Summer 8-5-2021

Police Spending and Crime Rates: Evidence from U.S. Cities, 1985 – 2010

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By

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Submitted in partial fulfillment

of the requirements for the degree of

Master of Arts in Economics, Hunter College

The City University of New York

2021

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Acknowledgement

I would like to thank the entire faculty of the Economics Department at Hunter College who continually fostered my interest in the subject. With particular appreciation to Professor Baker, Professor Basu, and Professor Deb who helped me complete this degree. I would also like to thank all my friends and family who supported me and pushed me on in my studies. Most importantly I would like to thank Professor Chernick and his continual support for my study of economics, without which this paper would not have been possible.

Abstract

Economists have long worked to understand the relationship between policing and crime. With a seemingly persistent issue of reverse causality, statistical methods including lagging and instrumental variables have been used in an attempt to work around that endogeneity problem. Recently COPS grants have been found to be a successful instrumental variable for sworn officer levels when predicting crime. Using panel data covering the largest U.S. cities from 1985-2010 to reevaluate the endogeneity issue between policing and crime rates, I test COPS grants to see if they are a suitable instrument variable for police spending and find them insufficiently correlated. I conclude that crime rates are not a strong predictor of police spending, based largely on the persistence of police budgets. This allows me to predict crime rates using police spending without reverse causality bias. These regressions find that increased police spending results in modest decreases in rates of robbery, burglary, larceny, and motor vehicle theft.

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Introduction and Background

Crime is an expensive problem. A study using the National Crime Survey calculated the cost to victims of violent crimes committed from 1987-1990 (Cohen, Miller, and Rossman 1993, 186). In 1989 dollars, the cost of each murder was close to $2.4 million, and the total lifetime costs from these violent crimes committed from 1987-1990 was $178 billion. That is just for violent crime, adding property crime, which is more numerous, would raise the cost. If the concern for public safety alone were not enough, the high monetary cost of crime makes it an issue that demands attention.

Some of the earliest writings about law enforcement relating to economics were written by philosophers in the 18th century (Polinsky and Shavell 2005, 3). Not much was written since then until Gary Becker's "Crime and Economics" was first published in 1968, a major moment in the economic analysis of crime. Becker created a model for how many offenses someone would commit. The main independent variables were probability of conviction and punishment if convicted, with remaining variables such as income from legal and illegal activities, and willingness to break the law (Becker 1974, 9). This was the groundwork for treating crime as a rational decision. Many of the implications of this research we still treat as standard assumptions today. Isaac Ehrlich expanded on the concept of treating criminals as rational beings. While acknowledging that much of the criminological literature of the day focused on deviant factors of criminal's behavior and their motivations, he noted that he had not seen strong empirical evidence to support this (Ehrlich 1973, 521 – 522). He discussed the decision to commit crimes or not in terms of expected payoffs. It is through this reasoning that we can see the pathways in which we expect someone to commit crime or not.

When the expected payoff from legitimate, law abiding activities goes up, we can expect a person to be less likely to commit a crime. When that expected payoff decreases, or the expected payoff from committing a crime goes up, someone becomes more likely to commit that crime. A true rational being will always choose whichever grants them a higher expected payoff. Hard to quantify variables, such as propensity towards crime, may remain. While this does not mean we see the whole picture, it does mean that we can predict changes in behavior based on how payoffs are changed.

The expected payoff of the crime-committing side of the equation is where we see the ways in which policing can decrease crime. Two important ways in which policing prevents crime are deterrence and incapacitation. Deterrence works by decreasing the expected payoff of committing a crime, thus deterring people from choosing crime. More policeman on the street can make it more difficult to successfully pull off a robbery, thus reducing the chance of success. By reducing that chance of success, the expected payoff of that illegitimate behavior is reduced. Harsher sentences mean that caught criminals will spend more time in jail, and that is more time that they cannot make money, thus further decreasing the expected payoff of crime. These longer sentences also involve incapacitation. Generally speaking, individuals cannot commit crimes (are incapacitated) while they are in prison. As such, crime is reduced when crime-committing individuals are in a place where they cannot commit crimes. Harsher sentences mean that at any given time there are fewer crime-committing individuals out on the street (Dills, Miron, and Summers 2008, 6-7).

As the study of crime has progressed, it has followed this same vein of thought. When looking for the effect of additional economic and demographic factors one must answer the same question: what effect, if any, do these variables have on an individual’s decision to commit crime? When one aggregates all those decisions, one effectively has the crime rate. All else being held equal, higher educated areas are expected to experience less crime, as people can earn strong incomes without the breaking the law. This does not consider the possibility that increased education can result in smarter criminals, who are likely better at avoiding detection and not being caught. Over time criminals can also become more proficient at committing crimes, which would further decrease their chances of getting caught. This would increase expected payoffs (İmrohoroğlu, Merlo, and Rupert 2006, 27). The way harsher sentencing was explained to reduce crime has no doubt influenced the harsher sentences seen in many parts of the country brought on to curb the increase in crime. More policing can reasonably be expected to decrease crime through the pathways just discussed.

Interestingly enough, the academic community has had trouble definitively concluding that increased policing reduces crime. In a time where many people feel that police departments are too powerful and overfunded, it is crucial that we evaluate just how effective police departments are in targeting crime. Are they the best recipient of public funds that are intended to reduce crime?

Unfortunately, this is not a simple question to answer. Society is complex, and as such, evaluating the effect of policing on crime is not easy. If it were, crime economists would have undoubtedly reached stronger conclusions by now. As regression analysis was used in an attempt to solve this question, new problems arose. One of the biggest hurdles, which has not yet been put to rest, is the possibility that crime affects policing. In an area with high crime, it reasonably follows that the level of policing might be increased in order to fight the high crime level. If this is true, a regression analysis of the effect of policing on crime would be tainted by reverse causality. Policing levels and crime would move in the same direction, showing a deceptive positive correlation where a negative one would be expected. This issue is one that many studies have attempted to remedy. Less studies have re-evaluated this initial relationship to see how much of a problem exists. The issue of simultaneity is often assumed without being tested.

Some attempts to avoid this simultaneity issue did so through lagged models. By testing the effect of one year prior's (or earlier) policing levels on today's crime, one can check for an effect. This approach works on the assumption that this year's crime cannot possibly affect last year's policing, and as such the reverse causality bias has been prevented. Unfortunately, due to the nature and persistence of policing levels and crime rates, this has not always been successful.

Many recent studies have used, both successfully and unsuccessfully, instrumental variables in an attempt to circumvent this issue (Kovandzic and Worrall 2010, 508). Hypothetically, a strong instrumental variable (IV) could be used to predict policing levels, so long as it is endogenous to crime levels (Baker, Bound, and Jaeger 1995). It has proven difficult to find an IV that is strong enough to predict policing levels, yet plausibly uncorrelated to crime levels. One well known example was a 1997 paper by Steven Levitt. He reported success using mayoral elections to predict sworn officer levels, his count of policing (Levitt 1997). His argument was that incumbents would increase policing in elections year to reduce crime and assist them with re-election. While initial results were successful, a calculation error was discovered a few years later, and the results did not hold when the error was corrected (McCrary 2002). Some newer studies have found success using COPS grants as instrumental variables for policing, again using sworn officer levels as their metric for policing.

In this paper, I will reevaluate this issue of policing on crime, picking up where the literature has left off. I will be looking at the effect of city police spending on crime levels. Many former studies have used sworn officer levels, while I will use spending on police. The number of officers in a police force and the amount of money budgeted to that force could have different effects. There have been documented measurement errors within the UCR data concerning sworn officer levels (Chalfin and McCrary 2013, 16). One benefit in using police spending instead is that I have sidestepped that issue. First, I will create a lagged model to see if crime rates affect police spending. This will be crucial in determining how large of an issue reverse causality is. Then I will add data on COPS grants to that model to see if the grants can still function as instrumental variables when predicting police spending, in contrast to sworn officer levels. Lastly, I will regress crime rates on police spending, to determine how effective, if at all, increased police spending is at reducing crime rates.

