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City Business Cycles and Crime

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Abstract

We explore the influence of city-level business cycle fluctuations on crime in 20 large cities in the United States. Our monthly time-series analysis considers seven crimes over an approximately 20-year period: murder, rape, assault, robbery, burglary, larceny, and motor vehicle theft. Short-run changes in economic conditions, as measured by changes in unemployment and wages, are found to have little effect on city crime across many cities, but property crimes are more likely to be influenced by changes in economic conditions than are more violent crimes. Contrary to the deterrence hypothesis, we find strong evidence that in many cities more arrests follow an increase in crime rather than arrests leading to a decrease in crime. This is true especially for the more visible crimes of robbery and vehicle theft and suggests that city officials desire to remove these crimes from the public's view.

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City Business Cycles and Crime

I. 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 adversely affect residential and business immigration. A city's crime rate is thus considered a factor in the city's economic success. Much academic research examines the effects that of crime on the economic growth of local areas (Burhham 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 models 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). Numerous studies estimate the effect of deterrence on crime, but with mixed results and no definitive conclusion (Grogger, 1991; Levitt, 1997, 1998; Cover and Thistle, 1988; Cornwall and Trumbull, 1994; Lee and McCrary, 2005). In addition, Decker and Kohfeld (1985) suggest that arrests do not influence crime, but rather that arrests follow an increase in crime.

Criminal behavior also depends on 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 rather than through legal channels.

Much research focuses 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, find that property crimes increase in response to an increase in the unemployment rate and decrease in response to a greater police presence.[2] Mocan and Bali (2005) also find a direct relationship between unemployment and crime using a panel of data for U.S. states. A direct relationship between unemployment and property crimes, and a weaker direct relationship between unemployment and violent crimes, was found by Raphael and Winter-Ember (2001) in their panel data analysis of U.S. states.[3] Less evidence of a relationship between unemployment and crime is a result in Imrohoroglu et al. (2004), who analyzed trends in U.S. property crimes. 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,

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[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] The authors find that deterrence (as measured by arrests) is more important in explaining crime rates than are economic conditions. 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.

[3] The authors find that declining unemployment between 1992 and 1997 explained more than 40 percent of the decline in property crimes.

find that both unemployment and wages are related to crime, but the effect of wages is greater than that of unemployment. Finally, Corman and Mocan (2005) find that changes in criminal activity are inversely related to changes in the real wage in New York City.[4]

Although some general patterns emerge regarding the relationship between crime and economic activity (and deterrence, to some degree), it is fair to say that the results of past studies do not provide conclusive evidence.[5] 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 crime and economic activity rather than on any short-run relationship, say, month to month or quarter to quarter. In this paper, we determine whether city-level crime varies with changes in local economic conditions and deterrence. We use monthly time-series data for 20 large U.S. cities to determine 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 more arrests follow an increase in crime. 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

[4] The authors find that a 10 percent increase in the growth of wages reduced the growth of various crimes by 4 to 6 percent.

[5] 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 United States over the period 1970 to 2003.

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 offers several advantages. The high-frequency time-series data used in our models allow 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 20 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, the results from a county- or state-level analysis may mask the greater crime rates and variability in economic conditions in urban areas relative to those in rural areas (Smith, 1980; Weisheit et al., 1994).

Our results show interesting differences in the effect of changing economic conditions on crime across cities, as well as differences in the responsiveness of city law enforcement to increases in different types of crimes. Some of our results are consistent with those of 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 from models of crime that consider the short run versus the long run. In addition to revealing intercity differences on the effects of economic conditions and deterrence on various categories of criminal activity, our results suggest intercity differences in the allocation of law enforcement resources and in the effectiveness of law enforcement, as well as possible economic development incentives pressuring city officials to reduce certain crimes but not others.

II. Data and Methodology

Data

Our city-level crime data are from the Federal Bureau of Investigation's *Uniform Crime Reports* (UCR).[6] We obtained the monthly number of offenses and arrests for seven categories of crime: murder, rape, assault, robbery, burglary, larceny, and motor vehicle theft.[7] 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 underreporting of crime by local police departments and differences in the collection and reporting of criminal activity across cities. Because we estimate crime models for each city (and each crime), cross-city contamination by variation in reporting methods is not a concern. Similarly, bias resulting from the underreporting of crime would be minimized in our time-series analysis if the underreporting were consistent over the sample period.

[6] The agency-level UCR data were retrieved from the National Archive of Criminal Justice Data via the Inter-University Consortium for Political and Social Research at the University of Michigan at http://www.icpsr.umich.edu/NACJD/ucr.html. We use agency-level data rather than incident-level or county-level data. Doing so provides a list of all criminal offenses and arrests for each city's police department.

[7] Murder includes nonnegligent 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).

