighth District Cities

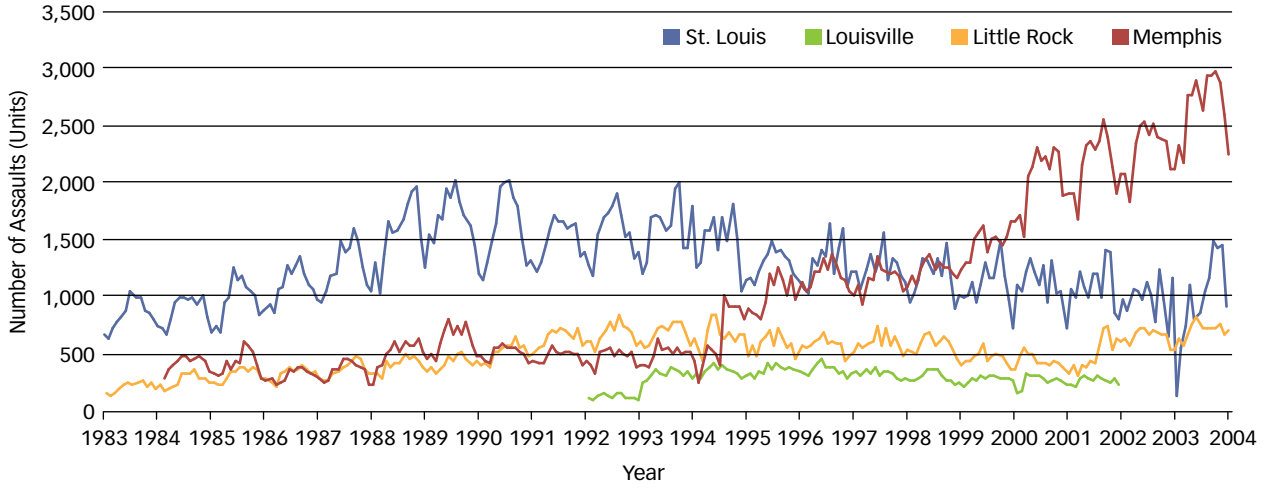


Figure 5: BURGLARIES—Eighth District Cities

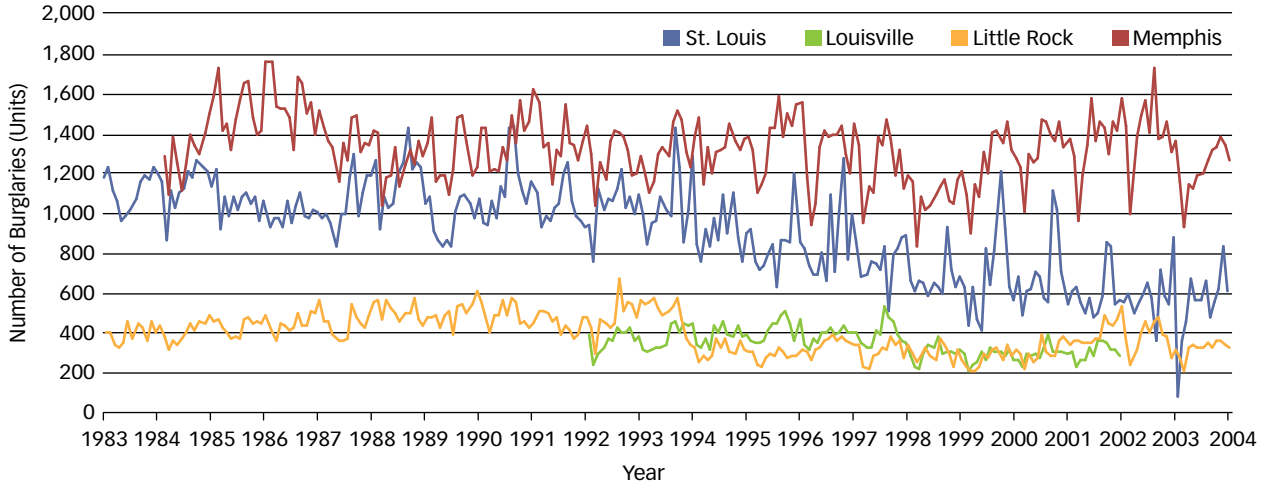


Figure 6: LARCENIES—Eighth District Cities

