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Paper More Cops or More Jobs? A Trade-Off Framework in Economics of Crime

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Abstract

This paper studies and theorizes the impact of law enforcement in cities on criminal activities. Exploring primarily causing elements, the results from two IV approaches show that increasing police officers per capita in regions does not reduce the corresponding crimes. There are two sets of data used in this research for each IV strategy—the US's city-level and state-level data. Falsification tests are conducted to validate the empirical conclusion. The results show that increasing the number of law enforcements does not lead to a lower crime rate in the US. Based on the results, I propose an alternative theoretical model compared to the conventional framework, in which there is a trade-off between budgeting police forces—leading to lower crimes—and higher unemployment rates—leading to more crimes. This new framework provides more insights on the roots of such societal tragedy and narrows the gap between the theoretical and empirical findings. Thus, an alternative to control crimes could be legalizing and taxing (possible) illicit activities reduces the crimes and provides funds for creating new jobs while alleviating the pressure on the police forces document.

Keywords

Economics of Crime, Instrumental Variable, Police Force, Theoretical Modeling, Trade-Off Analysis

1. Introduction

The causes and motives of city crime are varied and complex. Many criminologists have tried to understand the roots of crime and to verify the effects that demographic and socioeconomic statuses have had (Shaw & McKay, 1969; Kornhauser, 1978; Sampson & Groves, 1989; Bursik, 1988; Byrne & Sampson, 1986; Veysey & Messner, 1999; Lowenkamp et al., 2003; Fajnzylber et al., 2002; Buonanno & Leonida, 2009; Wilson & Petersilia, 2010; Draca et al., 2011). Glaeser et al. (1996) divide the connection between cities and crime into four categories; higher pecuniary returns to crime in urban areas, lower probability of arrest or being recognized in urban areas, features that affect crime, which are exogenous with respect to the location but that happened to be correlated with urban status, and characteristics that are endogenous with respect to location that both cause crime and are caused by urban status; and there is a rich body of literature examining and supporting the association between urban population and the prevalence of crime (Wirth, 1938; Jacobs, 1961; Ehrlich, 1975; Shichor et al., 1980; Chaiken & Chaiken, 1983; Glaeser & Sacerdote, 1999; Levitt, 2002; Buonanno, 2006; McDonald & McMillen, 2010).

In their analysis, Neanidis and Rana (2014) show that both common and organized crime react to the share of a region's economically active population and crime-deterrence variables. Draca et al. (2019) find strong evidence that changing economic incentives affect criminality in the same way in which changing returns to crime in the standard Becker/Ehrlich model propel crime rates.

The focus of this research is to verify whether the conventional methods—where to control the criminal activities, decision-makers need to mainly focus on funding law enforcement—were able to reduce or control crime rates. Traditionally, there are two mechanisms through which criminal justice policy reduces crime; incapacitation and deterrence. For the first mechanism, we need law enforcement officers and equipment, and for the second, laws and regulations[1]. While deterrence can arise in response to any policy that changes the costs or benefits of offending, incapacitation arises only when the probability of capture or the expected length of detention increases. The evidence shows that starting 1990's the crime rates started to shrink. Levitt (2004) believes that four factors explain the decline in crime during the 1990's; an increase in the number of the police, the recession of the crack epidemic, rises in the prison population, and the legalization of abortion. Di Tella and Schargrodsky (2004) make the same argument about the negative correlation between auto theft and visible police presence, but they argue that hiring more police officers is not cost-effective. Recent theoretical studies have focused on optimal law enforcement policies that discourage criminal coalitions (Chang et al., 2005; Mansour et al., 2006; Garoupa, 2007). The deterrence variables measure the risk of apprehension and punishment—which represent costs—in committing a crime (Viscusi, 1986; Neanidis & Papadopoulou, 2013). However, income and income growth rates can either boost the opportunity cost of committing a crime (which lowers crime rates) or draw more attention to criminal activity. As the expected benefits from crime rise, so also do crime rates. Therefore, these two variables have an ambiguous prognos-

[1]There is a clear correlation between these two factors, as having an effective deterrence, we might need some variation of incapacitation.

tic effect (Marselli & Vannini, 1997; Kelaher & Sarafidis, 2011), which might be the reason that some research finds that punishment and prison can have little to no empirical deterrence effect (Lee & McCrary, 2009; Paternoster, 2010).