It is important to note that while the study of crime has advanced, this general model remains very far from being able to grasp the scope and complexity of this issue. Perhaps the primary flaw in this sort of analysis is its inherent assumption of fairness. It is not well prepared to account for potential bias, with racial bias being a main example. When viewing the decision to commit crime, it is possible to consider racial bias in some ways. While discussing the effect of education of an individual's expected payoff to commit crime, Ehrlich notes that wage discrimination against non-white workers is higher in legitimate activities than in illegitimate activities (Ehrlich 1975, 322). This includes the return from education, nonwhites receive a smaller increase in expected legitimate earnings. The takeaway from this is that all else being equal, a nonwhite individual would be more likely to commit a crime than a white individual solely because nonwhites receive less from legitimate work. This does not say the nonwhite individual is more prone to commit crime in any behavioral sense, but rather they face a different set of circumstances, and therefore a different decision.

While with sufficient data these factors can be brought in when evaluating the decision-making process, this does not speak to how police and other public institutions may be biased towards nonwhite individuals. To properly investigate these possibilities, more data is needed. While this paper is focused on the relationship between police spending and city crime rates, it does not look to address these issues. If it were looking at how police spending affected crime rates amongst different racial groups, for example, the need for better data to compare how white and nonwhite individuals are treated differently would be clear.

Data

This paper uses panel data on the largest U.S. cities to observe the relationship between police spending and crime rates from 1985 to 2010. The unit of observation is the city, while the unit of time is the year. Descriptive statistics for all variables used in this paper are available at the end. There are three tables of descriptive statistics, each for a different year, in an attempt to demonstrate how the data has changed over time. Table 1.1 is for data in 1985, the first year of the study. Table 2.2 is for data in 1994, which is the first year that COPS grants were available. Table 3.3 gives descriptive statistics for 2010, the final year of this study. Table 6 contains a correlation matrix for all variables used.

Data from a variety of sources was gathered and merged to allow these regressions. The core of the dataset is annual urban financial data generously provided by the Lincoln Institute of Land Policy (Lincoln Institute of Land Policy). This Fiscally Standardized Cities (FiSC) dataset allots revenue and expenditures from cities and counties to their appropriate geographic locations for the largest US cities. This means that for spending variables, the FiSC will combine spending by the city, as well as the portion of spending by the county corresponding to the number of people from the county living within the city. While there are updated FiSC datasets with more cities, I am using the initial stage which contains 112 cities from 38 states (Langley 2016). For that stage, all cities with a population over 100,000 in 1980 were included so long as they had a population of at least 200,000 in 2010. All cities with a population above 150,000 in 1980 were included regardless of their population in 2010. The dataset was pared down to 103 cities that were deemed suitable for this analysis, representing 36 states. In 1985, the earliest year of my study, populations ranged from 113,243 to 7,234,514, with a median of 245,472. That median grew to 306,687 in 2010, the final year of the study, with a low of 82,724 and a high of 8,131,574. Per capita spending on police protection is used to represent police spending. The FiSC dataset also provides population data and data on intergovernmental grants coming from both the state and federal levels, as well as non-police spending per capita, which were all used in this analysis.

Data on crime rates comes from the Uniform Crime Reporting (UCR) Program run by the FBI, which has been available at the city level since 1985. All rates are per-100,000 population and are self-reported by local police departments to the FBI (Federal Bureau of Investigation 2004). This is the same data used in the majority of studies on crime rates in the U.S. There are seven different types of offenses, known as index crimes, organized into two categories: violent crime and property crime. Violent crime consists of criminal homicide, forcible rape, aggravated assault, and robbery. Property crime is made up of burglary, larceny-theft, and motor vehicle theft. These index crimes have an established hierarchy which applies in multiple-offense situations. A multiple-offense situation is when more than one offense is carried out at the same time by the same offender. For the purpose of crime reporting, only the most serious offence will be counted in the crime statistics when this happens. The hierarchy is as follows, beginning with the most severe; criminal homicide, forcible rape, robbery, aggravated assault, burglary, larceny-theft, and motor vehicle theft. The variables "New Violent Rate" and "New Property Rate" will be discussed later.

Data on COPS grants comes from the COPS office. The variable "COPS" represents the per capita dollar amount of all grants received by a city in a given year. These grants were first offered in 1994, and were offered through the end of the study, albeit there are many city-years during which no grants are received. There are a variety of different grants under the umbrella of COPS grants, all of which are for police departments. They are usually separated by their purpose, such as money for hiring officers or money for purchasing new equipment. I aggregated these amounts each year, resulting in 967 observations where grants are awarded. That is less than half the total number of observations available in the dataset.

The following demographic data comes from the decennial census (United States Census Bureau). "Age" represents the median age of the population, while "Youth" represents the percentage of the population aged 15 to 24. "High School" is the percentage of the population above the age of 25 that has a high school degree or greater, while "College" represents the percentage of the population older than 25 that has a college degree or higher. There are three variables to represent race & ethnicity. "White" is the percentage of the population that reports as non-Hispanic white. "Black" is the percentage of the population reported as black. "Hispanic" is the percentage of the population that reports to be Hispanic. These variables were linearly interpolated for the intercensal years.

Income data comes from the decennial census and the ACS. Median income is reported as well as income inequality, which was calculated as mean income divided by median income. After the 2000 Census, economic variables were moved from the decennial census to the ACS.

This means income data is available for 1980, 1990, 2000, 2007, and 2010. One benefit of switching to the ACS is having data points nearby on both sides of the 2008 financial crisis, which assisted with interpolating income data. Income data was linearly interpolated.

Incarceration rates are gathered from the National Prisoner Statistics (NPS) program, carried out by the Bureau of Justice Statistics. This is annual data present at the state level. A variable was created for the percentage of the state's population that is in prison, termed "Prison." Ideally city level data would be used, but reliable data was not readily available.

Unemployment data comes from the Local Area Unemployment Statistics (LAUS) and is at the metropolitan area level. Data from the LAUS is monthly, it was averaged to create annual values. This data is available beginning in 1990. For the years prior to 1990, I have state-level LAUS data. Metropolitan area values were extrapolated by making the metropolitan rates and their respective state rates have the same annual percent change for the years prior to 1990. I then worked backward from 1990 filling in each year. While city level data would usually be preferable, it is very common for people to commute to work in one part of a metropolitan area from another, so in this instance using metropolitan level data is suitable.

Many of the explanatory variables were interpolated, and as such there is surely variation, especially in the economic variables, that was not captured. A dataset with annual values for all variables would be ideal but was not possible for this timeframe. I feel comfortable interpolating those variables as they are not the main variables being scrutinized in this study. The primary variables being looked at, police spending and crime rates, are available annually, and no interpolation was necessary. All fiscal data is measured in 2010 U.S. dollars.

Methodology

The analyses in this paper are all panel regressions using fixed effects. Panel regressions are naturally performed due to the nature of the data. Fixed effects are used to focus on variation within cities over time. The dataset does not contain sufficient variables to explain the variation between cities, and many unobserved factors no doubt remain. Time independent city specific characteristics cannot be described with the available data. As such I chose to look at variation within cities. With 103 cities across 26 years there are 2678 observations. Due to cities lacking data for occasional years, and the use of lagged variables, the actual number of observations in each regression is between 2400 and 2600. This drops down to 939 when using COPS grants as an IV. All variables are presented in logs so as to represent percentage changes.

