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Abstract

We use monthly time-series data for 20 large U.S. cities to test the deterrence hypothesis (arrests reduce crimes) and the resource reallocation hypothesis (arrests follow from an increase in crime). We find (1) weak support for the deterrence hypothesis, (2) much stronger support for the resource reallocation hypothesis, and (3) differences in city-level estimates suggest much heterogeneity in the crime and arrest relationship across regions.

Keywords: Crime, Arrests, Deterrence, City
JEL Codes: K42, R10

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1. Introduction

Many studies find that increasing deterrence reduces crime (Levitt, 1997, 1998; Cornwall and Trumbull, 1994; Lee and McCrary, 2005; Klick and Tabarrok, 2005; Evans and Owens, 2007). Decker and Kohfeld (1985) suggest, however, that while deterrence may reduce crime rates, it is more likely that arrests follow from an increase in crime as police reallocate enforcement resources to combat the increase in crime (Benson et al., 1994). A majority of these studies have used county- or state-level data in cross-sectional or panel regressions, and they implicitly assume heterogeneity in the crime and arrest relationship across regions.

In this note we use monthly time-series data for 20 large U.S. cities to explore the short-run relationship between crime rates and arrests – specifically, we test both the deterrence hypothesis (arrests reduce crimes) and the resource reallocation hypothesis (arrests follow from an increase in crime). The city-level analyses conducted here afford several advantages over previous studies. First, 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 that has plagued studies using cross-sectional or panel data. Second, Topel (1994) and Glaeser and Sacerdote (1999) have shown that crime rates vary significantly across regions, so the individual analysis of 20 cities done here provides new insight not afforded by previous studies that have used more aggregated data and implicitly assume homogeneity across regions.

2. Data and Methodology

Our city-level crime data are from the Federal Bureau of Investigation's *Uniform Crime Reports* (UCR). We obtained the monthly number of offenses and arrests for seven categories of crime: murder, rape, assault, robbery, burglary, larceny, and motor vehicle theft.[1] Data were obtained for the 20 largest U.S. cities based on 1990 population for which sufficient data were available. The sample period for the majority of cities covers the period December 1983 to December 2004 (Table 1).[2]

2.1 Methodology

To test the deterrence hypothesis and the resource reallocation hypothesis, respectively, we estimate (by OLS) equations (1) and (2) for each of the seven crime categories in each of the 20 cities, as well as a panel (unbalanced) of the 20 cities:

$$C_t = \alpha + \sum_{1}^{r} \beta_r C_{t-r} + \sum_{1}^{r} \delta_r AR_{t-r} + \varepsilon_t \tag{1}$$

$$AR_t = \alpha + \sum_{1}^{r} \beta_r C_{t-r} + \sum_{1}^{r} \delta_r AR_{t-r} + \varepsilon_t \tag{2}$$

where C_t denotes criminal offenses and AR_r denotes arrests for the respective crime. To capture short-run changes, all variables are transformed into percent changes and are included with lag length *r* based on the Akaike information criterion.[3] Monthly dummy variables are included to account for any seasonality; the unemployment rate and real minimum wage are included in (1)

[1] 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 (last accessed March 6, 2010). 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. These include underreporting by police departments and differences in the collection and reporting of criminal activity across cities.

[2] 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 and arrest statistics for certain crimes over an extended period 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 to preserve the sample for estimation purposes (Maltz, 1999, p. 28).

[3] Our empirical model closely follows that of Corman and Mocan (2000, 2005).

to control for business cycle conditions that may influence crime rates (Gould et al, 2002; Corman and Mocan, 2000, 2005); and city- and year-specific dummy variables are included in the panel regressions.[4]

The total effect of arrests in equation (1) and crime in equation (2) is determined by summing the lagged coefficients for each variable and then calculating an elasticity using the means of the respective variables.[5] 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 dependent variable. The elasticities from equation (1) should be negative to support the deterrence hypothesis, and the elasticities from equation (2) should be positive to support the resource reallocation hypothesis.