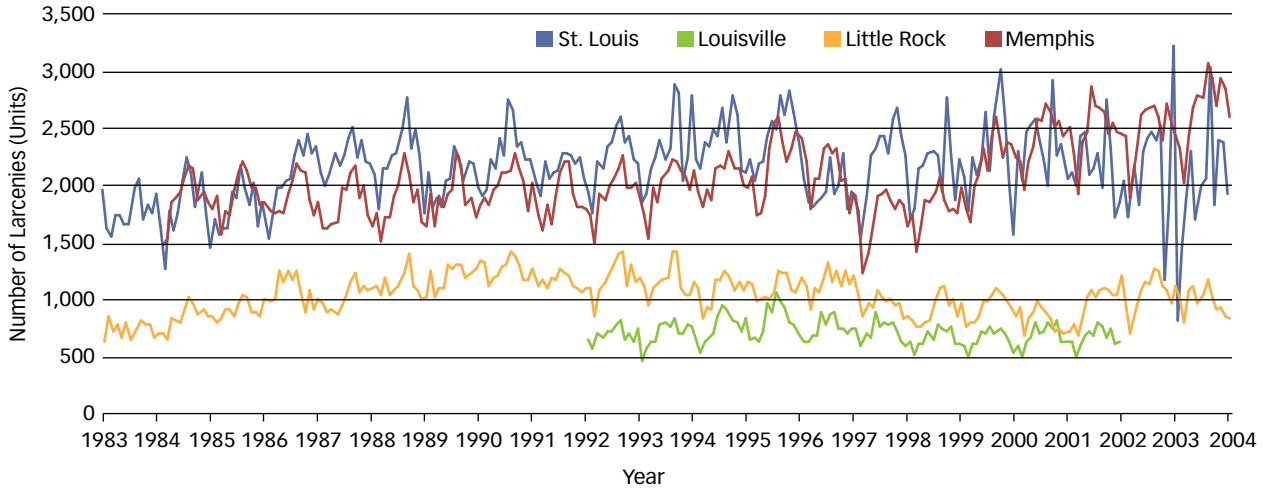
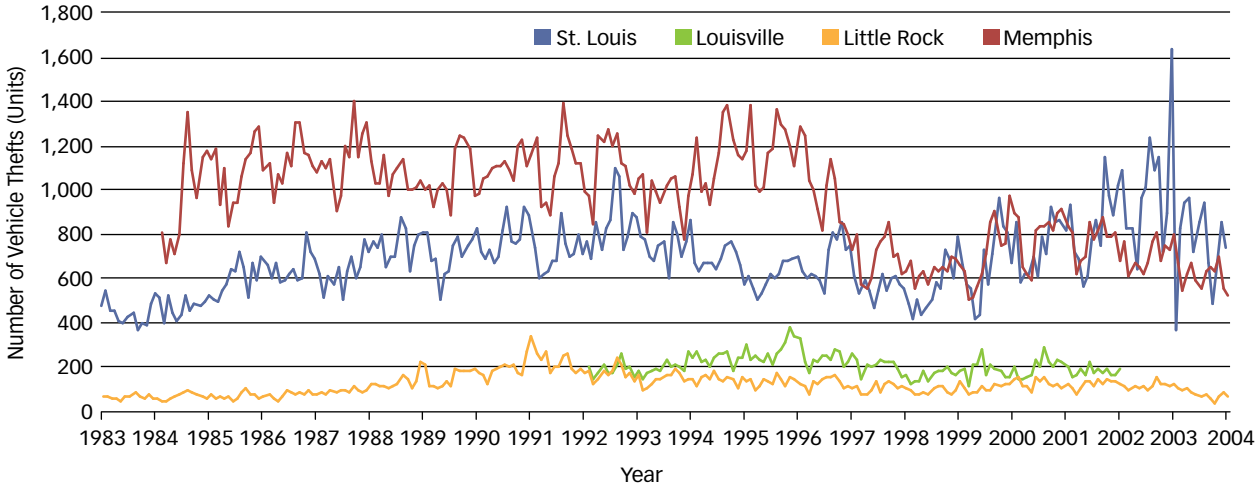


Figure 7: VEHICLE THEFTS—Eighth District Cities



(continued from p. 19)

the highest rate of larceny and has the highest rate of larceny arrests.