In this research, I attempt to empirically verify the hypothesis in which hiring more police officers per capita—as the deterrence factor in controlling the crime rates—has led to the lower criminal activities in the presence of key factors causing and shaping the criminal world since there is no concrete results considering different identification and given different crime categories. Also, previous studies that found a strong and positive relationship between the number of the police officers and the criminal activities, were suffered from using the weak instruments—firefighters and election cycles (Kovandzic et al., 2016). On the other hand, in the recent study, Piza and Chillar (2021) show that the police layoffs—due to the economic recession in 2008—in Newark associates with a significant raise in violent and property crimes. In this study, I use two different datasets: city-level and state-level to pursue this question and employ IV methods and other robustness checks to validate the results that have not been explored previously. In the end, I propose a new theoretical framework which better match the empirical findings.

Figure 1 displays the number of the police officers in selected cities compared to overall crime rates. It is interesting that while the population has been growing over the past decades, given the stable number of police officers, the crime rates fall over that same period. The formatter will need to create these components, incorporating the applicable criteria that follow.

2. Empirical Model

We expect that as the number of police officer increases, the probability of being known or noticed by the community also increases. Consequently, the likelihood of property crime declines as it increases. We expect violent crime to increase as the frequent interaction between individuals intensifies interpersonal friction (Levy et al., 2020); I modify the empirical strategy based on this argument. I control for a number of variables, using the existing literature, such as property rate[2]—which can be interpreted as the proxy for prices in the structural model—(Glaeser et al., 1996; Sun et al., 2004), income (Viscusi, 1986; Freeman, 1987; Grogger, 1998; Hansen & Machin, 2002; Gould et al., 2002), income inequality (Chiricos, 1987; Lee, 1993; Freeman, 1994, 1999; Ehrlich, 1975; Land et al., 1990; Machin & Meghir, 2004), education (Ehrlich, 1975; Witte & Tauchen, 1994; Lochner, 1999, 2004; Buonanno & Leonida, 2009), race heterogeneity (Shelley, 1981; Freeman, 1996; Sun et al., 2004), and unemployment (Chiricos, 1987; Grogger, 1994; Freeman, 1994, 1996, 1999; Elliott, 1994; Raphael & Winter-Ebmer, 2001; Buonanno, 2006; Chalfin & Raphael, 2011).

[2]Which can be a proxy for the quality of the neighborhood.

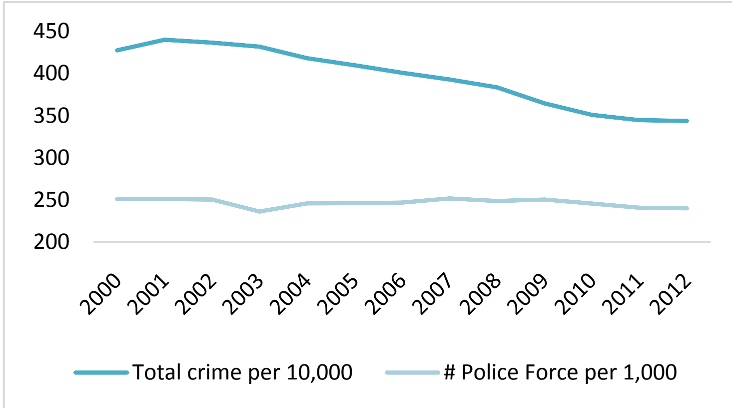

Figure 1. Number of the police officers and crime rates in 191 major cities in the US.

Raising the number of a police officer could lower offense rates by increasing the probability of arrest, thereby increasing the area's appeal by indicating its inhabitants' safety. While the rate of crime goes up, a city needs to hire more police officers (or/and implement more advanced instruments and technology) to control it. Therefore, there is an endogenous correlation that needs to be addressed here. To solve the endogeneity issue, I use an IV approach for the primary explanatory variable.