3. Empirical Results

3.1 Deterrence

Weak support for the deterrence hypothesis is found (Table 2), as most of the elasticities are not statistically significant. This supports the notion that criminals are myopic and also do not have perfect information regarding changes in deterrence (Wilson and Herrnstein, 1985; Lee and McCrary, 2005). The elasticity estimates are quite different across cities, however, thus suggesting heterogeneity in the crime and arrest relationship across cities. For the crimes of burglary and larceny, five and seven of the elasticities, respectively, are negative and significant, thus suggesting that, for those cities, increasing burglary and larceny arrests reduces the number

[4] We used Newey-West standard errors to correct for heteroskedasticity and serial correlation. Also, each empirical model includes an error-correction term to account for a long-run equilibrium relationship.

[5] 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 $\mathrm{Var}(\eta) = (\overline{X}/\overline{Y})^2 \cdot \mathrm{Var}(\Omega)$, where $\mathrm{Var}(\Omega)$ 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.

of these offenses. The responsiveness of crime to arrests appears to be less than one-to-one since most of the elasticities are less than one in absolute value.

3.2 Resource Reallocation

We find much stronger support for the resource reallocation hypothesis, as the effect of crime on arrests is positive and statistically significant for a large number of cities and crimes (Table 3). In addition, the elasticities are quite different across cities. Of the seven crime categories, an increase in less-violent crimes leads to greater arrests for these crimes, especially robbery (largest coefficients) and motor vehicle theft. A positive and significant robbery elasticity was found for 15 of the 20 cities and a positive and significant vehicle theft elasticity was found for 12 of the 20 cities. Six of the seven elasticities from the pooled sample of cities are positive and statistically significant.

4. Summary

Crime and arrest data were used to test the deterrence hypothesis and the resource reallocation hypothesis for 20 individual U.S. cities. We found weak support for the deterrence hypothesis and much stronger support for the resource reallocation hypothesis. The latter may reflect the possibility 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. Our results also reveal heterogeneity in the crime and arrest relationship across cities.

The views expressed here are those of the authors and not necessarily the views of the Federal Reserve Bank of St. Louis or the Federal Reserve System.

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Table 1: Cities and Sample Periods[a]

City	Sample Period	Sample Size	City	Sample Period	Sample Size
Baltimore	1983:12 to 1998:12	181	Memphis	1985:1 to 2004:12	240
Boston	1989:5 to 2004:12	188	Milwaukee	1983:12 to 2004:12	253
Cleveland	1983:12 to 1998:9	178	New Orleans	1983:12 to 2004:12	253
Columbus	1983:12 to 2002:12	229	Philadelphia	1983:12 to 2004:12	253
Dallas	1983:12 to 2004:12	253	Phoenix	1983:12 to 2004:11	252
Detroit	1983:12 to 2004:12	253	San Antonio	1983:12 to 2004:12	253
El Paso	1983:12 to 2004:12	253	San Diego	1983:12 to 2004:12	253
Houston	1983:12 to 2004:12	253	San Francisco	1983:12 to 2004:12	253
Indianapolis	1996:1 to 2004:12	108	San Jose	1983:12 to 2001:8	213
Los Angeles	1983:12 to 2004:12	253	Seattle	1983:12 to 1997:12	169

[a] The August 1997 missing value for murders was replaced with the August 1996 value for Baltimore, Dallas, Detroit, Houston, Los Angeles, Milwaukee, New Orleans, and Philadelphia. For Columbus, 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. For Milwaukee, the March 1986 missing values for all arrests were replaced with March 1985 values; the July 2002 missing value for rape was replaced with the July 2001 value. For Philadelphia, the November 1988 missing values for arrests for all crimes were replaced with the November 1987 values. For Seattle, 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).