It appears that, at least when comparing averages across cities, there is a positive relationship between arrest rates and crime rates. Of course, this positive relationship does not reveal any causal relationship. The empirical results shown in Tables 2 through 8 reveal little empirical evidence that changes in arrest rates lead to a reduction in the growth of crime. It may certainly be the case that a long-run negative relationship between arrests and crime exists. There is stronger evidence (Table 9) that the direction of causality is not from arrests to crime, but rather from crime to arrests. That is, police respond to higher crime by allocating more resources to reducing that crime. The point here is that although the crime rate and arrest rate statistics shown in Table 11 allow for interesting comparisons across Eighth District cities, they also reveal that the use of sample averages and the lack of formal modeling may provide misleading conclusions regarding the relationship between deterrence and crime.

VII. SUMMARY AND DISCUSSION

The majority of past work on the effects of economic conditions and deterrence on crime has tended to focus on the long-run relationship between these variables and has frequently used data at the county, state or national level. The use of high-frequency time-series data for individual cities allows empirical modeling that reduces the potential for simultaneity between crime and deterrence. In addition, the use of city-level data for multiple cities rather than more aggregated data reduces potential contamination of the key relationships that may exist given that crime and labor markets are different across cities as well as rural and urban areas.

Using monthly data for 23 large cities in the United States, including four cities in the Eighth Federal Reserve District, this report explored whether short-run changes in economic conditions and in deterrence caused changes in seven major crimes. We find weak evidence across U.S. cities that changes in economic conditions significantly influence short-run changes in crime. This suggests that short-run changes in economic conditions do not induce individuals to commit crimes. Although we find no significant relationships between short-run economic conditions and crime in many cities, we do find that short-run changes in economic conditions influence property crimes in a greater number of cities. This likely reflects the fact that nonviolent property crimes are more likely to result in financial gain than more violent crimes. Many of our significant elasticities are similar in magnitude to those of Corman and Mocan (2005) in their study of New York City. Although it seems reasonable that wages rather than unemployment would have a greater influence on crime in the long run, this is less clear in the short run.

We find little evidence to support the deterrence hypothesis in the short run, as changes in deterrence are found to have no influence on crime in many U.S. cities. It may be that arrests are not the best measure of deterrence, and thus our lack of a large number of significant relationships between arrests and criminal activity reflects this fact. But, we are not too concerned, given the wide use of arrests as a measure of deterrence in past studies and several plausible economic explanations for our findings. For example, our findings support the suggestion by previous authors (Wilson and Herrnstein, 1985; Lee and McCrary, 2005) that criminals are myopic with regard to changing probabilities of arrest and, thus, do not consider the likelihood of the negative consequences of committing a crime. Similarly, our results may reflect the reasonable possibility that criminals do not have perfect information regarding changes in deterrence and, thus, are not able to adjust their criminal activity accordingly. Both of these economic explanations seem particularly reasonable in the short run.

The hypothesis that arrests respond to increases in crime was also empirically tested. We find much stronger evidence that, in many U.S. cities, an increase in the growth rate of crime results in an increase in the growth of arrests for that crime. In other words, arrests follow crimes. This supports the notion that law enforcement reallocates its resources in response to increases in crime. One interesting finding was that the causal relationship from robbery to robbery arrests was statistically significant for 17 of the 23 cities and the relationship from vehicle thefts to vehicle theft arrests was statistically significant for 12 of the 23 cities in our sample.

It is reasonable to expect that, over time, an increase in all types of crimes would garner an increased response from law enforcement, especially the more violent crimes of murder and rape. Several factors explain why we find that increases in less violent crimes garner a law enforcement response in the short run while increases in the most violent crimes do not. First, violent crimes are committed with less forethought than property crimes and are often part of an overall increase in criminal activity, such as drugs and gangs, which may require years of law enforcement planning and strategy via task forces and interagency cooperation to reduce. (A classic example is New York City in the 1980s.) Second, preventing less violent crimes may also reduce the number of more violent crimes, as suggested by the "broken-windows" hypothesis of law enforcement (Wilson and Keeling, 1982; Corman and Mocan, 2005). Thus, combating a rise in less violent crimes is relatively less costly in terms of law enforcement resources and may, in fact, reduce the number of violent crimes. Finally, it seems reasonable that crimes that are more visible to businesses and tourists—such as robbery, vehicle theft and assault—are likely to result in greater attention by law enforcement in the short run, possibly through a relatively inexpensive increase in police presence. Therefore, from a citywide public relations and economic development perspective, as well as from an effective means of overall crime reduction, increases in visible crimes are more likely to attract greater police resources in the short run.