The current research's essential focus is to examine how increasing the number of police officers relative to the population density has on crime rates. One of the challenges this model faces would be an unobserved variable that may affect both the independent variables and dependents. A possible solution is to enter the lagged dependent variable into the model to absorb the impact of the unobserved variable on the dependent—specifically if the serial correlation is possible. Implicitly, the proposed model is interpreted as Coleman's solution (Morgan & Winship, 2014). Thus, I create the baseline model shown below:

$$C_{it} = \alpha_i + \delta_t + \beta\left(\frac{Police}{pop}\right)_{it} + \varphi_j X_{ijt} + \gamma\left(\frac{Police}{pop}\right)_{it-1} + \varepsilon_{it} \tag{1}$$

Here, C_{it} is crime rate in city I at time t; α_i and δ_t are city-fixed effect and year-fixed effect, respectively; the explanatory variable is the police-population ratio; and X_{ijt}s are the covariates that I control for, including housing rates, wage and real income, education, income inequality, race heterogeneity, and rate of unemployment—based on the suggested playing factors which are explained in the introduction section. After identifying the baseline results, I perform a placebo test to verify the robustness of the results in any stage of the proposed empirical models. The test's mechanism is such a way that if we observe any result from the model, using the lagged dependent variables, the power of the results should fade away (or even reverse). After testing the base model, I redo the analysis through the annual changes in the variables, and eliminate any possible yearly unobserved and autocorrelation.

The main concern is the reverse causality and existence of endogeneity between the explanatory variable and crime rates. To partially address this issue, I use an IV approach. Previous works utilize various types of IV for police forces, such as firefighters (Levitt, 2004), the size of the federal police grants awarded to cities (Evans & Owens, 2007), exposure to the exchange rate shocks based on local industry exports (Lin, 2009), and lagged crime rates applied to the current police force (Marvell & Moody, 1996). While Machin and Meghir (2004) find a persistence of crime rates across areas over time, in accordance with Glaeser et al. (1996), I use a five-year-lag on the number of police officers and population for the IV. This approach has more relevancy than the previous instruments such as firefighters[3], and is lagged enough to make the reverse causality transparent. The intuition behind this is that the variables during one given year may impact themselves after five years; but, the crime rates of the next five years do not have anything to do with the current population and police officers.

As it has been already discussed, one of the concerns that this model faces is an existence of an unobserved variable that may affect both the independent and dependent variables. Besides using the Coleman solution, I use the annual changes which take care of this issue and possible serial correlation at the same time. The main model is constructed in two steps. First, I assess the explanatory variable (police-population ratio) using a five-year-lag in the first stage. And then, using the proxied estimation, I evaluate the impact of the police force on the dependent variable (crime rates) in the second stage:

$$\left(\frac{Police}{pop}\right)_{it} = \delta_i + \gamma_1 \left(\frac{Police}{pop}\right)_{it-5} + \theta_j X_{ijt} + \epsilon_{1it} \tag{2}$$

$$Crime_{it} = \alpha_i + \beta_1 \widehat{\left(\frac{Police}{pop}\right)}_{it} + \varphi_j X_{ijt} + \epsilon_{2it} \tag{3}$$

I use the annual change of the variables to mitigate the possible yearly effect and auto-correlation at the same time. δ_i and α_i are the metro area's fixed effect to absorb any potential structural differences across the cities. X_{ijt}s are the covariates that are controlled by fair market rates, education, average income, rate of unemployment, income equality (estimated by Gini coefficient), and race heterogeneity across metro areas.

After verifying the model, I test if the rate of unemployment is the mechanism between the police force ratio and crime rates in such a way that providing the resources for the enforcement law officers shuts down some businesses who work in the perfectly competitive market. Therefore, newly unemployed individuals are attracted by the crime market, which leads to higher rates of illegal activity. To do

[3]There might be two issues using firefighters. First of all, both firefighters and police officers are correlated with the tax level. Therefore, households' income opens a backdoor channel to the dependent variable (crime rates). The other argument is that firefighter is a weak predictor of the police force, while there might be a high correlation between them because of the effect of unobservable such as income level; thus, having a weak instrument does not guarantee that the finite-sample biases will be eliminated (Bound et al., 1995).

that, I apply the Imai et al. (2010) mechanism approach. The key to understanding the mediation effect is the following counterfactual inquiry: How would the outcome differ if one were to alter the mediator from the control condition value to the treatment condition value while maintaining the treatment status at the same level?