Year fixed effects are included to account for any changes only correlated to time. There was a massive reduction in both violent and property crime in the United States in the 1990's (Donohue III and Levitt 2000, 1). Without variables for those years, the regression might attribute those decreases to other variables that changed throughout that timeframe in a similar manner, even if they are not plausibly correlated.

Regressing Police Spending on Crime

I begin the analysis by regressing police spending on crime in a fixed effects model:

$$\ln(\text{policespending})_{it} = \beta_0 + \beta_1\ln(\text{totalcrimerate})_{i,t-1} + \beta_2\ln(\text{policespending})_{i,t-1} + \beta_3\ln(\text{non-policespending})_{it} + \beta_4\ln(\text{citypopulation})_{i,t-1} + \beta_5(\ln(\text{citypopulation})^2)_{i,t-1} + \beta_6\ln(\text{medianincome})_{i,t-1} + \beta_7\ln(\text{stateaid})_{it} + \beta_8\ln(\text{federalaid})_{it} + \beta_9\ln(\text{age})_{i,t-1} + \beta_{10}\ln(\text{youth})_{i,t-1} + \beta_{11}\ln(\text{white})_{i,t-1} + \beta_{12}\ln(\text{black})_{i,t-1} + \beta_{13}\ln(\text{hispanic})_{i,t-1} + \beta_{14}\ln(\text{unemploymentmetro})_{i,t-1} + \beta_{15}\ln(\text{incomeinequality})_{i,t-1} + \beta_{16}\ln(\text{highschool})_{i,t-1} + \beta_{17}\ln(\text{college})_{i,t-1} + \beta_{18}\ln(\text{prison})_{i,t-1} + \delta_1\text{timedummy1986}_t + \delta_2\text{timedummy1987}_t \ldots \delta_{24}\text{timedummy2010}_t + \mu_{it}$$

The results for this regression are available in table 2.1. They appear alongside two variations: replacing totalcrimerate with violentcrimerate, and then with propertycrimerate. Table 2.2 shows the same regression but replacing totalcrimerate with the individual violent crime rate, while table 2.3 does the same for each category of property crime. Nearly all the variables here are lagged one year in an attempt to capture the situation in the city when the budget was being prepared. The variables that are not lagged are non-police spending, state grants, and federal grants. These are not lagged as the clearest way they affect police spending is by being present in the same budget, thus requiring them to be the same year.

Crime variables are lagged as far back as five years in order to test for significance. This is done for all variations mentioned prior; totalcrimerate, violentcrimerate, propertycrimerate, as well as for each category individually. The effect and statistical significance of these crime variables are inconsistent. Total crime rate is not significant at any point. Violent crime rate is only significant at one point, at the 95% level when lagged four years. Property crime rate is not significant at any point. Due to the size of the dataset, these longer lags start to substantially reduce the predictive power of the model. When looking at the regression using the total crime rate, the within R-squared falls from .7060 at a 1-year lag, to .6335 with a 5-year lag. That is one reason why the regressions included have a 1-year lag.

Discussion of other explanatory variables is based on the model using the total crime rate lagged one year. Lagged police spending, population (both linear and squared), age, and median income were the most statistically significant variables, all significant at the 99.9% level. Percent Hispanic was significant at the 99% level, while percent black, youth, federal grants, and non-police spending were significant at the 95% level. Lagged police spending, age, and the two population variables, while decreasing in significance, remained significant at the 99.9% level for each regression as the crime variables were lagged back to five years. Median income fell to 99% at the 5-year lag, and all the other variable decreased in significance and fell to lower significance levels or ceased to be significant. All of the significant coefficients were positive with the exception of population which had a coefficient of -2.628, though population squared was positive with a coefficient of .102. This indicates that all else being equal, increasing population would result in decreasing police spending per person until the population increase exceeds 25.76%, at which point per-person spending on policing would increase. With the average city population in this sample being 464,107 in 1985; a population increase of up to 119,531 would result in lower per capita police spending. After that point, police spending per capita would increase. In 2010, the point at which per capita police spending would increase would be at a population increase of 140,774. Non-police spending has a coefficient of .059 with a t-score of 2.25, and lagged police spending has a coefficient of .48 and a t-score of 25.64, by far the highest t-score in the regression.

This points to how persistent police spending is in cities. Spending is dominated by spending history with large influences from demographic variables. When coefficients on crime are significant, they are much smaller than these coefficients. So even then, the effect on police spending would be small compared to budgetary and other demographic factors. It is also curious as to how scattered many of the significant crime variables are, with many occurring at four and five year lags. This may be indicative of how people view crime. A Pew Research Study in 2016 found that the majority of those asked felt crime had gotten worse in the country since 2008 (Gramlich 2016). This is in contradiction to the fact that crime rates had fallen in that span. Perhaps when it comes to crime people are pessimistic. Or perhaps people hold onto older notions of crime, and even when things have improved, they still feel it is bad. This could explain how crime can have an effect with a significant lag, though that is only a theory than cannot be proven here.

Regressing police spending on crime has shown how persistent police budgets are, and crime rates have not been found to be a strong predictor of police levels. This seems to indicate that reverse causality is not a severe problem, as police spending has not been influenced by crime. However, as sporadic as they are, there are still points where crime rates can be seen to influence police spending, and as such I cannot say for certain that police spending is determined independently of crime rates.

COPS Grants as an IV

Here I test COPS grants as a viable IV for police spending. The first stage of the model is the same as the model from the prior section, with the addition of a variable to represent COPS grants.

$$\ln(\text{policespending})_{it} = \beta_0 + \beta_1\ln(\text{copsgrants})_{it} + \beta_2\ln(\text{non-policespending})_{it} + \beta_3\ln(\text{policespending})_{i,t-1} + \beta_4\ln(\text{totalcrimerate})_{i,t-1} + \beta_5\ln(\text{citypopulation})_{i,t-1} + \beta_6(\ln(\text{citypopulation})^2)_{i,t-1} + \beta_7\ln(\text{medianincome})_{i,t-1} + \beta_8\ln(\text{stateaid})_{it} + \beta_9\ln(\text{federalaid})_{it} + \beta_{10}\ln(\text{age})_{i,t-1} + \beta_{11}\ln(\text{youth})_{i,t-1} + \beta_{12}\ln(\text{white})_{i,t-1} + \beta_{13}\ln(\text{black})_{i,t-1} + \beta_{14}\ln(\text{hispanic})_{i,t-1} + \beta_{15}\ln(\text{unemploymentmetro})_{i,t-1} + \beta_{16}\ln(\text{incomeinequality})_{i,t-1} + \beta_{17}\ln(\text{highschool})_{i,t-1} + \beta_{18}\ln(\text{college})_{i,t-1} + \beta_{19}\ln(\text{prison})_{i,t-1} + \delta_1\text{timedummy1986}_t + \delta_2\text{timedummy1987}_t \ldots \delta_{24}\text{timedummy2010}_t + \mu_{\text{it}}$$

I run four versions of this regression to test the effectiveness of COPS grants as an instrumental variable. These are available in table 3, along with my baseline regression for predicting police spending for comparison, which is the first regression in the table. For the first COPS regression, the variable “COPS” represents the per capita value of COPS grants awarded to each city in the appropriate year. Seeing as these grants only began in 1994, this made the sample size much smaller. The sample size was further diminished by the fact that COPS grants were not awarded to all cities in all years. The number of observations dropped from 2506 down to 939. For the second variation, I created a new variable for COPS grants, “COPS2”, that gave all cities which did not receive a grant a grant value of .00000001 to allow them to be included in the sample. That value could not be set to zero, as those observations would again be omitted after the log transformation. For the third variation, I made a binary variable, “COPS Binary”, for weather or not a city received COPS grants. In the fourth variation, I included the binary variable, as well as an interaction between the binary variable and the COPS2 variable (COPS Interaction). The latter three variations brought the number of observations back up to 2506.

