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ESTIMATE THE EFFECT OF POLICE ON CRIME USING ELECTORAL DATA AND UPDATED DATA

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ABSTRACT

It is surprisingly difficult to isolate causal effects of police on crime empirically due to the simultaneous determination of crime and police presence. Instruments are used to address the simultaneity concerns in the previous crime literature. The 2SLS results provide evidence indicating that additional police reduce crime. However, we might suspect whether the same instruments can generate consistent results with previous studies by using datasets of more recent years instead of thirty years ago and considering the change of policies, crime situation, and other factors. This paper use electoral cycles as instrumental variable and updated data of the 1985-2010 period trying to explore the correlation between police and crime using electoral cycles as instruments in different situation. Results show that there are positive elasticities of violent crimes with respect to police as well as negative elasticities for property crimes. Overall, we cannot conclude with strong evidence that increased police reduce crime using electoral cycles as instruments.

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CHAPTER ONE

INTRODUCTION

The inherent nature of crime leads to substantial economic loss and threat to society and individuals. Crime reduction and prevention is always a top priority of the legislative, executive and judicial branches. While in the crime literature, an important challenge is to identify the causal effect of police presence on crime. Based on Gary Becker's (1968) theory, which looks at criminals as rational individuals seeking to maximize their own well-being through illegal ways, immense amounts of research are done by economists in an attempt to explain how deterrence works within the criminal justice system. One of the predictions of Becker's theory is that crime rates will decrease when police presence increases. However, the greatest challenge is to find empirical evidence supporting this prediction. In the studies of the crime literature, Samuel Cameron (1988) reports that among the 22 papers attempting to identify a causal effect of police on crime, only 18 found either no effect or a positive effect of police presence on crime.

The challenge in estimating the effect of police on crime is the endogeneity existed in the simultaneous determination of crime and police presence (Franklin Fisher and Daniel Nagin, 1978). Government in a city with high crime rates is likely to respond to crime problems by enlarging police force. Therefore, a positive correlation between police and crime can emerge. To break this endogeneity, several approaches are used in order to isolate causal effects of police on crime.

To address this problem, Levitt (1997) creates a strategy using electoral cycles as instrumental variables which affect the size of the police force, but is uncorrelated with crime. He employs the timing of gubernatorial and mayoral elections as instruments for police presence in panel data of 59 large U.S. cities from 1970-1992. By applying two-state least-squares (2SLS) techniques, Levitt uncovers a negative and significant effect of police on violent crimes and relatively weak impact on property crimes, while the point estimates generally are not statistically significant for individual crime categories. As times change, the crime situation in recent years is not similar to that of 1970s and ‘80s period. In the legislation aspect, legalized abortion may cause the drop in crime (Donohue and Levitt 2001). Also, the U.S. prison population grew by over half a million during the 1990s and continued to grow slowly. This increase in the size of the prison population could be another factor explaining the drop in crime. The overall crime trend is different from that of Levitt’s finding. So the conclusion generated by using the obsolete database of 1970-1992 in Levitt’s paper may not be convincing applied to today’s crime situation. In this paper, I will adopt an updated data set from 1985-2010 from the same 59 large U.S. cities are used in Levitt’s paper to test whether his method is applicable for the circumstance after the 1990s and explore the applicability of the instrument and estimate the correlation between police presence and crime rates.

CHAPTER TWO

LITERATURE REVIEW

Marvell and Moody (1996) employ the Granger causality test and analyze UCR crime rates and yearly police data at the state and city levels over two decades. They find Granger-causation in both directions and the impact of police on most crime types is substantial and robust at the city level. Tella and Schargrodsky (2004) find a large local deterrent effect of observable police on crime using data on the location of car thefts prior and post a terrorist attack on the main Jewish center in the city of Buenos Aires, Argentina. All Jewish and Muslim institutions received police protection in July 1994. Therefore, a geographical distribution of police forces, which can be presumed exogenous in a crime regression, was generated by this terrorist attack. This event constitutes a natural experiment, which broke the simultaneous determination of crime rates and police presence. Blocks that receive police protection suffer 0.081 fewer car thefts per month compared to blocks that do not. Police protection induces a decrease in auto theft of approximately 75 percent. However, blocks one or two blocks away from where protection is provided do not experience fewer auto thefts compared to the rest of the neighborhoods. Their results suggest a posted police guard generates a negative local effect on auto theft while generating little or no effect outside a narrow area. Nevertheless, the limitation of this approach restricts precise estimation of the extent of crime displacement to other areas.

Levitt (1997) developed an approach using instrumental variables to break the simultaneity between police and crime. He finds that police presence increases in mayoral and gubernatorial election years but not in off-election years. In order to identify the effect of police on crime, he documents a previously unrecognized electoral cycle in police force staffing and uses the timing of mayoral and gubernatorial elections as an instrument for police presence. Data of a panel of 59 large U.S. cities over the period 1970-1992 are collected. It demonstrates that there is a positive cross-city correlation between police and crime, the same as which is presented in previous studies. After applying first differences which identify the parameters using only within-city variation over time, a negative coefficient on police emerges. Adopting the two-stage least-square (2SLS) method, Levitt finds a more negative and significant effect of police on crime. Point estimate for violent crime with respect to police is about -0.1, and for property crime it is approximately -0.3. By using instrumental variables, the individual point estimates for each of the seven crime categories are negative in almost all cases, even though they are extremely imprecise. It is surprising that the result demonstrates murder exhibiting the largest and only significant coefficient. In the meantime, relatively large negative influences of police on crime are observed for robbery, aggravated assault, and motor vehicle theft. The reliability of electoral cycles serving as the instrumental variables might be questioned.

Klick and Tabarrok (2005) claim another research design to estimate the causal effect of police on crime using terror alert levels. The Office of Homeland Security began to use the Homeland Security Advisory System (HSAS) in order to notify the public and other government agencies of the risk of terrorist attacks on March 11, 2002. They use police presence increases on the streets of Washington, D.C. during high-alert periods which could be used to break the endogeneity to estimate the effect of police presence on crime. Their method is most closely related to the one adopted by Tella and Schargrodsky (2004). Both of them take advantage of presumed exogenous shocks to police force and the impact of these shocks across time and space. The difference between the two is that the attack in July 1994 Tella and Schargrodsky (2004) observed is one precipitating event, while what Klick and Tabarrok (2005) used is a repeated event with the terror alert level rose and fell four times in their sampling period. Instead of annual data, daily data focusing on a single city are collected in order to be less subject to endogeneity problems and reduce omitted-variable bias in the cross-sectional component. The results demonstrate that an increase in police presence of 50 percent leads to a statistically and economically significant decline of 15 percent in the level of crime. The decrease in the street crimes of auto theft and theft from automobiles contributes to the largest decline in crime with an elasticity of police on crime of -0.86. This result is proved to not be an artifact of changing tourism patterns resulting from the changes in the terror alert level. Even though his research provides a plausible estimate of the causal effect of police on crime, further research is needed to determine whether this effect can be generated to other cities or is particular to the Washington, D.C., area.

In previous studies, researchers have used financial variables as instruments for the police number or expenditure on police. Cornwell and Trumbull (1994) used per capita tax revenue in North Carolina as an instrumental variable for police numbers arguing that countries with greater preference for law enforcement would vote for higher taxes to fund a larger police force. In order to eliminate the problem of simultaneity between police presence and crime, Lin (2009) explores the pattern of the financial relations existing between state and local government, demonstrating that variations in state tax rates can be a valid instrumental variable for a local police force. He argues that state government revenues generated by state sales tax rates can be channeled by state transfers to local governments, therefore increasing the number of local police. Lin (2009) presents that fund transfers from the state governments to the local governments account for around 33.5% of the total local government revenues, while property tax accounts for 29.3%. At the state level, sales tax account for 28% of total state revenues. Other tax categories such as individual income tax and corporate income tax account for a much smaller proportion of overall state revenues relatively. Hence transfers from state to local government will generate a sufficient variation with the sales tax rate being the most identifiable source. According to the typical local government budget pattern, two thirds of the general funds are discretionary and three quarters of the discretionary funds available to city council are assigned to police and fire services (Coleman, 1997). Therefore, change in local government revenue from the state will have a high impact on police budgets and number of police presence. The results under the 2SLS method demonstrate the existence of a negative and significant police presence effect on crime, with the elasticity being about -1.1 for violent crime, and -0.9 for property crime.

According to Levitt's (1997) research, conclusion were made by analyzing relatively old data over the period 1970-1992 and using mayor and gubernatorial election timing as instruments for police. Due to the crime situation change and the imprecision of the point estimates, I will use the same instrument and method and update the data set of a more recent period to test whether the electoral cycle can also be an instrument to generate consistent results and to identify the causal effect of police on crime in an up-to-date condition.