To measure the mediation effect, I first verify the impact of police-population ratios on the dependent variable: the crime rate excluding the mechanism of unemployment (Equation (4)). Then, I measure the impact of the independent variable on the proposed mechanisms: the rate of unemployment (Equation (5)). At the last step, I estimate the primary model (including all the proposed variables) (Equation (6)).

$$Crime_{it} = \alpha_i + \beta_1 \left(\frac{Police}{pop} \right)_{it} + \varphi_j X_{ijt} + \varepsilon_{1it} \tag{4}$$

$$Unemployment_{it} = \alpha_i + \beta_2 \left(\frac{Police}{pop} \right)_{it} + \varphi_j X_{ijt} + \varepsilon_{2it} \tag{5}$$

$$Crime_{it} = \alpha_i + \beta_3 \left(\frac{Police}{pop} \right)_{it} + \gamma Unemployment_{it} + \varphi_j X_{ijt} + \varepsilon_{3it} \tag{6}$$

After estimating each linear equation, the product of coefficients method uses $\hat{\beta}_2 \hat{\gamma}$ as an estimated mediation effect. Similarly, the difference between coefficient methods yields an identical estimate by computing $\hat{\beta}_1 - \hat{\beta}_3$ in this linear case. Because $\hat{\beta}_1 = \hat{\beta}_2 \hat{\gamma} + \hat{\beta}_3$ and $\beta_1 = \beta_2 \gamma + \beta_3$ always hold, Equation (4) is redundant, given Equations (5) and (6).

3. Data

Before I use the yearly data—from 2005-2011—to examine the relationship between police officers with respect to the crime rates at the city level. The data are extracted from the FBI's online uniform crime statistics (UCR). Then, I collect and include the data for fair-market rates' efficiency from the US Department of Housing and Development. Then, I merge the data with the American Community Survey to calculate household information such as median income, education, and race. This is meant to identify whether results vary under different scenarios when the possible covariates that control the dependent variables' possible endogeneity are regulated. To compute race heterogeneity, I construct my indicator based on the Herfindahl index. Because there is heterogeneity in the household sample size, I calculate this index based on each metropolitan area's ethnicities. Table 1 shows the population-crime growth is selected cities in this study.

Thus, we have $\sum_i h_i^2$ in which "*i*" is race, and *h* is the fraction of that race in the metro areas. If the index is closer to one, it shows more homogeneity in that metro area. I also compute the Gini coefficient for the household. This could play a significant role in the analysis based on the emphasized role of income inequality and how it can incentivize the individuals to commit a crime in that neighborhood. Later, the unemployment rate—from BLS—has been merged to the dataset. The focus of this study is the digging into the relationship between the number of the police officers and the crime rates controlling for other major players. However, we cannot neglect the impact of the police instruments on the efficiency for controlling crimes. Therefore, I plot the number of law enforcements versus total justice expenditure as an insight to see whether we could detect any deviation in their trends. While they might not be an accurate projection of the overall costs, as it is shown in Figure 2, both indices follow the same trend over time.

4. Results

Define Table 2 represents the baseline model's raw analysis results, wherein I calculate the panel data regression for over 103 cities over seven years from 2005-2011 based on Equation (1). They give us a general overview of the possible correlations between the different elements in the current study. As shown in Table 2, the police-population ratio harms both crime rates (in the first two columns). The effect of the main variable on violent crime differs from property crime, and at the same time, none of them is significant. The proposed model may suffer from endogeneity issue between the main variables as a result of ill-defined modeling.

Table 1. Population growth in the US and selected cities.

Description (in million)	2000	2012	Ave. Growth
Population	282	314	0.9%
Urban pop.	79%	81%	0.2%
Sample size	68	74	0.7%
Violent crime	0.63	0.51	−1.7%
Property crime	3.64	2.92	−1.8%
Total crime	4.27	3.44	−1.8%

Source: World Bank data set, and UCR online data.

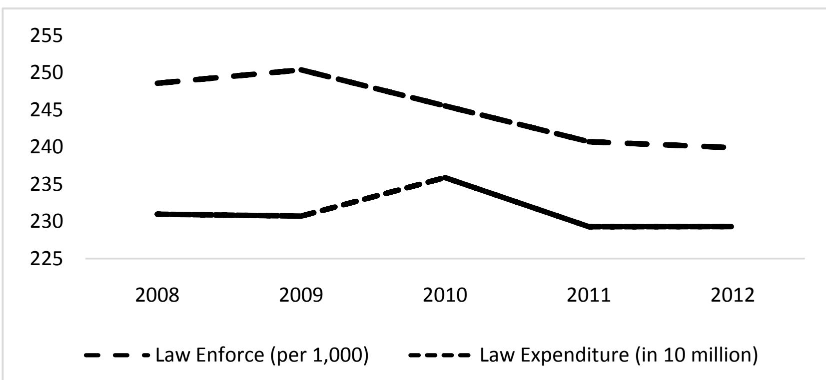

Figure 2. Total law enforcement employee and overall justice expenditure over the past decade.