These regressions do not produce any statistically significant coefficients for any of the COPS variables. The first variation changes many of the coefficients on the other explanatory variables, as so many observations are removed. The other three variations have almost identical coefficients to the original regression that does not have COPS grants. Having failed in the first stage, there will be no second stage regression.

While COPS grants have been used successfully in other studies, it is still worth addressing if they are reasonably endogenous in order to be used as an IV in this case. There are various different programs within the COPS grant program. These have different requirements, and the requirements also changed over time. One notable distribution requirement of COPS grants in the 1990’s was that half of the funds went to communities with populations greater than 150,000, and half went to communities with populations below that amount. Agencies had to apply for the grants, stating what community-oriented policing they would implement with the grants (U.S. Government Accountability Office 2005, 7). In a new series of COPS funds released in 2009, questions concerning fiscal health and crime rates were included in the application. Any agency with primary law enforcement responsibility was eligible to accept (Mello 2018, 5). At least half the funds had to go to jurisdiction with populations above 150,000, and each state was set to receive at least 1.5% of COPS Hiring Program (CHP) funding. In his 2018 paper, Steven Mello states that cites receiving grants had similar trends to police and crime prior to the 2009 round of funds which he was analyzing. I feel that while the application process is complicated and I cannot fully view it here, it cannot be said to be completely exogenous. Agencies choose to apply, and it follows that agencies with more severe crime issues would be more pressed to apply for funds, and furthermore that crime rates are a factor in the application process. Had this been successful in the first stage, a more thorough examination of the plausible endogeneity would be necessary.

COPS grants do have maintenance of effort conditions (Roth and Ryan 2000, 1). Additionally, it was often required that grantees matched a portion of the grant in the initial round of grants. The COPS Hiring Recovery Program (CHRP) began in 2009 and did not require any match, though it did continue the maintenance of effort requirement (Cook et al 2017, 7). CHRP grants are included in the COPS program data I used. If properly followed, this should prevent any displacement effect. Any deviation from this would greatly reduce the ability of the model to find a positive relationship between the grants and police spending.

There are differences between this test for an IV and those studies that have successfully used COPS grants. The primary difference is that other studies used sworn officer levels rather than police spending as their metric for police. This allows for more plausible endogeneity, as not all COPS grants are hiring grants. While the overall amount of grants could be connected to crime rates, the portion of those that are for hiring may not have as strong a connection. Furthermore, the analysis is more straightforward with police levels. When looking at overall grant amounts, the money could be earmarked for different areas of policing, some of which may be more effective at reducing crime than others.

Regressing Crime on Police Spending

I now proceed to regress crime on police spending. Still using a panel regression with fixed effects, it is specified as follows:

$\ln(\text{totalcrimerate})_{it} = \beta_0 + \beta_1\ln(\text{totalcrimerate})_{i,t-1} + \beta_2\ln(\text{policespending})_{it} + \beta_3\ln(\text{non-policespending})_{it} + \beta_4\ln(\text{citypopulation})_{it} + \beta_5(\ln(\text{citypopulation})^2)_{it} + \beta_6\ln(\text{medianincome})_{it} + \beta_7\ln(\text{stateaid})_{it} + \beta_8\ln(\text{federalaid})_{it} + \beta_9\ln(\text{age})_{it} + \beta_{10}\ln(\text{youth})_{it} + \beta_{11}\ln(\text{white})_{it} + \beta_{12}\ln(\text{black})_{it} + \beta_{13}\ln(\text{hispanic})_{it} + \beta_{14}\ln(\text{unemploymentmetro})_{it} + \beta_{15}\ln(\text{incomeinequality})_{it} + \beta_{16}\ln(\text{highschool})_{it} + \beta_{17}\ln(\text{college})_{it} + \beta_{18}\ln(\text{prison})_{it} + \delta_1\text{timedummy1986}_t + \delta_2\text{timedummy1987}_t \ldots \delta_{24}\text{timedummy2010}_t + \mu_{\text{it}}$

The results for this regression can be found in table 4.1, alongside regressions where violent crime rates and property crime rates str used. Table 4.2 breaks down violent crime into its individual index crimes and table 4.3 breaks down property crime into its index crimes. In all regressions the one-year lag of the crime variable being regressed is a strong predictor for all crime rates; always positive and significant at the 99.9% level. Police spending has a negative coefficient whenever it was significant. A 100% increase in police spending would cause reductions of 4.61% to the total crime rate, 4.19% to the violent crime rate, and 4.25% to the property crime rate. These are significant at the 99.9% level, 95% level, and 99% level, respectively. These strong inverse relationships mean this model is not affected by reverse causality when examining the relationship between police spending and crime, as that would require the signs for police spending on crime to be the same as those for crime on police spending, which is not the case.

Breaking down violent crime shows that robbery is the only type of violent crime significantly reduced by police spending, where doubling police spending would reduce robbery by 7.18%, significant at 99.9%. This is such a strong effect that it makes the whole category of violent crimes significant, even though it is the only violent index crime which is. For the property crimes, increasing police spending by 100% with all else equal would reduce burglary by 5.63%, larceny by 3.13%, and vehicle theft by 5.65%. The effect on burglary is significant at the 99% level, while the effects on larceny and vehicle theft are significant at 95%. When looking at the crime rates when grouped together, i.e. total crime, violent crime, or property crime, it is easy to assume that the reduction would apply equally to the individual index crimes. When examining the index crimes independently, it is apparent that they are not affected equally. Individual categories can have strong enough effects to sway the overall category. This reinforces the importance of examining index crimes individually, not just the categories in broad strokes.

To represent this another way, I have calculated the dollar cost of reducing crimes if the year were 2010, based on the average city. This city has a population of 546,485 and spends 378 dollars per person on policing for a total of $206,571,330. That city suffers 59 murders, 238 incidences of rape, 2,547 assaults, 1,580 robberies, 6,646 burglaries, 16,243 occurrences of larceny, and 2,740 cases of motor vehicle theft that year. By doubling their police spending to $413,142,660, we can expect 113 fewer robberies, 374 fewer burglaries, 508 fewer occurrences of larceny, and 155 fewer cases of motor vehicle theft. The reduction in murders, rapes, and assaults are not significant enough to be recorded here. I leave it up to the reader to determine if that is a worthwhile use of funds.

Categorizing Robbery

In the UCR database, robbery is considered a violent crime. This is because robbery involves force or force of threat, which makes it distinct from property crimes. I initially found this designation to be curious, as the motivation for robbery, presumable pecuniary gain, should be more similar to that of property crimes, than to that of the other violent crimes. When looking at the effect of crimes, designation as violent is reasonable, as the outcome is violent. When looking at how policing deters crime, the motivation becomes more important. Robbery is the only violent crime that is affected by police spending, while all the property crimes are. This supports the notion that robbery may better belong to property crimes for the purpose of this analysis. I have created new violent and property crime categories, which remove robbery from violent crimes, and places it in property crimes. The regression is then performed the same way as when regressing crime on police spending. The results can be seen in table 5. Policing has no effect on the new violent crime rate, and has a slightly stronger, and more significant, effect on the new property crime rate than on the old rate. A 100% increase in police spending would decrease property crime by 4.37%, significant at the 99% level. While I do not think that robbery should always be counted as a property crime, it can beneficial when evaluate the ways in which we expect policing to work. While robbery is a forceful, violent crime, the motivations, and as such the methods of determent, are more in line with the property crimes.