CHAPTER THREE

DATA

The data used in this paper are comprised of observations on a panel of 59 U.S. large cities covering the period from 1985-2010. Cities selected are limited to two criteria: the city population exceeds 250,000 at some point in the 1985-2010 period, and the mayor is directly elected. Annually data of seven crime categories on city level including murder, rape, assault and robbery (referred to as ‘violent crimes’) and burglary, larceny and motor vehicle theft (referred to as ‘property crimes’) are obtained from the Uniform Crime Report (UCR) issued by the Federal Bureau of Investigation (FBI). As the summary statistics in Table 1 shows, for every 100,000 residents, violent crime rates for the cities in the sample are more than twice as high for the nation as a whole, while for property crime rates it is almost twice. Numbers of sworn officers who carry a gun and have the power of arrest are also obtained from the UCR, with approximately 261 per 100,000 people. Data on police (sworn officers), and population are also obtained from UCR issued by the FBI.

Since the timing of elections may influence the crime by many channels other than the police presence, a number of demographic, government spending, and economic variables are collected to avoid some of these concerns. All of these data are available in the Statistical Abstract of the United States. To control for economic fluctuations, annual unemployment rates in the state level are collected. It would be more precise to estimate the effect by collecting all variable at the city level annually. However, some variables such as percentage of population between 18 and 24 ages, percentage of a city’s

Table 1

Summary Statistics

Variable	Mean	S.D. across cities	S.D. within-city	Min	Max
Population	778623	1084540	69136	199110	8400907
Violent	1286	690	337	220	4353
Murder	17	13	5	1	95
Rape	64	31	19	10	199
Robbery	524	342	163	73	2304
Assault	693	386	199	66	2368
Property	7068	2434	1691	1574	16739
Burglary	1647	751	544	219	4994
Larceny	4244	1518	957	0	10003
Motor vehicle theft	1176	668	417	126	5369
Sworn officer	259	106	22	112	781
State unemployment rate	6.0	1.8	1.6	2.3	13.4
Percent ages (18-24)	11.6	1.8	0.5	7.7	19.4
Percent black	25.4	19.4	1.9	0.7	82.7
Percent female-headed households	16.3	4.7	0.8	7.3	31.6
Public welfare spending per capita (1985 dollars)	486.8	199.4	151.2	136.8	1245.7
Education spending per capita (1985 dollars)	714.7	170.4	122.0	411.2	1377.5

Note: all variables are per 100,000 residents except population. Data used is a set of 59 U.S. large cities with directly elected mayors over 1985-2010. Data of crime, sworn officer, and population are from UCR issued by the FBI. All other data is obtained from the Statistical Abstract of the United States. Percentage of black, ages 18-24, and female-headed households are interpolated from data for decennial census years.

population that is black, and percentage of the population living in female-headed households are linearly interpolated for noncensus years due to the limitation of decennial census. Data on government spending for public welfare and education are combined state and local outlays per capita (in 1985 dollars) in a given state and year on the particular category instead of city level. This is because less than 10% of total state and local expenditures on those categories originate at the city level even though annual city government outlays on these programs are available. While according to the cities that receive the fund, state outlays are not broken down (Levitt, 1997).

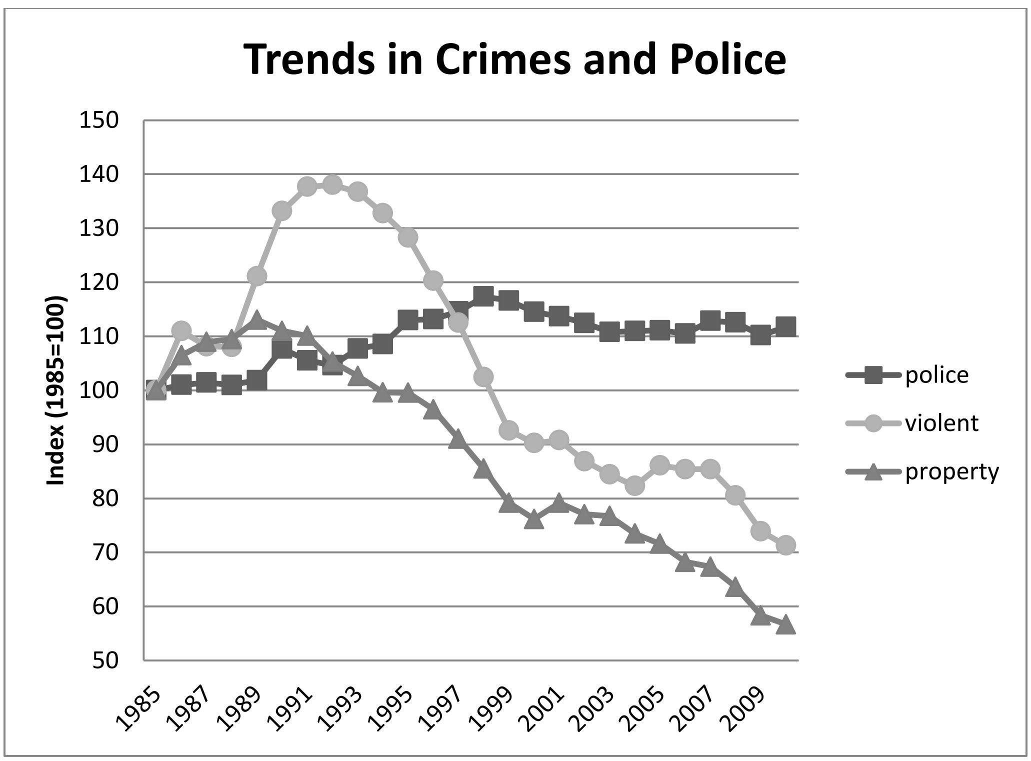

Figure 1: Trends in Crimes and Police

Figure 1 generally shows the trend of police, violent crime, and property crime (in per capita terms) over the period of 1985-2010 for the cities in the sample. Values of 1985 of each category are indexed as 100. All three categories start to rise from 1985. While on the overall trend, violent crime and property crime began to decline and tracked each other closely from the beginning of 1990s. Until 2010, violent crime decreased by 30% and property decreased almost by half. The police number grows slowly through the years overall.

I also include year dummies and nine region dummies corresponding to the census definitions in the model. In addition, four city size indicators which are consistent with populations below 250,000, between 250,000 and 500,000, between 500,000 and 1,000,000, and over 1,000,000 are generated as controls.

CHAPTER FOUR

MODEL AND SPECIFICATIONS

According to Levitt (1997), Americans ranked crime at or near the top of their list of urgent issues in opinion surveys. A city's economic performance is outside the control of the mayor's responsibility while police staffing is a desired area for political manipulation since most police departments are operated by a unit of the local government. Every politician was expected to have a crime-fighting agenda. Incumbents will try to increase police force in advance of elections considering the significance of crime as a critical political issue and stating their governance of crime. Unlike the city government, state government does not directly organize local police departments. While state governments provide substantial local aid and more limited amount of intergovernmental grants to city government and local law enforcement typically, there is still incentive for incumbent governors to increase police force in election years. Table 2 shows the mean percentage change in the police number per capita with respect to the election and nonelection years. Empirically, sworn officers' number rises by approximately 1.08 percent in mayoral election years and 1.97 percent in gubernatorial election years, while staying relatively flat (even decrease) in nonelection years. This is only a very simple comparison of the average percentage change in the sworn officers' number per capita across election and nonelection years.

Table 2

Sworn Officers Change in Election Cycle

	(1) Δln sworn officers per capita
Mayoral election years	0.0108
	(1.49)
Gubernatorial election years	0.0197^{***}
	(3.35)
No election years	-0.00712
	(-1.59)
N	1508

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The formal model is generated taking account of other factors that may affect the growth of police force.

$$\Delta \ln P_{it} = \beta_1 M_{it} + \beta_2 G_{it} + \eta X_{it} + \lambda_i + \gamma_t + \varepsilon_{it} \qquad (1)$$

Pit is the number of sworn officer per capita for city i in year t; M is the indicator variable which is one in mayor election years and zero otherwise; G is the indicator variable which is one in gubernatorial election years and zero otherwise; X is a matrix of covariates including the percent of age 18-24, percent of black, percent of female-headed households, state unemployment rate, public welfare spending per capita, and education spending per capita; city size indicator, year and region dummies. All variables except the indicator variables are log differenced.