Table 2. Benchmark regression of major variables on crime rates (2005-2011)—Equation (1).

	Base model: EQ 1		Placebo test	
	(1)	(2)	(3)	(4)
	Violent Crime	Property Crime	Lag Violent	Lag Property
Law-pop Ratio	−1612.2	−6572.7	−915.6	−4501.8
	(832.95)	(4083.72)	(938.85)	(4780.94)
Housing Rate	−1.897*	−7.190	−0.290	−4.282
	(0.78)	(3.80)	(0.91)	(4.65)
Income	−0.00113	0.00326	0.00479	0.0203
	(0.00)	(0.01)	(0.00)	(0.02)
Race Heterogeneity	1572.2	4043.9	1610.2	8337.8
	(814.78)	(3994.67)	(921.15)	(4690.81)
Education	−2040.2***	−8110.7**	−1467.0*	−7070.0*
	(547.24)	(2682.97)	(596.73)	(3038.76)
Gini	1538.9	17378.4	1244.2	−6583.7
	(2806.18)	(13757.99)	(3034.35)	(15451.96)
Unemployment	−70.98***	−353.1***	−34.15*	−240.7**
	(16.18)	(79.33)	(16.75)	(85.28)
Lagged Ratio	Yes	Yes	Yes	Yes
Fixed effects*	Yes	Yes	Yes	Yes
N	618	618	515	515
R^2	0.29	0.21	0.08	0.12

Standard errors in parentheses [*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$], *City fixed effect and year fixed effect.

The above issue raises the necessity for using possible IV to solve the endogeneity problem since Equation (1) suffers from reverse causality. Using the proposed IV explained in Equations (2) and (3), I get a positive, but not significant, the effect on the police/population ratio on both crime types. The results are in the direction and favor of the outcomes that are driven by the theoretical framework. As a rule of thumb, increasing the number of police officers may decrease the crime rates by increasing the risk of being captured and punished. However, as discussed before, in a perfectly competitive market, raising taxes to provide resources for such forces shuts down businesses. This phenomenon raises the rate of unemployment within an economy and fosters an environment for criminal activity growth. Thus, there needs to be an additional mechanism test in place to facilitate this analytical process. Using mechanism approach—previously used in an economic literature by Farhidi (2018)—which is illustrated in **Figure 3**, I verify the unemployment channel between police financing and crime rates.

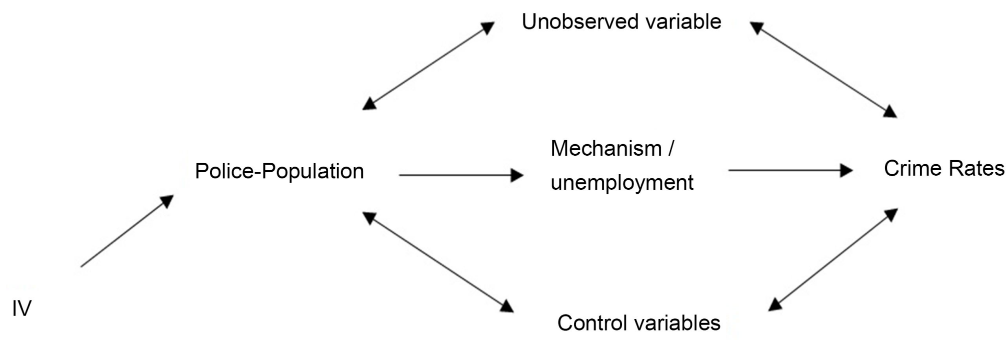

Figure 3. Illustrating the applied empirical model, and the channels of the impacts of the independent variable on the crime rates.

The results shown in **Table 3** cannot reject such a hypothesis. As it is shown, there is a small and negative (not significant) impact of the police/population ratio on unemployment (in column three of **Table 3**). At the same time, the effects of unemployment on both crime types are negative and significant. As a consequence, the overall effect is positive but not significant, and unemployment can be a weak channel between financing police forces and boosting criminal activities.