Conclusion

This paper is unable to reach a solid conclusion on how changes in crime lead to changes in police spending. Furthermore, using COPS grants as an instrumental variable is not successful here with police spending, as it has been with sworn officer levels. Despite that however, the model is able to predict that changes in police spending can reduce robbery, burglary, larceny, and vehicle theft, which is the expected result based upon the literature. These results show the model has not negatively affected by reverse causality, as is often the case in studies on crime and police spending. Lastly, this study has indicated that the categorization of robbery should be more closely examined and potentially reconsidered when looking at the motivations behind it, and the methods used to deter it.

Table 1.1 – 1985 Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Total Crime Rate	102	8813.632	2584.672	4006.700	16936.800
Violent Crime Rate	102	1021.329	588.035	176.000	2913.700
Property Crime Rate	103	7787.490	2167.267	3687.700	14587.900
Murder Rate	103	14.296	10.001	2.000	58.200
Rape Rate	102	72.503	33.892	15.600	191.000
Assault Rate	103	516.419	325.661	73.600	1913.200
Robbery Rate	103	427.245	301.216	47.200	1537.600
Burglary Rate	103	2234.330	811.157	1047.100	4665.200
Larceny Rate	103	4754.415	1377.726	1855.800	9001.300
Vehicle Theft Rate	103	798.743	569.571	144.200	3452.400
New Violent Rate	102	598.692	349.988	110.400	2135.700
New Property Rate	103	8214.732	2344.948	3787.200	15542.400
Police Spending	103	233.0822	75.227	118.983	446.905
Non-Police Spending	103	3500.420	1162.525	1711.312	8289.392
City Population	103	464016.500	820654.200	113243.000	7234514.000
Median Income	103	47769.890	10020.790	31163.35.	84500.460
State Aid	103	1044.435	482.870	429.796	3409.808
Federal Aid	103	210.948	113.412	46.678	569.719
Age	103	30.425	2.203	26.050	40.350
Youth	103	18.131	2.411	13.050	26.650
White	103	.645	.178	.158	.970
Black	103	.208	.173	.00450	.757
Hispanic	103	.112	.150	.00550	.810
Unemployment	103	6.833	2.257	3.696	14.650
Income Inequality	103	1.268	.0879	1.104	1.620
College	103	20.061	6.278	7.250	40.050
High School	103	71.612	8.653	48.200	89.350
Prison	103	.00201	.000661	.000560	.00437
COPS	0				

Table 1.2 – 1994 Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Total Crime Rate	101	9052.350	2867.186	4353.400	18070.800
Violent Crime Rate	101	1372.399	735.112	270.900	3750.700
Property Crime Rate	102	7676.373	2321.477	3758.900	16483.300
Murder Rate	102	18.667	14.1867	1.000	77.200
Rape Rate	101	68.200	29.124	20.700	155.900
Assault Rate	102	766.638	471.802	86.800	2243.400
Robbery Rate	102	532.429	329.405	89.400	1543.100
Burglary Rate	102	1731.275	657.620	714.300	3680.000
Larceny Rate	102	4721.993	1501.528	2073.600	10658.400
Vehicle Theft Rate	102	1223.102	683.569	221.300	3736.800
New Violent Rate	101	846.686	490.074	128.400	2379.700
New Property Rate	102	8208.799	2518.485	3895.000	17312.300
Police Spending	103	278.128	91.814	120.065	596.059
Non-Police Spending	103	4084.275	1298.561	1980.138	8829.075
City Population	103	499078.600	852162.100	113217.000	7506166.000
Median Income	103	48766.500	11150.540	30249.420	95160.860
State Aid	103	1277.844	517.00910	478.276	2782.225
Federal Aid	103	116.789	82.567	6.805	396.081
Age	103	32.006	2.101	26.140	38.880
Youth	103	15.868	2.356	11.200	24.480
White	103	.575	.183	.0978	.940
Black	103	.223	.186	.00860	.820
Hispanic	103	.146	.170	.00560	.887
Unemployment	103	5.847	2.363	2.217	15.808
Income Inequality	103	1.327	.101	1.135	1.745
College	103	23.420	7.427	8.540	44.480
High School	103	76.292	8.191	47.100	91.320
Prison	103	.00376	.00129	.000992	.00637
COPS	36	6.432	3.471	1.651	16.504

Table 1.3 – 2010 Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Total Crime Rate	99	5492.681	1784.432	1911.500	10501.000
Violent Crime Rate	101	807.827	412.333	189.700	2377.900
Property Crime Rate	100	4682.724	1499.807	1454.800	8557.600
Murder Rate	102	10.887	10.575	.800	64.800
Rape Rate	101	43.708	22.564	9.800	114.500
Assault Rate	102	466.609	261.228	76.500	1559.100
Robbery Rate	102	289.470	171.656	57.400	801.600
Burglary Rate	102	1217.293	632.126	219.300	3559.400
Larceny Rate	100	2974.937	952.470	1064.400	5460.700
Vehicle Theft Rate	102	501.865	284.254	113.100	1765.800
New Violent Rate	101	520.720	279.487	91.800	1700.600
New Property Rate	100	4972.068	1600.404	1686.900	9223.100
Police Spending	103	378.218	123.139	166.072	796.397
Non-Police Spending	103	5236.509	1586.625	2766.204	11948.850
City Population	103	546485.300	913982.300	82724.000	8131574.000
Median Income	103	43621.100	11342.560	24021.000	92269.000
State Aid	103	1618.815	717.059	515.073	4058.935
Federal Aid	103	175.214	102.389	23.395	568.894
Age	103	33.740	2.687	28.500	42.200
Youth	103	16.105	2.682	11.20	24.500
White	103	.459	.175	.0420	.840
Black	103	.238	.198	.0100	.848
Hispanic	103	.2163	.194	.0160	.947
Unemployment	103	9.657	2.349	4.225	16.892
Income Inequality	103	1.399	.109	1.174	1.763
College	103	29.465	9.487	11.400	56.500
High School	103	83.402	6.172	52.900	94.800
Prison	103	.00466	.00145	.00173	.00868
COPS	46	4.289	6.616	.185	24.769

Table 2.1 – Results of Police Spending – Total, Violent, Property

	With Total Crime Rate	With Violent Crime Rate	With Property Crime Rate
	Log Police Spending	Log Police Spending	Log Police Spending
Log Non-Police Spending	0.0590*	0.0579*	0.0573*
	(2.25)	(2.21)	(2.17)
Log Police Spending (Lagged)	0.480***	0.481***	0.447***
	(25.64)	(25.74)	(24.48)
Log Total Crime Rate (Lagged)	0.0293		
	(1.75)		
Log Violent Crime Rate (Lagged)		0.0137	
		(1.25)	
Log Property Crime Rate (Lagged)			0.0257
			(1.56)
Log City Population (Lagged)	-2.628***	-2.667***	-2.683***
	(-4.99)	(-5.04)	(-5.12)
Log City Population Squared (Lagged)	0.102***	0.104***	0.104***
	(4.90)	(4.95)	(5.03)
Log Median Income (Lagged)	0.349***	0.358***	0.385***
	(4.22)	(4.34)	(4.63)
Log State Aid	0.0270	0.0276	0.0282
	(1.46)	(1.50)	(1.52)
Log Federal Aid	0.0109*	0.0108*	0.0108*
	(2.20)	(2.19)	(2.17)
Log Age (Lagged)	0.681***	0.716***	0.734***
	(4.07)	(4.34)	(4.38)
Log Youth (Lagged)	0.164*	0.179*	0.182*
	(2.15)	(2.38)	(2.38)
Log White (Lagged)	-0.0555	-0.0555	-0.0630
	(-1.63)	(-1.63)	(-1.84)
Log White (Lagged)	0.0403*	0.0404*	0.0444*
	(2.22)	(2.22)	(2.44)
Log Hispanic (Lagged)	0.0398**	0.0430***	0.0431***
	(3.06)	(3.42)	(3.30)