Table 2: Testing the Deterrence Hypothesis - Results[a]

Dependent Variable: **P**ercentage Change in the Number of Crimes

City	Murder		Rape		Assault		Robbery		Burglary		Larceny		Vehicle Theft	
	Arrest Elasticity	Lags	Arrest Elasticity	Lags	Arrest Elasticity	Lags	Arrest Elasticity	Lags	Arrest Elasticity	Lags	Arrest Elasticity	Lags	Arrest Elasticity	Lags
Baltimore	0.199	1-2	0.543	1-2	-0.017	1	0.001	1	0.040	1	-0.070**	1-2	-0.060	1
Boston	--	--	0.002	1	0.000	1	-0.004	1	-0.039	1	-0.038	1-2	-0.035	1-4
Cleveland	--	--	-1.577	1-7	-0.214	1	-0.446	1-6	-0.013	1	0.435	1	-0.018	1
Columbus	--	--	-0.040	1	0.004	1-3	-0.170	1-3	0.395	1-10	-0.038	1-8	-0.006	1-3
Dallas	-0.039	1-3	0.010	1	0.766*	1-11	-0.113**	1	-0.229^{+}	1	-0.497**	1-2	-0.012	1
Detroit	-0.267	1	--	--	0.994*	1-5	0.017	1	0.007	1-3	0.799*	1-6	-0.177**	1-4
El Paso	--	--	0.002	1	0.0921	1	-0.762**	1-6	-0.005	1-3	-0.116^{+}	1-3	-0.018	1
Houston	-0.449	1-4	0.643	1	-0.050	1	-0.041	1	-0.185*	1-2	0.006	1-3	-0.340**	1-3
Indianapolis	--	--	-0.167	1	0.422	1-3	-0.171	1	0.203	1-8	0.557	1-11	-0.082	1-11
Los Angeles	-0.006	1-2	0.003	1	0.074	1	-0.366	1-9	-0.029^{+}	1	-0.895	1-11	0.022	1
Memphis	--	--	0.002	1-9	-0.368^{+}	1-9	-0.026	1	-0.008	1	-0.129**	1	-0.039^{+}	1
Milwaukee	0.002	1	-0.085	1	0.364	1-2	-0.020	1-2	0.005	1	-2.645**	1	0.078	1
New Orleans	-5.502**	1-7	-0.018	1-2	-0.017	1	-0.041*	1-2	-0.034	1-3	-0.012	1	-0.131	1
Philadelphia	0.006	1	-0.006	1	0.004	1	-0.379*	1	-0.030	1	2.273	1-4	-0.038	1-9
Phoenix	--	--	0.055	1-5	-0.138	1	0.004	1-2	-0.432**	1-3	-0.079**	1-2	0.043*	1
San Antonio	--	--	--	--	-0.005	1	0.048	1-2	0.006	1-6	0.015	1	-0.000	1
San Diego	--	--	0.192	1	0.026	1	-0.011	1-7	-0.011	1	0.759	1-8	1.148	1-13
San Francisco	--	--	--	--	-0.871*	1-4	0.003	1	-0.039^{+}	1	-0.007	1	0.035	1
San Jose	--	--	-0.061	1-2	-0.161*	1-2	0.010	1-2	0.003	1-4	-0.245*	1-4	-0.175	1
Seattle	--	--	0.022	1-2	0.014	1	-0.063	1	-0.026	1	0.066	1	0.046	1
Pooled Cities	-0.557	1-3	-0.037	1-2	-0.006	1-3	-0.070*	1-3	-0.009	1-2	-0.175	1-4	-0.002	1-3

[a] The elasticities are calculated from the sum of the arrest coefficients in equation (1). + denotes significance at 10 percent, * at 5 percent, and ** at 1 percent.

Table 3: Testing the Resource Reallocation Hypothesis - Results[a]

Dependent Variable: **P**ercentage Change in the Number of Arrests

City	Murder		Rape		Assault		Robbery		Burglary		Larceny		Vehicle Theft	
	Crime Elasticity	Lags	Crime Elasticity	Lags	Crime Elasticity	Lags	Crime Elasticity	Lags	Crime Elasticity	Lags	Crime Elasticity	Lags	Crime 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

[a] The elasticities are calculated from the sum of the crime coefficients in equation (2). + denotes significance at 10 percent, * at 5 percent, and ** at 1 percent.