Several limitations apply to this study. I use the number of law enforcement employees as a proxy for law enforcement activities. This estimate was stabilized over the past decades. However, the nature of the equipment they have been using—such as weapons, communication, and tracking instruments—may change over time. Therefore, it is a better idea to utilize an index that includes the law enforcement budget relative to each city; however, as **Table 4** shows a similar trend for the police expenditure and the number of the law forces, we can neglect this point.

5. Robustness Check

The purpose is to verify that the results are robust and do not change under different conditions. I present five different methods to verify that the results are unquestionable in the direction of interest. First, I perform a Placebo test. The intuition behind this is to determine whether the independent variable has a valid effect on the dependent variable. If so, by varying the time intervals, outcomes should change over time. Let's say instead of the impact of the time (0) on the time of the independent variable (0), I investigate the time (0) on time for the associated correlation (−1). There could be an ambiguous effect because of the possible serial correlation over time. To avoid this, I use annual changes to eliminate the unobserved correlation. As depicted in **Table 4** and **Table 5** (columns three and four), the results are reversed for the effects of police/population ratio on crime rates for the IV approach, but not fully for the regular annual changes. This finding verifies the results of the main model. Therefore, I conclude that the constructed model is well-specified as it passes the Placebo test.

Table 3. Identifying the unemployment as a mediation effect between the financing the police forces and the crime rates—Equations (4), (5) & (6).

IV approach without mechanism			Mechanism	Full analysis	
	(EQ 4)		(EQ 5)	(EQ 6)	
	(1)	(2)	(3)	(4)	(5)
	Violent Crime	Property Crime	Unemployment	Violent Crime	Property Crime
Law-pop Ratio	2455.9	13719.7	−0.161	2447.6	13684.6
	(2955.5)	(18767.4)	(7.65)	(2931.0)	(18707.2)
Unemployment	No	No	–	−51.70**	−219.0*
				(17.19)	(109.72)
Control vars.*	Yes	Yes	Yes	Yes	Yes
N	618	618	618	618	618
R^2	0.0002	0.002	0.089	0.018	0.01

Housing rate, income, race heterogeneity, education, Gini, unemployment, city and year fixed effects. Standard errors in parentheses [$p < 0.05$, **$p < 0.01$].

Table 4. Applying the annual changes approach (first difference) to the modified empirical model, excluding IV variable.

	Annual changes		Placebo test		Sensitivity test	
	(1)	(2)	(3)	(4)	(5)	(6)
	Violent Crime	Property Crime	Lag Violent	Lag Property	Violent Crime	Property Crime
Law-pop Ratio	−193.2	1994.1	−1018.9	−12992.0*	−183.0	2051.2
	(612.5)	(3946.3)	(846.6)	(5231.8)	(612.0)	(3944.5)
Control variables*	Yes	Yes	Yes	Yes	Yes	Yes
Unobserved	No	No	No	No	Yes	Yes
N	618	618	412	412	618	618
R^2	0.05	0.03	0.02	0.02	0.06	0.03

Housing rate, income, race heterogeneity, education, Gini, unemployment, city and year fixed effects. Standard errors in parentheses [$p < 0.05$].

Table 5. Applying IV approach to the main model (Equations (2) & (3)), including the falsification tests to identify the validity and sensitivity of the results.

	IV		Placebo test		Sensitivity test	
	(1)	(2)	(3)	(4)	(5)	(6)
	Violent Crime	Property Crime	Lag Violent	Lag Property	Violent Crime	Property Crime
Law-pop Ratio	2447.6	13684.6	−622.6	−46177.5	2288.4	12794.8
	(2931.0)	(18707.2)	(6188.1)	(40693.0)	(2913.7)	(18621.1)
Control variables*	Yes	Yes	Yes	Yes	Yes	Yes
Unobserved	No	No	No	No	Yes	Yes
N	618	618	412	412	618	618
R^2	0.02	0.01	0.02	0.03	0.03	0.02

*Housing rate, income, race heterogeneity, education, Gini, unemployment, city and year fixed effects.