Log Unemployment	0.0207	0.0236	0.0230
(Lagged)	(1.41)	(1.61)	(1.56)
Log Income Inequality	0.304	0.311	0.395*
(Lagged)	(1.72)	(1.76)	(2.24)
Log College	-0.122	-0.135	-0.125
(Lagged)	(-1.71)	(-1.91)	(-1.75)
Log High School	0.194	0.229	0.202
(Lagged)	(1.54)	(1.83)	(1.59)
Log Prison	-0.0131	-0.0154	-0.0109
(Lagged)	(-0.71)	(-0.84)	(-0.59)
N	2506	2511	2534

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

Table 2.2 – Results of Police Spending – Violent Breakdown

	With Murder Rate	With Rape Rate	With Assault Rate	With Robbery Rate
	Log Police Spending	Log Police Spending	Log Police Spending	Log Police Spending
Log Non-Police Spending	0.0546*	0.0571*	0.0562*	0.0553*
	(2.07)	(2.18)	(2.14)	(2.10)
Log Police Spending (Lagged)	0.449***	0.480***	0.448***	0.449***
	(24.56)	(25.69)	(24.57)	(24.60)
Log Murder Rate (Lagged)	0.00207			
	(0.29)			
Log Rape Rate (Lagged)		0.0113		
		(1.21)		
Log Assault Rate (Lagged)			0.00416	
			(0.54)	
Log Robbery Rate (Lagged)				0.0135
				(1.27)
Log City Population (Lagged)	-2.669***	-2.603***	-2.697***	-2.706***
	(-5.09)	(-4.95)	(-5.12)	(-5.16)
Log City Population Squared (Lagged)	0.104***	0.101***	0.105***	0.105***
	(4.99)	(4.86)	(5.02)	(5.06)
Log Median Income (Lagged)	0.392***	0.368***	0.396***	0.389***
	(4.72)	(4.44)	(4.77)	(4.69)
Log State Aid	0.0299	0.0282	0.0284	0.0305
	(1.61)	(1.53)	(1.53)	(1.64)
Log Federal Aid	0.0108*	0.0106*	0.0106*	0.0108*
	(2.18)	(2.16)	(2.14)	(2.18)
Log Age (Lagged)	0.767***	0.713***	0.783***	0.739***
	(4.62)	(4.32)	(4.75)	(4.40)
Log Youth (Lagged)	0.191*	0.189*	0.201**	0.189*
	(2.49)	(2.51)	(2.66)	(2.48)
Log White (Lagged)	-0.0573	-0.0537	-0.0608	-0.0606
	(-1.67)	(-1.58)	(-1.78)	(-1.78)
Log Black (Lagged)	0.0452*	0.0401*	0.0462*	0.0425*
	(2.48)	(2.20)	(2.55)	(2.30)

Log Hispanic	0.0469***	0.0433***	0.0474***	0.0433***
(Lagged)	(3.71)	(3.45)	(3.79)	(3.35)
Log Unemployment	0.0254	0.0252	0.0260	0.0241
(Lagged)	(1.73)	(1.71)	(1.77)	(1.64)
Log Income Inequality	0.391*	0.325	0.405*	0.392*
(Lagged)	(2.21)	(1.83)	(2.29)	(2.22)
Log College	-0.149*	-0.147*	-0.144*	-0.136
(Lagged)	(-2.11)	(-2.09)	(-2.04)	(-1.91)
Log High School	0.246	0.248*	0.240	0.241
(Lagged)	(1.95)	(1.98)	(1.91)	(1.92)
Log Prison	-0.0119	-0.0158	-0.0132	-0.0112
(Lagged)	(-0.64)	(-0.86)	(-0.71)	(-0.60)
N	2531	2511	2539	2539

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

Table 2.3 – Results of Police Spending – Property Breakdown

	With Burglary Rate	With Larceny Rate	With Vehicle Theft Rate
	Log Police Spending	Log Police Spending	Log Police Spending
Log Non-Police Spending	0.0545*	0.0590*	0.0558*
	(2.07)	(2.24)	(2.12)
Log Police Spending (Lagged)	0.449***	0.447***	0.448***
	(24.58)	(24.45)	(24.56)
Log Burglary Rate (Lagged)	0.0123		
	(0.96)		
Log Larceny (Lagged)		0.0300	
		(1.93)	
Log Vehicle Theft (Lagged)			0.00286
			(0.36)
Log City Population (Lagged)	-2.672***	-2.689***	-2.673***
	(-5.11)	(-5.14)	(-5.10)
Log City Population Squared (Lagged)	0.104***	0.105***	0.104***
	(5.01)	(5.04)	(5.00)
Log Median Income (Lagged)	0.398***	0.384***	0.391***
	(4.79)	(4.61)	(4.69)
Log State Aid	0.0298	0.0260	0.0294
	(1.61)	(1.40)	(1.58)
Log Federal Aid	0.0107*	0.0108*	0.0105*
	(2.16)	(2.18)	(2.13)
Log Age (Lagged)	0.758***	0.736***	0.775***
	(4.55)	(4.42)	(4.68)
Log Youth (Lagged)	0.196*	0.179*	0.200**
	(2.58)	(2.34)	(2.62)
Log White (Lagged)	-0.0628	-0.0623	-0.0599
	(-1.84)	(-1.83)	(-1.76)
Log Black (Lagged)	0.0455*	0.0459*	0.0459*
	(2.51)	(2.53)	(2.51)
Log Hispanic (Lagged)	0.0437***	0.0429***	0.0467***
	(3.35)	(3.32)	(3.70)

Log Unemployment	0.0237	0.0242	0.0253
(Lagged)	(1.60)	(1.65)	(1.72)
Log Income Inequality	0.402*	0.383*	0.400*
(Lagged)	(2.28)	(2.17)	(2.27)
Log College	-0.139	-0.122	-0.143*
(Lagged)	(-1.96)	(-1.71)	(-2.03)
Log High School	0.226	0.184	0.242
(Lagged)	(1.78)	(1.43)	(1.93)
Log Prison	-0.0113	-0.0132	-0.0115
(Lagged)	(-0.61)	(-0.71)	(-0.62)
N	2539	2534	2539

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

Table 3 – Results of COPS First Stage IV

	Without COPS	With COPS	With COPS2	With COPS Binary	With COPS Binary and COPS Interaction
	Log Police Spending	Log Police Spending	Log Police Spending	Log Police Spending	Log Police Spending
Log Non-Police Spending	0.0590* (2.25)	0.208** (3.11)	0.0590* (2.25)	0.0590* (2.25)	0.0591* (2.25)
Log COPS		-0.00329 (-0.98)			
Log COPS2			0.0000201 (0.06)		
COPS Binary				0.000497 (0.08)	0.000841 (0.13)
COPS Interaction					-0.000391 (-0.15)
Log Police Spending (Lagged)	0.480*** (25.64)	0.452*** (11.57)	0.480*** (25.63)	0.480*** (25.63)	0.480*** (25.63)
Log Total Crime Rate (Lagged)	0.0293 (1.75)	-0.0229 (-0.58)	0.0293 (1.75)	0.0293 (1.75)	0.0294 (1.75)
Log City Population (Lagged)	-2.628*** (-4.99)	-1.093 (-0.73)	-2.625*** (-4.98)	-2.625*** (-4.97)	-2.621*** (-4.96)
Log City Population Squared (Lagged)	0.102*** (4.90)	0.0472 (0.81)	0.102*** (4.89)	0.102*** (4.88)	0.102*** (4.87)
Log Median Income (Lagged)	0.349*** (4.22)	-0.0725 (-0.36)	0.349*** (4.21)	0.349*** (4.21)	0.349*** (4.21)
Log State Aid	0.0270 (1.46)	0.106** (2.64)	0.0271 (1.46)	0.0271 (1.46)	0.0270 (1.46)
Log Federal Aid	0.0109* (2.20)	0.0456*** (4.10)	0.0109* (2.20)	0.0109* (2.20)	0.0109* (2.20)
Log Age (Lagged)	0.681*** (4.07)	0.187 (0.42)	0.681*** (4.07)	0.681*** (4.07)	0.682*** (4.08)
Log Youth (Lagged)	0.164* (2.15)	0.266 (1.33)	0.164* (2.15)	0.164* (2.15)	0.165* (2.15)