Table 3

Predict the Change of Police Force Using the Election Cycle

	(1) Δln sworn officer	(2) Δln sworn officer	(3) Δln sworn officer
Mayoral election year	0.0101**	0.0115**	0.0126**
	(0.00382)	(0.00389)	(0.00399)
Gubernatorial election year	0.0155**	0.0170**	0.0168**
	(0.00596)	(0.00625)	(0.00632)
ΔState unemployment rate		-0.176	-0.188
		(0.331)	(0.337)
ΔPercent ages (18-24)		-0.188	-1.855
		(1.929)	(2.432)
ΔPercent black		0.425	1.150
		(0.756)	(1.169)
ΔPercent female-headed households		0.436	0.237
		(1.814)	(2.918)
Δln Public welfare spending per capita		0.0265	0.0262
		(0.0149)	(0.0151)
Δln education spending per capita		-0.0152	-0.0153
		(0.0292)	(0.0297)
Year indicators?	Yes	Yes	Yes
City size indicators?	No	Yes	Yes
City-fixed effects?	No	No	Yes
Region indicators?	Yes	Yes	No
N	1451	1371	1371
R^2	0.067	0.078	0.096

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Dependent variable in all columns is Δln sworn officers per capita. Year dummies included in all regressions.Three city-size indicators are included in column (2). City –fixed effects are included in column (3).

Table 3 exhibits the estimates for variations in the equation (1). Column (1) contains only year and region dummies, and then city-size indicators are added to column (2). To explore the trend of police presence in city level, region dummies are replaced with city fixed effects in column (3). The results demonstrate that sworn officers per capita grow more than one percent in mayoral election years, and even higher (1.55%, 1.7%, 1.68% in three columns, respectively) in gubernatorial election years. All of the coefficients of election years are jointly significant and consistent with Levitt's results which indicate a greater than 1 percent increase in sworn officer per capita in mayoral election years and greater than 2 percent increase in gubernatorial election years. On the contrary, the other variables in the regression are statistically insignificant.

When applying the electoral cycles as instruments, the impact of police presence on crime is estimated using two-stage least squares (2SLS) as the following:

$$\Delta \ln C_{ijt} = \beta_{1j}\Delta \ln P_{ijt} + \beta_{2j}\,\Delta \ln P_{ijt-1} + \eta_j X_{it} + \lambda_i + \gamma_{tj} + \varepsilon_{ijt} \quad , \qquad (2)$$

where C_{ijt} is the crime rate per capita in city i for crime category j in year t; P is the number of sworn officers as the endogenous variable; X is the same matrix of covariates, which is described above. Since crime may be reduced by police through deterrence which potentially prevent initial crime commission by increasing the probability of being caught, or through incapacitation which arrest repeat offenders to prevent committing future crimes, an arrest today may have an impact on the crime in the future. With such consideration, the deterrence impact will not be immediate. Also, the incapacitation effect will be revealed after the offenders are sent to prison if lags in police exist. Therefore, lags in the police force will be included in the regression. The elasticities for all crime with respect to sworn officers are the sum of the coefficients for the contemporaneous and once-lagged values. The reason to include controls for public welfare spending per capita and education spending per capita is to avoid the situation that those variables may be correlated to crime by changing the opportunities sets of potential criminals, and affected by electoral cycles (Levitt 1997). Otherwise, the electoral cycle might be an invalid instrument. Unemployment rates in the state level are also included to control for the economic fluctuations.

In addition, as election timing variables are fairly weak instruments for isolating the causal effect of police on crime, we could develop variation in the size of electoral effects on police so that more efficient estimation can be generated by expanding the sets of instruments to interactions between election years and city size or region indicators.

CHAPTER FIVE

RESULTS

Table 4 presents the OLS estimates of the violent crime with respect to sworn officers. Instead of simply summing up the total number of crimes across categories, four violent crime categories (murder, rape, robbery, and assault) are stacked together and estimated jointly. This will provide more effective means of involving the information included in the time series of individual crime categories since some crimes are much more frequent than others but much less sever. Column (1) shows the OLS estimates of equation (2) in log-levels. After summing up the contemporaneous and once-lagged values, a positive coefficient of 0.312 with 0.119 standard errors is obtained meaning that rising police presence will induce higher crime rates. Column (2) presents the OLS estimates of equation (2) in log-levels with all data first differenced. By doing so, all of the parameters are identified using only within-city variation over time. The result shows that the coefficient on sworn officers becomes smaller but still positive which is around 0.218. Compared to column (1) results, which estimate using cross-city variation, it indicates that the unobserved heterogeneity across cities impose an upward bias on the coefficient. The other coefficients are generally statistically insignificant and carry an unexpected sign after the data differencing.

Table 4

OLS Estimates of Violent Crime with Respect to Sworn Officer

	(1) ln violent	(2) Δln violent
ln sworn officer	0.381**	0.252**
	(0.119)	(0.0770)
Lag ln sworn officer	-0.0688	-0.0345
	(0.119)	(0.0504)
Sum of ln sworn officer	0.312	0.218
	（0.037）	（0.070）
State unemployment rate	3.543***	0.622
	(0.719)	(0.579)
Percent ages 18-24	-0.0470	4.663
	(0.417)	(3.793)
Percent black	1.690***	0.966
	(0.101)	(1.218)
Percent female-headed household	-0.846**	-0.00156
	(0.312)	(2.968)
ln public welfare spending per capita	0.0473	-0.00407
	(0.0302)	(0.0190)
ln education spending per capita	-0.192***	0.0397
	(0.0456)	(0.0454)
N	5411	5107
R^2	0.931	0.081
Data differenced?	No	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: dependent variable in column (1) is ln one of the four crime categories (murder, rape, robbery, and assault) in log-levels, rather than log-differences. In column (2), dependent variable and right-hand-variables are all differenced. Estimates are obtained estimating all violent crime categories jointly, allowing for a city-fixed effect across crime rates and heteroskedasticity across crime categories. Crime specific year dummies, region dummies and city-size indicators are included in all regressions.

By applying the 2SLS method to the equation (2), column (1) in table 5 shows that the pooled estimates of the effect of police on violent crime is around 2.531, implying that violent crime per capita raises by 25.31 percent, which is associated with 10 percent increase in police per capita. The 2SLS estimates for police is statistically significant at the 0.01 level substantially larger in magnitude than their OLS counterparts. The coefficients of other variables are insignificant, except state unemployment rate and public welfare spending per capita being statistically significant at the 0.05 level. It implies that 1 percent increase in the unemployment rate leads to 1.52 percent increase in violent crime per capita. Based on the regression that uses election cycles as instruments, public welfare spending per capita shows a negative coefficient and significance at the 0.05 level. Column (2) expands the set of instruments by interacting two election variables with four city size indicators and column (3) uses two election variables interacted with nine census-region indicators as instruments. This exploits variation in the size of the electoral impacts on police since electoral cycles only account for a small proportion of the overall variation in police presence. After the interactions between election and city size indicators are replaced as instruments in column (2), the coefficient of police still remain positive but shrinks to approximately 0.886 and becomes insignificant. Column (3) employs the interaction between election timing and nine region dummies as instruments, leading to a slightly higher coefficient of approximately 0.909. However, those results and coefficients of all other variables in column (2) and (3) become insignificant.

Table 5

2SLS Estimates of Violent Crime with Respect to Sworn Officer

	(1) Δlnviolent	(2) Δlnviolent	(3) Δlnviolent
ln sworn officer	1.135**	0.517	0.436
	(0.437)	(0.346)	(0.260)
Lag ln sworn officer	1.396**	0.369	0.473
	(0.481)	(0.322)	(0.274)
Sum of ln sworn officer	2.532	0.886	0.909
	（0.784）	（0.526）	（0.449）
State unemployment rate	1.520*	0.884	0.866
	(0.702)	(0.629)	(0.599)
Percent ages 18-24	4.326	4.575	4.485
	(3.779)	(3.724)	(3.718)
Percent black	0.674	0.884	0.865
	(1.361)	(1.233)	(1.235)
Percent female-headed household	0.306	0.0758	0.185
	(3.461)	(3.062)	(3.073)
ln public welfare spending per capita	-0.0672*	-0.0223	-0.0231
	(0.0316)	(0.0240)	(0.0231)
ln education spending per capita	0.0916	0.0546	0.0558
	(0.0530)	(0.0462)	(0.0456)
N	5107	5107	5107
R^2	.	0.063	0.056
Instruments:	Elections	Election* city-size interactions	Election*region interactions

Note: Dependent variable is Δln crime rate per capita for one of the four crime categories (murder, rape, robbery, and assault). Right-hand-variables are all first differenced. Estimates are obtained estimating all violent crime categories jointly, allowing for a city-fixed effect across crime rates and heteroskedasticity across crime categories. Crime specific year dummies, region dummies and city-size indicators are included in all regressions. Column (1) instruments using mayoral and gubernatorial election-year indicators. Column (2) instruments using interactions between the city-size indicators and election years. Column (3) instruments using interactions between the region dummies and election years. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Other than the estimates of elasticity of violent crimes with respect to police, Table 6 and 7 provide the OLS and 2SLS estimates of equation (2) for property crime, respectively. The results present a different pattern of coefficients from the case for violent crime. OLS estimates in column (1) of Table 6 find a positive coefficient on police (an elasticity of 0.155) when using cross-city variation and slightly larger (an elasticity of 0.181) after data is differenced in column (2). Unexpectedly, by employing election timing as instruments, 2SLS yields a negative insignificant estimate for property crime (an elasticity of -0.420) in Table 7. As the number of instruments increase, coefficients in column (2) and (3) shrink to -0.079 and -0.017, respectively.