Crime data were obtained from the 20 largest U.S. cities based on 1990 population for which sufficient crime data were available.[8] Our sample period for the majority of cities covers the period 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 midsample 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 to preserve the sample for estimation purposes (Maltz, 1999, p. 28).[9] Table 1 lists the cities in the analysis, the sample period for each city, and notes on data editing.

[Table 1]

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.[10] 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).[11] Although the unemployment rate

[8] 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 because of a lack of data include New York City, Chicago, Jacksonville, and Washington, DC. Corman and Mocan (2005) obtained their New York City crime data from the New York City Police Department.

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

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

[11] The monthly unemployment rate for each city was obtained from the Bureau of Labor Statistics (BLS). The city unemployment rates from the BLS were seasonally adjusted 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

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.[12] This demographic group is also the most likely to commit property-related crimes (Grogger, 1998).

Model and Hypotheses

Our objective is to determine whether changes in deterrence and economic conditions influence monthly changes in crime. We estimate the following crime equation for each of seven crimes in each of the 20 cities:

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

The number of criminal offenses is denoted by C_t and the number of arrests for the respective crime is denoted by AR_r. UN_r and MW_r 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 before estimation. Monthly dummy variables (S) are included to account for any seasonality in crime.

In addition to estimating regressions for each of the 20 cities, we pool the data and estimate our crime model using panel data methods. Our (unbalanced) panel contains the same variables as in equation (1), but we also include city and year fixed effects to capture unobserved heterogeneity across cities and time. Pooling the data not only provides for a greater number of cross-sectional observations, it also allows us to assess how the city-specific results compare with the results from pooled data for the 20 cities.

summary of state and federal minimum wages. These data can be accessed at http://www.taxpolicycenter.org/taxfacts/content/PDF/state_min_wage.pdf.

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

Differences in the city-specific and pooled results can provide further evidence that crime and labor markets vary across cities and regions (Topel, 1994; Glaeser and Sacerdote, 1999).

Because the effects of deterrence and economic conditions on crime may extend over several months, we include lags of arrests, unemployment, and the minimum wage. The number of lags (r) captures the degree to which each variable's effect on crime persists. As in Corman and Mocan (2005), no contemporaneous value of arrests is included in the empirical models to minimize any simultaneity between arrests and crime. The model does include a contemporaneous value for both economic variables. Lag length for each variable in each regression equation was determined by the Akaike information criterion (AIC) following the methodology of Burnham and Anderson (2002, p. 71). We used Newey-West standard errors to correct for heteroskedasticity and serial correlation.[13] Finally, each empirical model includes an error-correction term to account for any long-run equilibrium relationship between crime and the explanatory variables.

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.[14] The

[13] 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.

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

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 crime.

Several points regarding the elasticity estimates are worth mentioning. Importantly, comparisons of elasticities across cities may reflect different time spans depending on the lag length of each variable. In addition, the size of an elasticity estimate depends not only on the sum of the coefficients (and thus the number of lags), but also the magnitude of the respective variables' means. Because we are looking at percentage changes in growth rates rather than 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 arrests to crime - 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, 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 situation 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 rates? Gould et al. (2002) find evidence that wages played a greater role in county-level 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 than creates a greater incentive for individuals to commit crimes. Because we are studying changes in wages and unemployment, it is less clear that we would expect to find that 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.

III. Empirical Results

The empirical results are presented in Tables 2 through 8; each table contains the elasticities of arrests, unemployment, and wages on the respective crime for each of the 20 cities. Recall that 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. 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), the evidence suggests that changes in deterrence and economic conditions have a significant influence on the growth of murders and rapes in only a few cities and not in the full sample. 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 a higher growth 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.

[Table 2]

[Table 3]

As with murder and rape, the regression results for assault (Table 4) show 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 elasticities with the correct sign, the unemployment elasticities for assault are generally larger (in absolute value) than the minimum wage elasticities for assault.

[Table 4]

The elasticities for robberies are shown in Table 5. Unlike for the crimes of murder and rape, changes in arrests and economic conditions significantly influence the growth in robberies in a larger number of U.S. cities. The arrest elasticity for robbery ranges from -0.04 in New Orleans to -0.66 in El Paso. The arrest elasticity in the pooled sample is -0.07 and is statistically significant. Unemployment growth caused an increase in robberies in Baltimore, Houston, Indianapolis, Milwaukee, and San Diego, with elasticities ranging from roughly 0.10 in Milwaukee to 1.87 in Indianapolis. Real minimum wage growth resulted in lower growth in the number of robberies for four cities – Baltimore, Cleveland, Columbus, and San Diego. In Baltimore and San Diego, robbery growth is influenced by both changes in the unemployment rate and wage growth. A visual comparison across cities suggests that the unemployment elasticities for robbery are slightly higher (in absolute value), on average, than the minimum wage elasticities for robbery.