Log White	-0.0555	0.0672	-0.0555	-0.0554	-0.0553
(Lagged)	(-1.63)	(0.65)	(-1.63)	(-1.62)	(-1.62)
Log Black	0.0403*	0.0928	0.0403*	0.0403*	0.0403*
(Lagged)	(2.22)	(1.46)	(2.22)	(2.22)	(2.22)
Log Hispanic	0.0398**	0.0193	0.0398**	0.0398**	0.0398**
(Lagged)	(3.06)	(0.45)	(3.06)	(3.06)	(3.06)
Log Unemployment	0.0207	0.0487	0.0207	0.0207	0.0208
(Lagged)	(1.41)	(1.49)	(1.41)	(1.41)	(1.41)
Log Income Inequality	0.304	0.138	0.304	0.304	0.304
(Lagged)	(1.72)	(0.33)	(1.72)	(1.72)	(1.72)
Log College	-0.122	0.190	-0.122	-0.122	-0.122
(Lagged)	(-1.71)	(0.97)	(-1.71)	(-1.71)	(-1.72)
Log High School	0.194	-0.0902	0.195	0.195	0.195
(Lagged)	(1.54)	(-0.25)	(1.54)	(1.54)	(1.54)
Log Prison	-0.0131	-0.0484	-0.0131	-0.0131	-0.0132
(Lagged)	(-0.71)	(-0.88)	(-0.71)	(-0.71)	(-0.72)
N	2506	939	2506	2506	2506

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

Table 4.1 – Results of Crime Rates – Total, Violent, Property

	With Total Crime Rate	With Violent Crime Rate	With Property Crime Rate
	Log Total Crime Rate	Log Violent Crime Rate	Log Property Crime Rate
Log Police Spending	-0.0461***	-0.0419*	-0.0425**
	(-3.40)	(-2.06)	(-3.14)
Log Total Crime Rate (Lagged)	0.810***		
	(66.96)		
Log Violent Crime Rate (Lagged)		0.809***	
		(67.94)	
Log Property Crime Rate (Lagged)			0.803***
			(65.92)
Log Non-Police Spending	0.0272	0.0197	0.0267
	(1.39)	(0.67)	(1.33)
Log City Population	0.176	0.893	0.117
	(0.45)	(1.51)	(0.29)
Log City Population Squared	-0.00877	-0.0358	-0.00666
	(-0.57)	(-1.52)	(-0.42)
Log Median Income	0.0354	-0.109	0.0644
	(0.60)	(-1.24)	(1.06)
Log State Aid	-0.00232	0.0227	-0.00725
	(-0.17)	(1.13)	(-0.53)
Log Federal Aid	-0.000944	0.00112	-0.00184
	(-0.26)	(0.21)	(-0.50)
Log Age	0.472***	0.128	0.521***
	(3.96)	(0.72)	(4.25)
Log Youth	0.152**	0.106	0.155**
	(2.77)	(1.30)	(2.75)
Log White	0.00837	0.0804*	0.00530
	(0.34)	(2.18)	(0.21)
Log Black	0.0308*	0.0428*	0.0294*
	(2.33)	(2.15)	(2.17)
Log Hispanic	0.0359***	0.00856	0.0401***
	(3.78)	(0.62)	(4.11)

Log Unemployment	-0.00987	-0.0224	-0.0105
	(-0.93)	(-1.41)	(-0.97)
Log Income Inequality	-0.243	-0.567**	-0.157
	(-1.93)	(-2.99)	(-1.22)
Log College	-0.0699	-0.0609	-0.0760
	(-1.37)	(-0.80)	(-1.46)
Log High School	0.0570	0.0261	0.0737
	(0.63)	(0.19)	(0.79)
Log Prison	-0.0110	-0.00435	-0.0116
	(-0.82)	(-0.21)	(-0.84)
N	2472	2479	2503

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

Table 4.2 – Results of Crime Rates – Violent Breakdown

	With Murder Rate	With Rape Rate	With Assault Rat	With Robbery Rate
	Log Murder Rate	Log Rape Rate	Log Assault Rate	Log Robbery Rate
Log Police Spending	-0.0421	0.0289	-0.0264	-0.0718***
	(-0.85)	(0.92)	(-0.94)	(-3.31)
Log Murder Rate (Lagged)	0.294***			
	(14.90)			
Log Rape Rate (Lagged)		0.669***		
		(42.13)		
Log Assault Rate (Lagged)			0.802***	
			(67.48)	
Log Robbery Rate (Lagged)				0.771***
				(60.76)
Log Non-Police Spending	-0.175*	0.00805	0.00860	0.0390
	(-2.37)	(0.18)	(0.21)	(1.21)
Log City Population	0.904	-0.294	1.841*	0.00315
	(0.62)	(-0.32)	(2.22)	(0.00)
Log City Population Squared	-0.0467	0.00809	-0.0712*	-0.00365
	(-0.81)	(0.22)	(-2.17)	(-0.14)
Log Median Income	-0.0441	-0.442**	-0.241	0.0811
	(-0.20)	(-3.23)	(-1.94)	(0.84)
Log State Aid	0.0740	-0.0612*	0.0624*	-0.0358
	(1.48)	(-1.97)	(2.20)	(-1.62)
Log Federal Aid	0.0178	-0.00811	0.00535	-0.00589
	(1.32)	(-0.97)	(0.70)	(-1.00)
Log Age	1.458**	0.282	-0.241	0.832***
	(3.26)	(1.02)	(-0.96)	(4.22)
Log Youth	1.002***	-0.214	0.0651	0.286**
	(4.82)	(-1.70)	(0.57)	(3.18)
Log White	0.00825	0.00505	0.123*	0.0268
	(0.09)	(0.09)	(2.38)	(0.67)
Log Black	0.145**	0.0658*	0.0370	0.0767***
	(2.93)	(2.12)	(1.32)	(3.48)

Log Hispanic	0.121***	0.0279	-0.0125	0.0568***
	(3.51)	(1.31)	(-0.65)	(3.68)
Log Unemployment	0.0588	-0.0852***	-0.0157	-0.0204
	(1.47)	(-3.44)	(-0.70)	(-1.17)
Log Income Inequality	0.911	-0.568	-0.804**	-0.343
	(1.93)	(-1.93)	(-3.02)	(-1.66)
Log College	-0.234	0.230*	-0.0149	-0.104
	(-1.24)	(1.97)	(-0.14)	(-1.25)
Log High School	0.424	-0.673**	0.110	-0.235
	(1.25)	(-3.20)	(0.57)	(-1.58)
Log Prison	-0.249***	0.0305	0.0225	-0.0667**
	(-4.89)	(0.97)	(0.78)	(-3.00)
N	2496	2479	2510	2510