The coefficient change from OLS estimates to 2SLS estimates for violent and property crimes are both substantial (go from 0.218 to 2.531 for violent crime and from 0.181 to -0.420) suggesting that instrumenting does have a large impact on the parameter estimates for the crime. The elasticities of both violent and property crimes with respect to the state unemployment rate indicate a positive effect of the unemployment rate on the crimes. A one percentage point increase in the state unemployment rate induces to roughly one percent increase in violent crime and over 0.3 percent increase in property crime, even though these estimates are never statistically significant. Similarly, the percentage of population between age 18 and 24 has positive signs when estimated in log-levels and log differenced. A one percentage point increase of population of ages 18 to 24 induce approximately 4.4 percent increase in violent crimes and approximately 3.6 percent increase in property crimes. But all coefficients of these variables are never statistically significant.

Table 6

OLS Estimates of Property Crime with Respect to Sworn Officer

	(1) lnproperty	(1) dlnproperty
ln sworn officer	0.258*	0.224**
	(0.112)	(0.0723)
Lag ln sworn officer	-0.103	-0.0429
	(0.112)	(0.0374)
Sum of ln sworn officer	0.155	0.182
	（0.035）	（0.054）
State unemployment rate	2.482***	0.616
	(0.704)	(0.452)
Percent ages 18-24	2.133***	3.673
	(0.427)	(2.640)
Percent black	0.896***	0.650
	(0.0935)	(0.900)
Percent female-headed household	-0.594	0.484
	(0.324)	(2.303)
ln public welfare spending per capita	-0.199***	-0.00581
	(0.0328)	(0.0160)
ln education spending per capita	-0.0905*	0.0165
	(0.0413)	(0.0327)
N	4073	3845
R^2	0.756	0.121

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: dependent variable in column (1) is ln one of the three crime categories (burglary, larceny, motor vehicle theft) in log-levels, rather than log-differences. In column (2), dependent variable and right-hand-variables are all differenced. Estimates are obtained estimating all property crime categories jointly, allowing for a city-fixed effect across crime rates and heteroskedasticity across crime categories. Crime specific year dummies, region dummies and city-size indicators are included in all regressions.

Table 7

2SLS Estimates of Property Crime with Respect to Sworn Officer

	(1) Δlnproperty	(2) Δlnproperty	(3) Δlnproperty
ln sworn officer	-0.164	0.117	0.0493
	(0.334)	(0.328)	(0.195)
Lag ln sworn officer	-0.256	-0.196	-0.0324
	(0.351)	(0.261)	(0.208)
Sum of ln sworn officer	-0.420	-0.079	0.0169
	（0.601）	（0.479）	（0.332）
State unemployment rate	0.329	0.511	0.516
	(0.522)	(0.508)	(0.467)
Percent ages 18-24	3.612	3.703	3.591
	(2.684)	(2.655)	(2.641)
Percent black	0.690	0.679	0.649
	(0.910)	(0.898)	(0.897)
Percent female-headed household	0.572	0.450	0.589
	(2.375)	(2.335)	(2.338)
ln public welfare spending per capita	0.0102	0.00134	-0.00162
	(0.0228)	(0.0205)	(0.0182)
ln education spending per capita	0.00412	0.0108	0.0135
	(0.0354)	(0.0344)	(0.0328)
N	3845	3845	3845
R^2	0.088	0.115	0.114
Instruments:	Elections	Election* city-size interactions	Election*region interactions

Note: Dependent variable is Δln crime rate per capita for one of the three crime categories (burglary, larceny, motor vehicle theft). Right-hand-variables are all first differenced. Estimates are obtained estimating all property crime categories jointly, allowing for a city-fixed effect across crime rates and heteroskedasticity across crime categories. Crime specific year dummies, region dummies and city-size indicators are included in all regressions. Column (1) instruments using mayoral and gubernatorial election-year indicators. Column (2) instruments using interactions between the city-size indicators and election years. Column (3) instruments using interactions between the region dummies and election years. S.D. in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8 presents the estimates of seven specific crime categories eliminating all cross-crime restrictions. The seven columns correspond to the seven crime categories and each row presents a different specification. Only the sum of the contemporaneous coefficients and once-lagged values of sworn officers in each case are displayed. OLS in log levels yields positive coefficients on sworn officers in six of seven categories except rape. After first differences, only the murder presents negative coefficients leaving all others positive. Instrumenting for sworn officers leads to more positive to all violent crimes and more negative to all property crimes in spite of the extreme imprecision of the individual point estimates. Except for murder and larceny, expanding the set of instruments generally induces the coefficients to shrink. Unlike Levitt's (1997) results, in which murder yields the greatest apparent negative effect of police, larger positive impacts of police are observed for rape, robbery, and aggravated assault.

Table 8

Crime-Specific Estimates of the Effect of Changes in Sworn Officers

	OLS (levels)	OLS (differences)	2SLS(electi-onas instruments)	2SLS(electi-on*city-size interactions as instruments)	2SLS(elec-tion *region interactions as instruments)
murder	0.466	-0.104	1.405	-0.943	0.612
	(0.070)	(0.232)	(1.958)	(1.530)	(1.227)
Rape	-0.308	0.414	2.918	1.407	0.507
	(0.066)	(0.190)	(1.592)	(0.945)	(0.830)
Robbery	0.758	0.140	2.972	1.204	1.097
	(0.066)	(0.180)	(1.246)	(0.753)	(0.623)
Assault	0.262	0.418	2.755	1.826	1.360
	(0.063)	(0.196)	(1.340)	(0.903)	(0.795)
Burglary	0.037	0.219	-0.015	0.709	-0.334
	(0.046)	(0.147)	(0.873)	(0.665)	(0.511)
Larceny	0.175	0.279	-0.092	0.024	0.669
	(0.044)	(0.163)	(0.829)	(0.728)	(0.469)
Motor vehicle theft	0.253	0.043	-1.149	-0.984	-0.298
	(0.063)	(0.171)	(1.258)	(0.986)	(0.676)

Note: Dependent variable is Δln crime per capita for the named crime category, except in first row where log-levels, instead of log-differences, are used. Right-hand-variables also are differenced except in first row. The cross-crime restrictions on police elasticities are removed. Each row of the table presents crime-specific coefficients on the police from a separate regression. All coefficients are the sum of contemporaneous and once-lagged coefficients. Estimates are obtained estimating all property crime categories jointly, allowing for a city-fixed effect across crime rates and heteroskedasticity across crime categories. Crime specific year dummies, region dummies and city-size indicators are included in all regressions. All separate regressions are done corresponding to each column of Table 4-7, respectively. S.D. in parenthes.

The results in the Appendix B shows that F test on the excluded instruments are all above 10 for violent crime estimates, while are less than 10 for property crime estimates. Based on this, we cannot conclude that electoral cycles are strong instruments for all crime categories. In order to explain the difference between my results and Levitt's (1997), the 2SLS estimates of crimes with respect to sworn officers are replicated using the overlapping research years between Levitt's (1997) data and mine. Results in the Appendix C displays the 2SLS estimates of the violent crime and property crime with respect to sworn officers for the research years overlapping with Levitt's (researched year 1985-1992 in sample), respectively. The coefficient on sworn officer is -0.550 for violent crime and -0.728 for property crime. After expanding the instrument sets, the coefficient become positive. The bias source might be the imprecision of 2SLS estimate, insufficient observation years or some other factors. However, for both pooled crime categories with election years as instruments, police do have a negative effect on crime. This indication is consistent with Levitt's (1997) research results and shows that the changing sign of the coefficient estimated using the whole period of 1985-2010 might be resulted from new dataset.