[Table 5]

The results for burglary, larceny, and motor vehicle theft reveal 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 five cities and ranges from -0.03 (Los Angeles) to -0.43 (Phoenix). Growth in unemployment increased the growth in burglaries in six cities, with elasticities ranging from 0.04 (Los Angeles) to 0.23 (Boston). Minimum wage growth reduced 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. All of the coefficients in the pooled burglary model have the predicted sign, but none are statistically significant.

[Table 6]

The larceny elasticities are presented in Table 7. The arrest elasticity for larceny is negative and significant for seven 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 is 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 four cities (range of -0.19 to -3.57) as well as for the pooled model (-0.29). The elasticities are generally larger than the minimum wage elasticities for burglary shown in Table 6.

[Table 7]

The results for motor vehicle theft are shown in Table 8. Changes in arrests have a negative influence on motor vehicle thefts in three cities, with the elasticities ranging from -0.04 to -0.34. The unemployment elasticity for motor vehicle theft is positive and significant for six cities. Increases in the real minimum wage lead to lower motor vehicle thefts in five cities and in the pooled sample of cities. Changes in both the unemployment rate and the real minimum wage influence motor vehicle thefts in both 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.

[Table 8]

The volume of empirical results presented thus far warrants a brief summary. For many cities, we found no significant short-run relationship between arrests and crime and between economic conditions and crime. We did find, however, that changes in economic conditions explain nonviolent crimes such as larceny, burglary, and motor vehicle theft to a greater degree than the more violent crimes of murder and rape. Although the number of cities in which a statistically significant relationship exists is small, the relative importance of economic conditions in explaining property crimes rather than violent crimes supports previous empirical work (Raphael and Winter-Ember, 2001). Another finding is that no consistent difference in the magnitude of the elasticities appears across crimes or cities. This suggests that determining whether crime is influenced more by changes in economic conditions or by changes in deterrence must be made on a city-by-city basis. More discussion of these empirical results is reserved for the final section of the paper.

IV. Do Arrests Follow Crime?

The previous section of this paper 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 on 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 semi-perfect, knowledge of increased police activity to deter crime.

Although 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 captured 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 and, 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), questions any significant linkage from arrests to criminal activity, especially in the short run.

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 underlying idea is that police resources are adjusted in response to increases in criminal activity (Benson et al., 1994). In this section, we use our sample of 20 cities to test the hypothesis that arrests *follow* crime. We estimate the following regression for each of the seven crimes for each of the 20 cities and for the pooled sample cities (including fixed effects):

$$\mathrm{AR}_t = \alpha + \sum_{1}^{r} \beta_r \mathrm{C}_r + \sum_{1}^{r} \delta_r \mathrm{AR}_r + \sum \tau \mathrm{S} + \varepsilon_t \qquad (2)$$

As in equation (1), the number of criminal offenses (lagged) is denoted by C_r, the number of arrests for the respective crime is denoted by AR_t, 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. 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. As in equation (1), an error-correction term was included in equation (2); variable lag length was determined by the AIC following the methodology of Burnham and Anderson (2002, p. 71), and Newey-West standard errors were used to correct for heteroskedasticity and serial correlation.

The elasticities shown in Table 9 provide evidence for the hypothesis that arrests follow crime. Unlike earlier tests of the deterrence hypothesis, which revealed relatively little statistical evidence that arrests influence crime, the effect of crime on arrests is 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 15 of the 20 cities and a positive and significant relationship from motor vehicle theft to vehicle theft arrests was found for 12 of the 20 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 residents, as well as to businesses and tourists.

Six of the seven elasticities from the pooled sample of cities are positive and statistically significant. Robbery and burglary have the largest elasticities (0.42 and 0.35, respectively), whereas rape and larceny have the lowest (0.19 and 0.02, respectively). The elasticity for assault is not statistically significant. These results, combined with the city-specific results, provide strong evidence that arrests follow crime. As in the previous crime results (see Tables 3 through 8), the results in Table 9 highlight the difference in city-specific elasticities compared with those obtained with the pooled sample of cities.

There appears to be no consistent difference in the magnitude of the crime elasticities across crimes or cities. Although many of the elasticities are less than one, some elasticities are large by conventional standards (e.g., the larceny elasticity for Phoenix is 66.7). It is important to keep in mind that the elasticities capture percentage changes in growth rates and not levels, with the former much smaller numbers than the latter. 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 reveal that the large elasticities are a result of 1) a very small average monthly arrest growth rate compared with the average monthly crime growth rate and 2) a larger sum of coefficients due to longer lag length than those variables with smaller elasticities.[15]

[Table 9]

V. Discussion and Summary

The majority of past work on the effects of economic conditions and deterrence of crime has focused 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

[15] For example, consider the difference in the larceny elasticities 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 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 7 times that of Houston: 1.18 for Phoenix and 0.174 for Houston. Thus, the large elasticity estimate for Phoenix ($66.7 = 1.18 \cdot 56.5$) relative to Houston ($0.099 = 0.174 \cdot 0.571$) is predominately the result of a much greater average monthly growth in larcenies compared with the average monthly growth in larceny arrests.