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

Table 4.3 – Results of Crime Rates – Property Breakdown

	With Burglary Rate	With Larceny Rate	With Vehicle Theft Rate
	Log Burglary Rate	Log Larceny Rate	Log Vehicle Theft Rate
Log Police Spending	-0.0563**	-0.0313*	-0.0565*
	(-3.19)	(-2.09)	(-2.34)
Log Burglary Rate (Lagged)	0.795***		
	(63.79)		
Log Larceny Rate (Lagged)		0.782***	
		(61.52)	
Log Vehicle Theft Rate (Lagged)			0.849***
			(79.58)
Log Non-Police Spending	0.0446	0.0116	0.0653
	(1.70)	(0.52)	(1.82)
Log City Population	-0.166	0.00589	1.490*
	(-0.32)	(0.01)	(2.09)
Log City Population Squared	0.00354	-0.00210	-0.0606*
	(0.17)	(-0.12)	(-2.15)
Log Median Income	-0.0554	0.110	0.126
	(-0.70)	(1.64)	(1.17)
Log State Aid	-0.0117	0.00213	-0.0613*
	(-0.65)	(0.14)	(-2.49)
Log Federal Aid	-0.00337	-0.00266	-0.00577
	(-0.70)	(-0.65)	(-0.88)
Log Age	0.527***	0.486***	0.421
	(3.31)	(3.60)	(1.93)
Log Youth	0.193**	0.197**	-0.0269
	(2.65)	(3.17)	(-0.27)
Log White	0.0183	-0.00681	0.00685
	(0.56)	(-0.24)	(0.15)
Log Black	0.0374*	0.0239	0.0476
	(2.12)	(1.59)	(1.95)
Log Hispanic	0.0477***	0.0370***	0.0474**
	(3.73)	(3.47)	(2.82)

Log Unemployment	0.0309*	-0.00914	-0.0844***
	(2.16)	(-0.76)	(-4.32)
Log Income Inequality	-0.594***	0.100	-0.122
	(-3.54)	(0.70)	(-0.53)
Log College	-0.0229	-0.116*	-0.0568
	(-0.34)	(-2.01)	(-0.61)
Log High School	0.0266	0.205*	-0.168
	(0.22)	(1.96)	(-1.02)
Log Prison	-0.0241	0.00694	-0.0773**
	(-1.33)	(0.45)	(-3.09)
N	2510	2503	2510

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

Table 5 – Results of New Crime Categories

	With New Violent Rate	With New Property Rate
	Log New Violent Rate	Log New Property Rate
Log Police Spending	-0.0237	-0.0437**
	(-0.91)	(-3.27)
Log New Violent Rate (Lagged)	0.802***	
	(66.29)	
Log New Property Rate (Lagged)		0.808***
		(67.24)
Log Non-Police Spending	0.00686	0.0277
	(0.18)	(1.39)
Log City Population	1.692*	0.107
	(2.24)	(0.27)
Log City Population Squared	-0.0659*	-0.00627
	(-2.20)	(-0.40)
Log Median Income	-0.223*	0.0614
	(-1.99)	(1.03)
Log State Aid	0.0484	-0.00694
	(1.89)	(-0.51)
Log Federal Aid	0.00387	-0.00194
	(0.56)	(-0.53)
Log Age	-0.220	0.530***
	(-0.97)	(4.37)
Log Youth	0.0282	0.160**
	(0.27)	(2.88)
Log White	0.109*	0.00512
	(2.31)	(0.21)
Log Black	0.0350	0.0303*
	(1.39)	(2.26)
Log Hispanic	-0.0140	0.0398***
	(-0.80)	(4.12)
Log Unemployment	-0.0218	-0.0108
	(-1.08)	(-1.00)

Log Income Inequality	-0.660**	-0.177
	(-2.73)	(-1.39)
Log College	-0.0111	-0.0725
	(-0.12)	(-1.41)
Log High School	0.0961	0.0514
	(0.56)	(0.56)
Log Prison	0.0214	-0.0134
	(0.83)	(-0.98)
N	2479	2503

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

Bibliography

Baker, Regina M., John Bound, and David A. Jaeger. 1995. "Problems with Instrumental Variables Estimation When the Correlation Between the Instruments and the Endogenous Explanatory Variable is Weak." *Journal of the American Statistical Association* 90, no. 430 (June): 443-450

Becker, Gary S. 1974. "Crime and Punishment: An Economic Approach." *Essays in the Economics of Crime and Punishment*: 1-54

Chalfin, Aaron, and Justin McCrary. 2013. "The Effect of Police on Crime: New Evidence from U.S. Cities, 1960-2010." *NBER Working Paper Series* (February)

Cohen, Mark A., Ted R. Miller, and Shelli B. Rossman. 1993. "Victim Costs of Violent Crime and Resulting Injuries." *Health Affairs* 12, no. 4: 186-197

Cook, Philip J., Max Kapustin, Jens Ludwig, and Douglas L. Miller. 2017. "The Effects of COPS Office Funding on Sworn Force Levels, Crime, and Arrests: Evidence from a Regression Discontinuity Design."

Dills, Angela K, Jeffrey A. Miron, and Garrett Summers. 2008. "What Do Economists Know About Crime?" *NBER Working Paper Series* (January)

Donohue III, John J, and Steven D. Levitt. 2000. "The Impact of Legalized Abortion on Crime." *NBER Working Paper Series* (November)

Ehrlich, Isaac. 1973. "Participation in Illegitimate Activities: A Theoretical and Empirical Investigation." *The Journal of Political Economy* 81, no. 3 (May/June): 521-565.

Ehrlich, Isaac. 1975. "On the Relation Between Education and Crime." *Education, Income, and Human Behavior*: 313-338.

Fajnzylber, Pablo, Daniel Lederman, and Norman Loayza. 2002. "Inequality and Violent Crime." *Journal of Law and Economics* 45 (April): 1-40

Federal Bureau of Investigation. 2004. "Uniform Crime Reporting Handbook."

Glaeser, Edward L., Matt Resseger, and Kristina Tobio. 2008. "Urban Inequality." *Taubman Center for State and Local Government*

Gramlich, John. 2016. "Voter's Perceptions of Crime Continue to Conflict with Reality." *Pew Research Center*, November 16, 2016. https://www.pewresearch.org/fact-tank/2016/11/16/voters-perceptions-of-crime-continue-to-conflict-with-reality/

İmrohoroğlu, Ayse., Antonio Merlo, and Peter Rupert. 2000. "*What Accounts for the Decline in Crime*?" *Federal Reserve Bank of Cleveland Working Paper*

Kovandzic, Tomislav V., and John L. Worrall. 2010. “Police Levels and Crime Rates: An Instrumental Variables Approach.” *Social Science Research* 39: 506-516

Langley, Adam. 2016. “Methodology Used to Create Fiscally Standardized Cities Database.” *Lincoln Institute of Land Policy*

Levitt, Steven D. 1997. “Using Electoral Cycles in Police Hiring to Estimate the Effect of Police on Crime.” *The American Economic Review* 87, no. 3 (June): 270-290.

Levitt, Steven D. 2002. “Using Electoral Cycles in Police Hiring to Estimate the Effects of Police on Crime: Reply.” *The American Economic Review* 92, no.4 (September): 1244-1250.

Lincoln Institute of Land Policy. *Fiscally Standardized Cities database*. https://www.lincolninst.edu/research-data/data-toolkits/fiscally-standardized-cities

McCrary, Justin. 2002. “Using Electoral Cycles in Police Hiring to Estimate the Effect of Police on Crime: Comment.” *American Economic Review* 92, no. 4 (September): 1236-1243.

Mello, Steven. 2018. “More COPS, Less Crime.”

Polinsky, A. Mitchell, and Steven Shavell. 2005. “The Theory of Public Enforcement of Law.” *NBER Working Paper Series* (November)

Roth, Jeffrey A, and Joseph F. Ryan. 2000. “The COPS Program After 4 Years – National Evaluation.” *National Institute of Justice Research in Brief* (August)

United States Census Bureau. https://data.census.gov/cedsci/

U.S. Government Accountability Office. 2005. “COPS Grants Were a Modest Contributor to Declines in Crime in the 1990s,” *GAO Report*, October 2005