CHAPTER SIX

CONCLUSION

Based on Levitt's innovation of using electoral cycles as instruments for police, this paper use an updated dataset which covers the 1985-2010 period. The estimates in this paper preclude a strong conclusion that electoral cycles can be used in a later period to demonstrate the reducing crime effect of increasing police force. The elasticities of crime with respect to sworn officer are mostly positive instead of negative results generated by using the period of 1970-1992 in Levitt's paper. Since election cycles explain only a small fraction of the overall variation in police, the instrumental variables' estimates are imprecise.

Comparing the two different data periods, we can conclude that the basic trend for violent and property crime in the 1985-2010 period (Figure 1) is completely different from the previously twenty years. Between 1970 and 1992, violent crime has seen the greatest increase, more than doubling in these 59 cities. Until the mid 1980's, violent crime and property crime tracked each other fairly closely. Since that time, violent crime has steadily increased while property crime has flattened, but still increasing overall. While in the period I researched, trends in crime are quite different from 20 years earlier. Property crime displays a downward trend over the 26 years and violent crime tracked a similar path, even though it has a rising period before 1991. Another reason that might contribute to the unexpected positive relationship between police and crime will be the policy changes in the 1990s. According to Levitt (2001), legalized abortion may cause the drop of crime, so the crime situation might be different from the period Levitt (1997) researched.

Overall, this paper used electoral cycles as instruments while failing to provide evidence that additional police do reduce crime in different research periods and the instrumental variables' estimates are imprecise. However, we cannot say electoral cycles are not valid instrument for police officer to identify the relationship between police and crime. The unexpected positive correlation may be resulted from imperfection of model or data which are not all from city levels, as well as many other factors. Levitt's (1997) research uncovers the heretofore unnoticeable link between police presence and electoral cycles and provides a pioneering method to solve the endogeneity problem in simultaneous determination between police and crime. Still, more future studies of isolating the causal effect of police on crime will be necessary.

APPENDICES

Appendix A

Data Sample (Partial)

M-elect	G-elect	year	agencyname	sworn officers	state	population	violent crime	murder	rape	robbery	assault	property crime	burglary	larceny	mvtheft	unemployement rate	18-24 pct	black pct	femaleheaded household pct	public welfare spending	education spending
0	0	1985	Akron Ci	194	OH	226704	826.2	7.5	69.7	225.4	523.6	5849.5	1410.2	4025.5	413.8	0.089	0.114	0.22515	0.1605	325.198	505.953
0	1	1986	Akron Ci	207	OH	226877	1077.7	11	71.8	298	696.9	6678.9	1452.3	4659.4	567.3	0.082	0.116	0.22914	0.1616	361.867	538.708
1	0	1987	Akron Ci	199	OH	227552	943.1	9.2	56.7	309.4	567.8	7034	1789.9	4546.7	697.4	0.07	0.118	0.23313	0.1627	371.479	565.357
0	0	1988	Akron Ci	192	OH	227158	885.7	13.2	66	291.4	515.1	6555.8	1586.6	4357.8	611.5	0.061	0.12	0.23712	0.1638	343.051	532
0	0	1989	Akron Ci	201	OH	222588	1011.3	9	80.4	334.7	587.2	6503.5	1508.6	4258.1	736.8	0.055	0.122	0.24111	0.1649	351.055	552.983
0	1	1990	Akron Ci	191	OH	223019	1158.6	8.1	86.5	346.6	717.4	6686.4	1575.2	4362.9	748.4	0.057	0.124	0.2451	0.166	383.889	585.93
1	0	1991	Akron Ci	191	OH	224907	1256.5	17.8	99.2	442.4	697.2	6809	1771.4	4252.9	784.8	0.066	0.1221	0.24909	0.1671	412.785	578.745
0	0	1992	Akron Ci	192	OH	226490	1167.8	10.6	90.1	426.5	640.6	6442.7	1480.4	4004.2	958.1	0.074	0.1202	0.25308	0.1682	452.561	591.593
0	0	1993	Akron Ci	209	OH	225040	946.1	8.4	90.7	373.3	473.7	6258.9	1496.2	3854.9	907.8	0.067	0.1183	0.25707	0.1693	472.679	589.757
0	1	1994	Akron Ci	200	OH	225262	960.7	10.2	86.6	360.5	503.4	6142.2	1350.4	3879.9	911.8	0.056	0.1164	0.26106	0.1704	520.036	579.898
1	0	1995	Akron Ci	230	OH	222864	1017.7	8.1	93.8	392.6	523.2	6117.2	1252.8	3959.4	905	0.049	0.1145	0.26505	0.1715	478.531	623.346
0	0	1996	Akron Ci	217	OH	223303	1050.1	6.3	86.9	363.2	593.8	6118.1	1283.5	3924.3	910.4	0.05	0.1126	0.26904	0.1726	450.899	629.21
1	0	1999	Akron Ci	223	OH	216620	359.2	2.8	51.7	184.7	120	4675.9	1075.2	3245.8	355	0.043	0.1069	0.28101	0.1759	473.002	702.238
0	0	2000	Akron Ci	222	OH	217074	281	1.4	42.4	171.4	65.9	2523.6	627.4	1510.1	386	0.04	0.105	0.285	0.177	498.661	729.179
0	0	2001	Akron Ci	212	OH	217464	499.9	6	57.9	274.5	161.4	5689.2	1290.3	3662.2	736.7	0.044	0.1051	0.288	0.1788	556.284	776.757
0	1	2002	Akron Ci	230	OH	218377	552.3	8.7	76.9	299.9	166.7	5544.1	1419.1	3453.7	671.3	0.057	0.1052	0.291	0.1806	603.115	819.179
1	0	2003	Akron Ci	226	OH	214622	607.1	7.5	100.6	290.7	208.3	5756.6	1495.2	3691.1	570.3	0.062	0.1053	0.294	0.1824	640.621	834.925
0	0	2004	Akron Ci	224	OH	212646	591.6	6.6	88.4	284.5	212.1	6057.5	1542	3795.5	720	0.061	0.1054	0.297	0.1842	673.634	844.94
0	0	2005	Akron Ci	220	OH	212272	602.5	12.7	91.4	294.4	204	5743.1	1621	3466.3	655.8	0.059	0.1055	0.3	0.186	689.774	859.509
0	1	2006	Akron Ci	214	OH	211052	637.3	12.8	77.2	338.3	209	5012.5	1552.7	2803.6	656.2	0.054	0.1056	0.303	0.1878	744.14	869.834
1	0	2007	Akron Ci	217	OH	208701	759	10.5	86.7	350.7	311	5131.3	1609	2938.7	583.6	0.056	0.1057	0.306	0.1896	736.736	887.517
0	0	2008	Akron Ci	228	OH	206845	928.7	7.7	84.6	390.1	446.2	5236.8	1830.4	2943.3	463.1	0.065	0.1058	0.309	0.1914	698.562	872.248
0	0	2009	Akron Ci	222	OH	206497	927.9	9.7	91.5	352.1	474.6	5077.6	1820.4	2790.8	466.4	0.101	0.1059	0.312	0.1932	716.648	929.685
0	1	2010	Akron Ci	224	OH	199110	841.2	11.6	82.4	302.3	445	5498	2140.5	2979.8	377.7	0.1	0.106	0.315	0.195		
1	0	1985	Albuquer	180	NM	357051	1149.7	11.8	66.7	349.2	722	8136.9	2572.7	5023.1	541.1	0.087	0.109	0.0292	0.117	295.665	458.955
0	1	1986	Albuquer	188	NM	364196	1178.5	13.5	67.8	342.7	754.5	8573.4	2676	5351.5	545.9	0.092	0.1088	0.02932	0.1178	317.762	504.683
0	0	1987	Albuquer	191	NM	371756	1034.3	12.9	56.8	265.5	699.1	8920.6	2680.5	5625.5	614.7	0.09	0.1086	0.02944	0.1186	332.027	538.165
0	0	1988	Albuquer	193	NM	378176	1130.4	13	50.2	245.4	821.8	9174.8	2919.8	5539.7	715.3	0.076	0.1084	0.02956	0.1194	332.826	561.271
1	0	1989	Albuquer	198	NM	384801	1220.4	10.7	46.3	268.2	895.3	8744.3	2513.5	5631.5	599.3	0.067	0.1082	0.02968	0.1202	354.689	617.214
0	1	1990	Albuquer	206	NM	384736	1331	8.8	57.7	267.7	996.8	8733.3	2468.4	5752	512.8	0.068	0.108	0.0298	0.121	368.07	574.031
0	0	1991	Albuquer	204	NM	393148	1422.1	13	66.4	332.4	1010.3	8862.3	2632.1	5602	628.3	0.072	0.1078	0.02992	0.1218	425.776	593.027
0	0	1992	Albuquer	196	NM	401529	1536.1	10.5	73.2	363.6	1088.8	7931.2	2168	5039.7	723.5	0.075	0.1076	0.03004	0.1226	593.675	688.88
1	0	1993	Albuquer	199	NM	407286	1644.1	12.3	63.6	381.1	1187.1	7937.7	2013.1	5046.1	878.5	0.073	0.1074	0.03016	0.1234	544.158	674.325
0	1	1994	Albuquer	190	NM	416917	1608.7	10.8	69.1	344	1184.9	8105.5	1837.1	5057.8	1210.6	0.066	0.1072	0.03028	0.1242	541.239	699.429
0	0	1995	Albuquer	201	NM	419714	1128.1	12.6	70.5	386.7	658.3	8772.2	1992.3	5589.8	1190.1	0.068	0.107	0.0304	0.125	360.726	969.943
0	0	1996	Albuquer	209	NM	426736	1468.6	16.4	87.9	468.2	896.1	9838.9	2117.7	6083.6	1637.5	0.075	0.1068	0.03052	0.1258	437.812	961.854
1	0	1997	Albuquer	205	NM	431027	1317.1	11.4	62.6	401.1	841.9	9801.2	1982	6021.4	1797.8	0.066	0.1066	0.03064	0.1266	473.256	950.12
0	1	1998	Albuquer	207	NM	422417	1316.9	8.8	51.8	400.8	855.6	9489.4	1902.6	6086.2	1500.6	0.062	0.1064	0.03076	0.1274	470.028	965.57
0	0	1999	Albuquer	203	NM	420169	1250.7	11.4	52.4	396.7	790.2	8515.4	1620.5	5777.9	1116.9	0.056	0.1062	0.03088	0.1282	478.158	1000.56
0	0	2000	Albuquer	189	NM	448607	1144.9	7.4	53.3	344.8	739.4	7648.3	1587.1	5091.8	969.4	0.05	0.106	0.031	0.129	502.505	1087.4
1	0	2001	Albuquer	192	NM	451098	1165.8	7.5	48.5	356.9	752.8	7599.7	1459.8	5217.3	922.6	0.049	0.1052	0.0312	0.1304	579.836	1083.5
0	1	2002	Albuquer	195	NM	457488	1068.7	11.1	64	283.1	710.4	6748.4	1191.7	4671.4	885.3	0.055	0.1044	0.0314	0.1318	655.045	1134.91