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 and rural and urban areas.

Using monthly data for 20 large U.S. cities, we determined whether short-run changes in economic conditions and 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 15 of the 20 cities and the relationship from vehicle thefts to vehicle theft arrests was statistically significant for 12 of the 20 cities in our sample.

It is reasonable to expect that, over time, an increase in all types of crime would garner an increased response from law enforcement, especially the more violent crimes of murder and rape. Several factors explain our finding 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.[16] 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; that is, 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 with 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-

[16] A classic example is New York City in the 1980s.

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 with a lower level of initial law enforcement resources allocated to combat robberies (Benson et al., 1994). Thus, cities already allocating a relatively large percentage of their resources to combat robberies may be unwilling (or unable) in the short run to allocate additional 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.[17] 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; these factors are based on the preferences of the citizenry, public officials, and law enforcement, as well as 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

[17] See Garoupa (1997) for a survey of the literature on optimal law enforcement.

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). It would be interesting to see whether temporal differences exist 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 to implement effective public policy at the local level.

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Table 1: Cities, Sample Periods, and Data Notes

City	Sample Period	Sample Size	Data Notes[a]
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	-------
Los Angeles	1983:12 to 2004:12	253	The August 1997 missing value for murders was replaced with the August 1996 value.
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	-------
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.

[a] The method used to impute missing UCR crime and arrest data for individual jurisdictions is based on Maltz (1999, p. 28).

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	--	--	--	--	--	--	--	--	--
Los Angeles	-0.006	0.106	1-2	0.039	0.152	0-1	-0.142	0.121	0-1
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	--	--	--	--	--	--	--	--	--
San Antonio	--	--	--	--	--	--	--	--	--
San Diego	--	--	--	--	--	--	--	--	--
San Francisco	--	--	--	--	--	--	--	--	--
San Jose	--	--	--	--	--	--	--	--	--
Seattle	--	--	--	--	--	--	--	--	--
Pooled Cities	-0.557	0.403	1-3	-0.340	0.284	0-1	1.148	1.217	0-1

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 murders resulting from a percentage increase in the growth rate of murder arrests, unemployment, and the real minimum wage.

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
Los Angeles	0.003	0.005	1	0.058	0.048	0	0.006	0.023	0
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
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
Pooled Cities	-0.037	0.024	1-2	0.277	0.253	1-2	-0.331	0.237	1-2

Note: Elasticities are calculated from the sum of coefficients in equation (1). + denotes significance at 10 percent, * at 5 percent, and ** at 1 percent. 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.

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
Los Angeles	0.074	0.009	1	0.146	0.131	0-1	-0.005	0.034	0-1
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
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
Pooled Cities	-0.006	0.045	1-3	-0.061	0.074	0-2	0.074	0.048	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 assault resulting from a percentage increase in the growth rate of assault arrests, unemployment, and the real minimum wage.

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
Los Angeles	-0.366	0.235	1-9	0.179	0.122	0-6	-0.003	0.029	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
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
Pooled Cities	**-0.070***	0.033	1-3	-0.034	0.113	0-1	-0.162	0.115	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 robbery resulting from a percentage increase in the growth rate of robbery arrests, unemployment, and the real minimum wage.

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
Los Angeles	**-0.029+**	0.016	1	**0.041+**	0.022	0	**-0.024****	0.009	0-1
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
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
Pooled Cities	-0.009	0.017	1-2	0.125	0.092	0-1	-0.097	0.087	0-1

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.

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
Los Angeles	-0.895	0.580	1-11	**0.125**+	0.074	0-1	-0.030	0.024	0-1
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	2.650	1-4	**-1.830****	0.683	0-4	**-3.574***	1.820	0-1
Phoenix	**-0.079****	0.028	1-2	**0.018**+	0.010	0	0.129	0.170	0-1
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
Pooled Cities	-0.175	0.112	1-4	0.185	0.228	0-2	**-0.288**+	0.156	0-1

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.

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
Los Angeles	0.022	0.027	1	**0.155****	0.050	0	-0.034	0.061	0-1
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
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
Pooled Cities	-0.002	0.024	1-3	0.123	0.091	0-1	**-0.233****	0.084	0-1

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.

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
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
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
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
Pooled Cities	**0.304****	1-4	**0.192****	1-3	0.148	1-3	**0.347****	1-3	**0.416****	1-3	**0.022***	1-2	**0.290****	1-3

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.