The degree to which the effect of crime on arrests persists over time is quite different across cities. For example, robbery arrests are a result of the change in robberies from only the prior month in some cities to the last 10 months in other cities. Longer lag length may indicate a greater severity of crime waves in terms of duration. Similarly, lag length may reflect differences in the effectiveness of law enforcement across cities to respond to crime (i.e., shorter lag lengths on changes in crime suggest law enforcement is more effective at reallocating resources and responding to increases in crime.) This second point is especially interesting if one considers two cities each having different crime elasticities but each based on the same lag length. For example, the estimated robbery elasticities are 4.58 and 0.13 for El Paso and Philadelphia, respectively, each based on a two-month lag of robberies. This suggests that, over a two-month period, the responsiveness of law enforcement in El Paso to changes in robberies is much greater than in Philadelphia.

Two points should be considered, however, when attempting to infer the effectiveness of law enforcement. First, the initial level of crime and arrests is an important factor in evaluating the effectiveness of changes in law enforcement. For a city that is already allocating a large percentage of its law enforcement resources to combat robberies, for example, the opportunity cost of allocating further resources to robberies is much higher than it would be in cities that have a lower level of initial law enforcement resources allocated to combat robberies (Benson et al., 1994). Thus, cities already having a relatively large percentage of their resources allocated to combat robberies may be unwilling (or unable) in the short

run to allocate further resources to combat a further increase in robberies. Second, this partial equilibrium analysis does not consider the optimal allocation of law enforcement resources to combat other crimes (Garoupa, 1997). Clearly zero crime in a city is not an optimal level of crime, given the nearly infinite resources it would require to achieve this objective, if it could be achieved at all. The optimal level of each crime and the desired level of resources to combat each crime certainly differ across cities and are based on the preferences of the citizenry, public officials and law enforcement, as well as on different law enforcement strategies (Miceli, 2007).

Several final thoughts and directions for future research are worth mentioning. First, it can be argued that an individual's cost-benefit calculation more often favors crime when his or her longer-run economic situation is considered, thus suggesting that changing economic conditions and deterrence levels may have a greater influence on city crime over long-time horizons. An interesting research question is how long a time horizon? At what point, both in duration and severity, do worsening economic conditions induce criminal activity?

Second, it may serve future research to obtain city-level unemployment rates and wage data for young males in each city rather than overall unemployment rates and minimum wage data because many property crimes are committed by young males (Grogger, 1998).

Third, the high-frequency time series data used here could be used to further explore the deterrence versus incapacitation hypotheses as described in Levitt (1998). Here it would be interesting to see whether there are temporal differences in the relationship between arrests for one crime and the occurrence of other crimes.

Finally, our results reveal that relationships between economic conditions and crime and between deterrence and crime are not likely to be the same across cities or regions, and, thus, suggest the importance of local analyses using more disaggregated data in order to implement effective public policy at the local level. ■

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ENDNOTES

[1] Numerous other studies have been conducted on the issue. See Freeman (1999), Gould et al. (2002) and Corman and Mocan (2005) for additional surveys of the literature.

[2] Rather than using unemployment and wages to measure economic activity, Rosenfeld and Fornango (2007) explore how changes in consumer sentiment influenced crime rates in the U.S. over the period 1970 to 2003.

[3] This report is based on the work of Garrett and Ott (2008).

[4] The agency-level FBI Uniform Crime Reporting Program data series was retrieved from the National Archive of Criminal Justice Data via the Inter-University Consortium for Political and Social Research at the University of Michigan (ICPSR) at www.icpsr.umich.edu/NACJD/ucr.html. We use the agency-level data rather than incident-level or county-level data. Doing so provides us with a list of all criminal offenses and arrests for each city's police department.

[5] Murder includes non-negligent manslaughter. Robbery is the taking or attempting to take anything of value from a person by use of force. Burglary is the unlawful entering of a property with the intent to commit a felony or theft. Larceny is the unlawful taking of property from an individual (no use of force).

[6] We chose the 1990 population as the basis for our samples because it is roughly the midpoint of each sample period. Cities in the top 20 that were not considered here due to lack of data include New York City, Chicago, Jacksonville and Washington, D.C. Corman and Mocan (2005) obtained their New York City crime data from the NYPD.