Appendix B

F Statistics on the Excluded Instruments

First-Stage Regressions of Column (1) in Table 5

dlnofficer	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
dunem	-.5557061	.2168887	-2.56	0.010	-.9809021	-.1305101
dyoung	-.3031931	.9138517	-0.33	0.740	-2.094739	1.488353
dblack	-.0094806	.3608311	-0.03	0.979	-.7168661	.697905
dfemaleh	.4965967	.9833648	0.50	0.614	-1.431225	2.424418
dlnpubwel	.0282374	.0072641	3.89	0.000	.0139967	.0424782
dlneduc	-.0125812	.025058	-0.50	0.616	-.0617058	.0365435
crime1	5.14e-15	.0046144	0.00	1.000	-.0090462	.0090462
crime2	-.0002518	.0046646	-0.05	0.957	-.0093965	.0088929
crime3	4.30e-15	.0046144	0.00	1.000	-.0090462	.0090462
year3	.0076972	.0064629	1.19	0.234	-.0049729	.0203674
year5	.0238031	.0064108	3.71	0.000	.0112352	.036371
year6	.0202282	.006897	2.93	0.003	.0067071	.0337493
year7	-.0007772	.0075911	-0.10	0.918	-.0156591	.0141048
year8	-.0041086	.0059697	-0.69	0.491	-.0158119	.0075946
year9	.0255737	.0055318	4.62	0.000	.014729	.0364184
year10	.0014533	.0098695	0.15	0.883	-.0178952	.0208019
year11	.0441541	.0103762	4.26	0.000	.0238122	.064496
year12	.0130531	.005283	2.47	0.014	.002696	.0234101
year13	.00367	.0051198	0.72	0.474	-.0063671	.0137071
year14	.0165354	.0073773	2.24	0.025	.0020728	.0309981
year15	.0205987	.0060139	3.43	0.001	.008809	.0323885
year16	-.024421	.0058936	-4.14	0.000	-.0359751	-.0128669
year17	-.0018018	.0056619	-0.32	0.750	-.0129015	.0092979
year18	-.0070287	.0071761	-0.98	0.327	-.021097	.0070397
year19	.001012	.0063782	0.16	0.874	-.011492	.013516
year20	-.0017791	.0054125	-0.33	0.742	-.0123899	.0088317
year21	-.0025201	.0047781	-0.53	0.598	-.0118873	.0068471
year22	-.0096586	.0061765	-1.56	0.118	-.0217672	.0024501
year23	.0247551	.0086002	2.88	0.004	.0078951	.0416152
year24	.0214681	.0068859	3.12	0.002	.0079688	.0349675
year25	.01722	.0101499	1.70	0.090	-.0026782	.0371182
region1	-.004943	.0055441	-0.89	0.373	-.015812	.0059259
region2	-.0023322	.0032899	-0.71	0.478	-.0087818	.0041175
region3	-.0067744	.0034043	-1.99	0.047	-.0134483	-.0001005
region5	-.0011451	.0030269	-0.38	0.705	-.0070791	.0047889
region6	.0089722	.0034478	2.60	0.009	.0022129	.0157314
region7	-.0011639	.0037557	-0.31	0.757	-.0085267	.0061989
region8	-.0024221	.003205	-0.76	0.450	-.0087053	.0038612
region9	-.0023107	.0036492	-0.63	0.527	-.0094647	.0048434
citysize1	.0157124	.0062156	2.53	0.012	.0035272	.0278977
citysize2	.0029537	.0024583	1.20	0.230	-.0018656	.007773
citysize3	.0038494	.003198	1.20	0.229	-.00242	.0101188
ecrime1	.0123576	.0039424	3.13	0.002	.0046288	.0200864
ecrime2	.012562	.0040003	3.14	0.002	.0047196	.0204044
ecrime3	.0123576	.0039424	3.13	0.002	.0046288	.0200864
ecrime4	.0123576	.0039424	3.13	0.002	.0046288	.0200864
ecrime5	.0148827	.0062438	2.38	0.017	.0026422	.0271232
ecrime6	.0144988	.0062902	2.30	0.021	.0021673	.0268303
ecrime7	.0148827	.0062438	2.38	0.017	.0026422	.0271232
ecrime8	.0148827	.0062438	2.38	0.017	.0026422	.0271232
lagecrime1	-.0023787	.0045625	-0.52	0.602	-.0113232	.0065658
lagecrime2	-.0020887	.0046487	-0.45	0.653	-.0112022	.0070249
lagecrime3	-.0023787	.0045625	-0.52	0.602	-.0113232	.0065658
lagecrime4	-.0023787	.0045625	-0.52	0.602	-.0113232	.0065658
lagecrime5	-.0134049	.0054723	-2.45	0.014	-.0241331	-.0026768
lagecrime6	-.0134037	.005505	-2.43	0.015	-.0241959	-.0026115
lagecrime7	-.0134049	.0054723	-2.45	0.014	-.0241331	-.0026768
lagecrime8	-.0134049	.0054723	-2.45	0.014	-.0241331	-.0026768
_cons	-.0093573	.0067111	-1.39	0.163	-.0225139	.0037994

Test of excluded instruments:

$F(58, 5048) = 10.53$

Prob > F =0.0000

lagdlnoffi~r	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
dunem	-.35327	.2256789	-1.57	0.118	-.7956985	.0891586
dyoung	.5351363	.8391147	0.64	0.524	-1.109893	2.180165
dblack	.1962774	.3627028	0.54	0.588	-.5147776	.9073324
dfemaleh	-.7455128	1.05905	-0.70	0.481	-2.82171	1.330684
dlnpubwel	.0265776	.0076121	3.49	0.000	.0116546	.0415005
dlneduc	-.0287682	.0222989	-1.29	0.197	-.0724837	.0149473
crime1	-4.99e-15	.0050195	-0.00	1.000	-.0098405	.0098405
crime2	.0001465	.0050781	0.03	0.977	-.0098088	.0101017
crime3	-4.11e-15	.0050195	-0.00	1.000	-.0098405	.0098405
year3	.0030132	.006521	0.46	0.644	-.0097707	.0157972
year5	.0058704	.0059975	0.98	0.328	-.0058873	.0176281
year6	.0226862	.0066617	3.41	0.001	.0096262	.0357461
year7	.0195587	.0077852	2.51	0.012	.0042962	.0348211
year8	-.0128262	.0060048	-2.14	0.033	-.0245981	-.0010542
year9	-.0027579	.0046777	-0.59	0.555	-.0119282	.0064124
year10	.0250692	.0062181	4.03	0.000	.012879	.0372594
year11	.0018969	.0100611	0.19	0.850	-.0178273	.0216211
year12	.0394287	.0096266	4.10	0.000	.0205564	.058301
year13	.0141998	.0051012	2.78	0.005	.0041993	.0242003
year14	.0058834	.005514	1.07	0.286	-.0049265	.0166933
year15	.0115965	.0071712	1.62	0.106	-.0024621	.0256551
year16	.0164251	.0047145	3.48	0.000	.0071827	.0256675
year17	-.0202164	.0063699	-3.17	0.002	-.0327041	-.0077287
year18	-.003654	.0065322	-0.56	0.576	-.01646	.0091519
year19	-.015439	.0063404	-2.44	0.015	-.0278689	-.003009
year20	-.0092455	.0052852	-1.75	0.080	-.0196069	.0011158
year21	-.000522	.0054341	-0.10	0.923	-.0111752	.0101311
year22	-.0011312	.0054342	-0.21	0.835	-.0117846	.0095222
year23	-.0124599	.0063385	-1.97	0.049	-.024886	-.0000337
year24	.0215309	.0086576	2.49	0.013	.0045582	.0385036
year25	.0324344	.0104284	3.11	0.002	.0119902	.0528787
region1	.0081836	.0055454	1.48	0.140	-.0026878	.019055
region2	.0001496	.0032197	0.05	0.963	-.0061623	.0064616
region3	-.0001245	.0037005	-0.03	0.973	-.0073792	.0071302
region5	.0015828	.0030424	0.52	0.603	-.0043817	.0075474
region6	.0110336	.0035574	3.10	0.002	.0040595	.0180077
region7	.0040527	.0041527	0.98	0.329	-.0040885	.0121938
region8	.002347	.0034093	0.69	0.491	-.0043368	.0090308
region9	.0012757	.0037846	0.34	0.736	-.0061438	.0086952
citysize1	-.0026236	.0040014	-0.66	0.512	-.0104681	.0052209
citysize2	.0028657	.0026347	1.09	0.277	-.0022995	.0080308
citysize3	-.0012315	.0032766	-0.38	0.707	-.0076551	.005192
ecrime1	-.000034	.0041874	-0.01	0.994	-.0082432	.0081752
ecrime2	-.0002748	.0042447	-0.06	0.948	-.0085963	.0080466
ecrime3	-.000034	.0041874	-0.01	0.994	-.0082432	.0081752
ecrime4	-.000034	.0041874	-0.01	0.994	-.0082432	.0081752
ecrime5	.0050629	.0048568	1.04	0.297	-.0044584	.0145843
ecrime6	.0049597	.0049001	1.01	0.312	-.0046466	.0145661
ecrime7	.0050629	.0048568	1.04	0.297	-.0044584	.0145843
ecrime8	.0050629	.0048568	1.04	0.297	-.0044584	.0145843
lagecrime1	.0104266	.0043516	2.40	0.017	.0018955	.0189578
lagecrime2	.0103784	.0044393	2.34	0.019	.0016754	.0190813
lagecrime3	.0104266	.0043516	2.40	0.017	.0018955	.0189578
lagecrime4	.0104266	.0043516	2.40	0.017	.0018955	.0189578
lagecrime5	.022457	.0061935	3.63	0.000	.010315	.034599
lagecrime6	.022034	.0062236	3.54	0.000	.009833	.0342351
lagecrime7	.022457	.0061935	3.63	0.000	.010315	.034599
lagecrime8	.022457	.0061935	3.63	0.000	.010315	.034599
_cons	-.0138537	.0060793	-2.28	0.023	-.0257718	-.0019356

Test of excluded instruments:

$F(58, 5048) = 10.04$

Prob > F = 0.0000

First-Stage Regressions of Column(1) in Table 7

dlnofficer	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
dunem	-.5755805	.2501565	-2.30	0.021	-1.066035	-.0851261
dyoung	-.2912522	1.055093	-0.28	0.783	-2.359857	1.777352
dblack	-.0287412	.4172	-0.07	0.945	-.8466993	.7892169
dfemaleh	.4721961	1.130266	0.42	0.676	-1.743792	2.688184
dlnpubwel	.0280618	.0083818	3.35	0.001	.0116286	.044495
dlneduc	-.013408	.028961	-0.46	0.643	-.0701885	.0433726
crime1	-.0001716	.0046271	-0.04	0.970	-.0092435	.0089002
crime3	-.0001716	.0046271	-0.04	0.970	-.0092435	.0089002
year3	-.0161217	.0077252	-2.09	0.037	-.0312677	-.0009757
year4	-.0247299	.0073637	-3.36	0.001	-.039167	-.0102927
year6	-.0042401	.008493	-0.50	0.618	-.0208915	.0124113
year7	-.024034	.0085083	-2.82	0.005	-.0407154	-.0073527
year8	-.0280395	.0069288	-4.05	0.000	-.0416241	-.0144548
year9	.0012244	.0068036	0.18	0.857	-.0121147	.0145634
year10	-.0224962	.0114874	-1.96	0.050	-.0450182	.0000259
year11	.0200162	.0119754	1.67	0.095	-.0034627	.0434952
year12	-.0111939	.0065454	-1.71	0.087	-.0240268	.001639
year13	-.0203115	.006372	-3.19	0.001	-.0328042	-.0078187
year14	-.0076659	.0089528	-0.86	0.392	-.0252186	.0098868
year15	-.0037292	.0068922	-0.54	0.588	-.0172419	.0097835
year16	-.0483869	.0070738	-6.84	0.000	-.0622558	-.034518
year17	-.0256967	.0065992	-3.89	0.000	-.038635	-.0127583
year18	-.0309246	.0085866	-3.60	0.000	-.0477593	-.0140899
year19	-.0229956	.0073939	-3.11	0.002	-.037492	-.0084992
year20	-.0260083	.0070017	-3.71	0.000	-.0397357	-.0122809
year21	-.0266625	.0061722	-4.32	0.000	-.0387637	-.0145613
year22	-.0335556	.0078901	-4.25	0.000	-.0490248	-.0180864
year23	.0005991	.0097423	0.06	0.951	-.0185016	.0196997
year24	-.0027533	.0080494	-0.34	0.732	-.018535	.0130283
year25	-.0059047	.0113313	-0.52	0.602	-.0281207	.0163114
region2	.0026099	.0063632	0.41	0.682	-.0098657	.0150856
region3	-.001334	.0059257	-0.23	0.822	-.0129518	.0102838
region4	.0049765	.0064054	0.78	0.437	-.0075818	.0175348
region5	.0038505	.0056653	0.68	0.497	-.0072568	.0149578
region6	.0140177	.0060152	2.33	0.020	.0022243	.025811
region7	.0038543	.0065939	0.58	0.559	-.0090737	.0167823
region8	.0026417	.0059938	0.44	0.659	-.0091098	.0143931
region9	.0026088	.006851	0.38	0.703	-.0108232	.0160408
citysize1	.0153529	.0071432	2.15	0.032	.0013481	.0293578
citysize2	.0026535	.0027716	0.96	0.338	-.0027804	.0080875
citysize3	.0036212	.0036152	1.00	0.317	-.0034666	.0107091
ecrime1	.0123066	.0039599	3.11	0.002	.004543	.0200703
ecrime2	.0121449	.0039655	3.06	0.002	.0043702	.0199196
ecrime3	.0123066	.0039599	3.11	0.002	.004543	.0200703
ecrime5	.0147596	.0066834	2.21	0.027	.0016562	.0278631
ecrime6	.0148499	.0066915	2.22	0.027	.0017306	.0279693
ecrime7	.0147596	.0066834	2.21	0.027	.0016562	.0278631
lagecrime1	-.0022554	.004606	-0.49	0.624	-.0112859	.0067751
lagecrime2	-.002547	.0046178	-0.55	0.581	-.0116006	.0065067
lagecrime3	-.0022554	.004606	-0.49	0.624	-.0112859	.0067751
lagecrime5	-.0133163	.0058486	-2.28	0.023	-.024783	-.0018495
lagecrime6	-.0133864	.0058434	-2.29	0.022	-.0248428	-.00193
lagecrime7	-.0133163	.0058486	-2.28	0.023	-.024783	-.0018495
_cons	.0100839	.0096518	1.04	0.296	-.0088393	.0290072