[7] This is true of the arrest data as well.

[8] As in Corman and Mocan (2005), we do not normalize the number of crimes or arrests by city population because population changes very little from month to month and data are only available at census dates.

[9] The monthly unemployment rates for each city were obtained from the Bureau of Labor Statistics (BLS). The city unemployment rates from the BLS were adjusted seasonally, using the U.S. Census Bureau's X-12-ARIMA Seasonal Adjustment Program. The minimum wage in each city was obtained from January issues of the *Monthly Labor Review* published by the BLS. We deflated the nominal minimum wage by the CPI. For each city, we used the highest minimum wage set by law (local, state or federal). When a state's minimum wage changed from one year to the next (if it was higher than the federal minimum wage), we contacted the state's labor department or found documentation online (from local newspapers) that listed the month of the year that the new minimum wage went into effect. For the majority of cities, the federal minimum wage always trumped the state's minimum wage. The Tax Policy Center provides an annual summary of state and federal minimum wages. These data can be accessed at www.taxpolicycenter.org/taxfacts/content/PDF/state_min_wage.pdf.

[10] See *Characteristics of Minimum Wage Workers, 2007*. Bureau of Labor Statistics.

[11] Lag length for each variable (for each crime for each city) was determined by the Akaike Information Criterion following the methodology of Burnham and Anderson (2002, p. 71). We used Newey-West standard errors to correct for heteroskedasticity and serial correlation. We used the following formula to determine the number of lags for the Newey-West standard errors: 4(n/100)^(2/9), where n is the number of observations. The integer portion of the result was then taken as the number of Newey-West lags. See Wooldridge (2003, p. 412) for further details. Finally, each empirical model includes an error-correction term to account for the long-run equilibrium relationship (cointegration) between crime and the explanatory variables.

[12] Let Ω be the sum of coefficients for a respective variable X. The elasticity of Y (dependent variable) with respect to changes in X is computed as $\eta = \Omega \cdot \left|\left(\overline{X}/\overline{Y}\right)\right|$. The variance of Ω is calculated using the standard formula for the variance of a sum; that is, summing the variances of each individual coefficient and the covariance between each coefficient pair. The variance of the elasticity (η) is calculated as $\mathrm{Var}(\eta) = \left(\overline{X}/\overline{Y}\right)^2 \cdot \mathrm{Var}(\Omega)$.

[13] The large (in absolute value) arrest elasticity for St. Louis is due to the fact that the average monthly change in robbery arrests is – 0.45656 and the average monthly change in the number of robberies is 0.0433, thus giving a very large proportion of 10.5441. This proportion multiplied by the sum of coefficients (of – 0.8406) gives an elasticity of – 8.86.

[14] As before in equation (1), an error-correction term was included in the equation (2), variable lag was determined by the Akaike Information Criterion following the methodology of Burnham and Anderson (2002, p. 71), and Newey-West standard errors were used to correct for heteroskedasticity and serial correlation. An error-correction term is also included in equation (2).

[15] For example, a 100 percent increase in a 2 percent growth rate yields a 4 percent growth rate, quite a reasonable growth rate despite the large percentage increase.

[16] For example, consider the difference in the larceny elasticity for Phoenix (66.7) and for Houston (0.099). The average monthly percent change in larceny for Houston is 0.0012 and 0.0013 for Phoenix, two very similar numbers. However, the monthly percentage change in larceny arrests for Houston is 0.0021, whereas the monthly percentage change in larceny arrests for Phoenix is a much smaller 0.000023. Thus, the ratio of variable means is much greater for Phoenix (0.0013/0.000023 = 56.5) than for Houston (0.0011/0.0021 = 0.571). The average monthly larceny growth rate in Phoenix is nearly 57 times greater than the city's monthly larceny arrest growth rate, whereas the average monthly larceny growth rate in Houston is about half of the city's monthly larceny arrest growth rate. In addition to this large difference in the ratio of variable means for Houston and Phoenix, the sum of coefficients for Phoenix is nearly seven times that of Houston (1.18 for Phoenix and 0.174 for Houston). Thus, the large elasticity estimate for Phoenix (66.7 = 1.18 . 56.5) relative to Houston (0.099 = 0.174 . 0.571) is a result of a much greater average monthly growth rate in larceny compared to the average monthly growth rate in larceny arrests and a greater sum of coefficients.

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