Test of excluded instruments:

F (58, 5048) =8.53

Prob > F =0.0000

lagdlnoffi~r	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
dunem	-.3522695	.2615713	-1.35	0.178	-.8651035	.1605645
dyoung	.5318251	.9673314	0.55	0.582	-1.364715	2.428365
dblack	.186721	.4195262	0.45	0.656	-.6357977	1.00924
dfemaleh	-.7820237	1.214973	-0.64	0.520	-3.164087	1.600039
dlnpubwel	.0269396	.0088289	3.05	0.002	.0096297	.0442495
dlneduc	-.0276891	.0258149	-1.07	0.284	-.0783016	.0229234
crime1	.0001715	.0050368	0.03	0.973	-.0097035	.0100465
crime3	.0001715	.0050368	0.03	0.973	-.0097035	.0100465
year3	-.0025414	.0075292	-0.34	0.736	-.0173031	.0122203
year4	-.0048754	.0068919	-0.71	0.479	-.0183876	.0086368
year6	.0176454	.0078942	2.24	0.025	.0021682	.0331226
year7	.013757	.0087851	1.57	0.117	-.0034671	.0309811
year8	-.0177478	.0069152	-2.57	0.010	-.0313057	-.0041898
year9	-.0082761	.0057567	-1.44	0.151	-.0195626	.0030105
year10	.0195843	.0076724	2.55	0.011	.0045418	.0346268
year11	-.003154	.0115141	-0.27	0.784	-.0257286	.0194205
year12	.0342255	.0112083	3.05	0.002	.0122506	.0562004
year13	.0087353	.0062421	1.40	0.162	-.003503	.0209736
year14	.0007234	.0067707	0.11	0.915	-.0125511	.0139979
year15	.0062013	.0081986	0.76	0.449	-.0098728	.0222754
year16	.0109155	.0056664	1.93	0.054	-.0001941	.0220251
year17	-.0255013	.0072145	-3.53	0.000	-.0396459	-.0113567
year18	-.0089576	.0075158	-1.19	0.233	-.0236929	.0057777
year19	-.0207993	.0070205	-2.96	0.003	-.0345636	-.007035
year20	-.014465	.006304	-2.29	0.022	-.0268246	-.0021055
year21	-.0059035	.0063903	-0.92	0.356	-.0184323	.0066254
year22	-.0067061	.0065439	-1.02	0.306	-.0195361	.0061238
year23	-.0174952	.0070404	-2.48	0.013	-.0312985	-.003692
year24	.0161472	.0100924	1.60	0.110	-.0036398	.0359342
year25	.0267179	.011728	2.28	0.023	.0037242	.0497117
region2	-.0080158	.0063105	-1.27	0.204	-.0203881	.0043566
region3	-.008059	.0058317	-1.38	0.167	-.0194926	.0033747
region4	-.0081348	.0063993	-1.27	0.204	-.0206812	.0044116
region5	-.0065287	.0055695	-1.17	0.241	-.0174483	.0043908
region6	.0030355	.005842	0.52	0.603	-.0084182	.0144892
region7	-.0040919	.0064505	-0.63	0.526	-.0167387	.0085548
region8	-.0059665	.0058569	-1.02	0.308	-.0174495	.0055165
region9	-.0068115	.0069039	-0.99	0.324	-.0203473	.0067243
citysize1	-.0029565	.0045145	-0.65	0.513	-.0118076	.0058946
citysize2	.0027132	.0029814	0.91	0.363	-.0031321	.0085585
citysize3	-.0014761	.0036945	-0.40	0.690	-.0087195	.0057673
ecrime1	8.87e-06	.0041822	0.00	0.998	-.0081907	.0082085
ecrime2	.0001974	.004189	0.05	0.962	-.0080155	.0084103
ecrime3	8.87e-06	.0041822	0.00	0.998	-.0081907	.0082085
ecrime5	.0050592	.005165	0.98	0.327	-.0050672	.0151855
ecrime6	.0049524	.0051705	0.96	0.338	-.0051849	.0150897
ecrime7	.0050592	.005165	0.98	0.327	-.0050672	.0151855
lagecrime1	.0103668	.0043899	2.36	0.018	.0017601	.0189736
lagecrime2	.010536	.0044002	2.39	0.017	.001909	.0191629
lagecrime3	.0103668	.0043899	2.36	0.018	.0017601	.0189736
lagecrime5	.0222799	.0066538	3.35	0.001	.0092344	.0353253
lagecrime6	.0224127	.0066541	3.37	0.001	.0093667	.0354586
lagecrime7	.0222799	.0066538	3.35	0.001	.0092344	.0353253
_cons	-.0003789	.0097131	-0.04	0.969	-.0194223	.0186645

Test of excluded instruments:

F (58, 5048) =8.15

Prob > F =0.0000

Appendix C

2SLS Estimates of Crimes (Partial)

2SLS Estimates of Violent Crime with Respect to Police Using Data of Year 1985-1992

	(1) Δln violent	(2) Δln violent	(3) Δln violent
ln sworn officer	0.601	0.583	0.376
	(0.725)	(0.342)	(0.246)
Lag ln sworn officer	-1.151	0.00196	0.240
	(0.756)	(0.275)	(0.254)
Sum of ln sworn officer	-0.550	0.584	0.616
	(0.903)	(0.480)	(0.398)
State unemployment rate	-1.006	-1.354	-1.596
	(1.412)	(1.172)	(1.161)
Percent ages 18-24	-8.836	-12.04	-12.37
	(8.964)	(8.398)	(8.364)
Percent black	1.224	2.571	2.570
	(2.873)	(2.377)	(2.340)
Percent female-headed household	-1.558	-2.853	-2.997
	(7.561)	(7.044)	(7.053)
ln public welfare spending per capita	-0.00148	-0.0429	-0.0494
	(0.0508)	(0.0447)	(0.0462)
ln education spending per capita	-0.0521	-0.0960	-0.113
	(0.0999)	(0.0896)	(0.0894)
N	1294	1294	1294
R^2	.	0.106	0.102

Note: Dependent variable is Δln crime rate per capita for one of the three crime categories (burglary, larceny, motor vehicle theft). Right-hand-variables are all first differenced. Estimates are obtained estimating all property crime categories jointly, allowing for a city-fixed effect across crime rates and heteroskedasticity across crime categories. Crime specific year dummies, region dummies and city-size indicators are included in all regressions. Column (1) instruments using mayoral and gubernatorial election-year indicators. Column (2) instruments using interactions between the city-size indicators and election years. Column (3) instruments using interactions between the region dummies and election years. S.D. in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All data are from the 1985-1992 period.

2SLS Estimates of Property Crime with Respect to Police Using Data of Year 1985-1992

	(1) Δln property	(2) Δln property	(3) Δln property
ln sworn officer	0.568	0.700**	0.416*
	(0.614)	(0.271)	(0.192)
Lag ln sworn officer	-1.296*	-0.366	0.335
	(0.614)	(0.261)	(0.189)
Sum of ln sworn officer	-0.728	0.335	0.751
	（0.743）	（0.401）	（0.304）
State unemployment rate	0.352	0.191	-0.256
	(1.285)	(0.903)	(0.863)
Percent ages 18-24	-4.548	-7.394	-8.885
	(6.948)	(5.714)	(5.515)
Percent black	0.0464	1.366	1.827
	(2.522)	(1.853)	(1.706)
Percent female-headed household	3.171	2.158	1.625
	(6.919)	(6.005)	(5.932)
ln public welfare spending per capita	0.0538	0.0177	-0.00595
	(0.0416)	(0.0334)	(0.0338)
ln education spending per capita	0.0418	0.00858	-0.0309
	(0.0782)	(0.0658)	(0.0674)
N	975	975	975
R^2	.	0.104	0.142

Note: Dependent variable is Δln crime rate per capita for one of the three crime categories (burglary, larceny, motor vehicle theft). Right-hand-variables are all first differenced. Estimates are obtained estimating all property crime categories jointly, allowing for a city-fixed effect across crime rates and heteroskedasticity across crime categories. Crime specific year dummies, region dummies and city-size indicators are included in all regressions. Column (1) instruments using mayoral and gubernatorial election-year indicators. Column (2) instruments using interactions between the city-size indicators and election years. Column (3) instruments using interactions between the region dummies and election years. S.D. in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All data are from the 1985-1992 period.

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