I execute another test as a sensitivity analysis to verify the results with a different approach. I aim to include an arbitrary variable and run the analysis to see if the results are consistent when an irrelevant independent variable is added to the model. I create the new column of data w for the unknown variable C by generating the random dataset that is distributed uniformly and have them interact with the principle independent's variable to measure the sensitivity of the results to the newly constructed variable, as the formula displayed below:

$$C = w * (\text{Pop. Den.}) + (1 - w) * (\text{Law Enforce}) \quad (7)$$

The directions of the impact of the studied elements on the crime rates are shown in the last two columns of **Table 4** and **Table 5**, which are consistent with the first two columns' outcomes. The analysis passed the latter test as well as the previous one. In another attempt, I perform another sensitivity test for the mechanism approach—used in Farhidi and Mawi (2022)—based on the correlation between the error for the mediation model, ε_{2it} (Equation (5)), and the error for the outcome model, ε_{3it} (Equation (6)). Imai et al. (2010) argue that this correlation between the two error terms served as the sensitivity parameter. Such a correlation can arise if omitted variables affect both mediator and outcome variables since these omitted variables will be part of the two error terms. As it is tested in **Table 6**, there is no such correlation between error terms that increases the likelihood of having no omitted variables in the proposed model.

Table 7 shows the impact of the main variable on the total burglary. The idea here is to isolate the crime's pecuniary incentives, and see if the model is robust; which is the case.

6. State Level Analysis

At the end and in the final effort to mitigate the reverse causality, since the previously developed instrument is weak (five-year lag). In another attempt, I utilize political affiliation of the state governors as an IV for the police force to redo the analysis and check whether the results are consistent or not by extracting the relevant data at the state level for 50 states (including District of Columbia) from 2001 to 2015. **Table 8** summarizes the findings, which show that there is no clear correlation between the number of police force per population and the illegal activities.

Table 6. Test for the endogeneity of the error terms in mechanism approach.

	Violent crime	Property crime
	ε3vc	ε3pc
ε2vc	−0.893	
	(−0.05)	
ε2pc		−10.39
		(−0.10)
N	618	618

t statistics in parentheses.

Table 7. Testing for the effect of the main model approach on the burglary.

	IV			Placebo test		
	(1)	(2)	(3)	(4)	(5)	(6)
	Violent Crime	Property Crime	Burglary	Lag Violent	Lag Property	Lag Burglary
Law-pop Ratio	2447.6	13684.6	4553.0	−622.6	−46177.5	−234.8
	(2931.0)	(18707.2)	(3354.8)	(6188.1)	(40693.0)	(6386.1)
Control vars.*	Yes	Yes	Yes	Yes	Yes	Yes
N	618	618	618	412	412	618
R^2	0.02	0.01	0.0005	0.02	0.03	0.03

*Housing rate, income, race heterogeneity, education, Gini, unemployment, city and year fixed effects.

Table 8. IV approach at the state level.

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
	Total Crime	Violent Crime	Property Crime	Total Crime	Violent Crime	Property Crime
Law-pop Ratio	1.29***	0.34***	0.95**	4.11	−1.06	5.17
	(0.37)	(0.06)	(0.34)	(10.81)	(2.31)	(10.54)
Control vars.*	Yes	Yes	Yes	Yes	Yes	Yes
N	816	816	816	816	816	816
R^2	0.693	0.328	0.698	0.668	0.308	0.634

*Housing prices, income, unemployment, state fixed effect and year fixed effect. Standard errors in parentheses [** $p < 0.01$, *** $p < 0.001$].

7. Alternative Theoretical Framework

Becker (1968) proposed that individuals commit crimes when the benefits exceed the costs. Pursuing this method, most of the economic analysis of crime has concentrated on the individual's optimal choice between illegal and legal activities (e.g., Ehrlich, 1973; Taylor, 1978; Levitt, 1996). In a standard model, the rule is to commit a crime whenever:

$$MB > CS + \rho * CR + \sigma CA$$

where MB reflects the marginal benefits of crime, CS represents the individual specific costs that occur whether or not the individual is arrested or incarcerated. ρ refers to the probability of being known by one's victim or noticed by community members, and CR is the stigma if the individual is identified as a criminal. σ refers to the probability of arrest, and CA is the cost of arrest and incarceration to the individual. CS can refer to time costs, inconvenience, and the psychological costs of breaking the law. To extending Becker's idea, using insights from this study's empirical finding—in which the number of the police officers do not necessarily decreases crime rates—I have developed a new structural model in the crime literature, which can explain illegal activity at the household level by introducing the pecuniary value of crime returns into the household decision-making process, and by constructing the production function and the market for the supply and demand of the crime, as well as the normal good. The prevalence of law enforcement officers has its costs and benefits, which I try to investigate at the same time as their effect has been verified on the overall economy. In this model, there are two goods in the market, a normal good or numeraire (c_1) with the price of p_1, and a crime good (c_2) with the price of p_2. Therefore, in their utility maximization decision, an individual has to decide which they want to use, considering that the crime good brings them a possible disutility[4] as well as a utility. Now, they can dedicate their time to work in the labor force (n_{lf} with the wage of w_{lf}), work as a law enforcement officer (n_{el} with wage of w_{el}), or work in the crime market (n_{cr} with the wage of w_{cr}) where there is also a trade-off between working time and leisure time l. One could think of labor force participation as the total population of a region normalized to one in which the whole sample size is represented by one individual who has to decide in which sector he or she wants to work, and what percentage of his or her time to allocate to it. Therefore, household decision making is constructed as follows:

$$\text{Max } U = c_1^{\alpha} c_2^{1-\alpha} + \beta \ln l - \gamma \ln n_{cr} \quad \text{s.t.}$$

$$p_1 c_1 + p_2 c_2 \le w_{lf} n_{lf} + w_{el} n_{el} + w_{cr} n_{cr}$$

$$n_{lf} + n_{el} + n_{cr} + l \le 1$$

Solving for the first-order conditions for a household we have:

$$\frac{\partial L}{\partial c_1} \to \alpha c_1^{\alpha-1} c_2^{1-\alpha} = \lambda_1 p_1$$

$$\frac{\partial L}{\partial c_2} \to (1-\alpha) c_1^{\alpha} c_2^{-\alpha} = \lambda_1 p_2$$

$$\frac{\partial L}{\partial l} \to \frac{\beta}{l} = \lambda_2$$

$$\frac{\partial L}{\partial n_{cr}} \to -\frac{\gamma}{n_{cr}} = \lambda_2 - \lambda_1 w_{cr}$$

$$\frac{\partial L}{\partial n_{lf}} \to \lambda_2 = \lambda_1 w_{lf}$$

$$\frac{\partial L}{\partial n_{el}} \to \lambda_2 = \lambda_1 w_{el}$$

Then, the Euler's equations would be as follows:

$$\frac{c_2}{c_1} = \left(\frac{1-\alpha}{\alpha}\right)\left(\frac{p_1}{p_2}\right) \tag{8}$$

$$\frac{\gamma}{n_{cr}} = -\frac{\beta}{l} + w_{cr} \frac{(1-\alpha) c_1^{\alpha} c_2^{-\alpha}}{p_2} \tag{9}$$

[4]Or non-pecuniary utility, if the marginal return in the crime market is lower than the normal one, as Levitt & Venkatesh (2000) emphasis.

$$w_{lf} = w_{el} \tag{10}$$

On the demand side, we have two markets and two firms that produce goods. One is a normal good, and the other is the criminal element. Both utilize their respective labor force to produce their goods. But the distinction here is that the government imposes taxes on the firm that makes a normal good to hire the police officers who control the crime market. But they cannot tax the crime market. Productions for the numeraire and crime goods show in the third and fourth equations:

$$y_1 = A_0 n_{lf}^{\delta} \tag{11}$$

$$y_2 = B_0 n_{cr}^{\eta} \tag{12}$$

Setting up profit maximization conditions for each firm, we get:

$$\pi_1 = p_1 y_1 - w_{lf} n_{lf} - t p_1 y_1$$

The government charges the firm sales tax[5] t to hire law enforcement employees to control the crime. On the other hand, as the number of police officers goes up, the criminal's probability of being arrested goes up as well, which increases the cost of the crime.

$$\pi_2 = p_2 y_2 - w_{cr} n_{cr} - \rho n_{el}$$

ρ is the cost of the likelihood of being arrested by the police forces. Government runs a balanced budget to hire law enforcement officers as below:

$$t p_1 y_1 = w_{el} n_{el} \tag{13}$$

Deriving the first order conditions for the firms, we get:

$$\frac{\partial \pi_1}{\partial n_{lf}} \to n_{lf} = \left(\frac{w_{lf}}{(1-t) p_1 A_0 \delta} \right)^{\frac{1}{\delta - 1}} \tag{14}$$

$$\frac{\partial \pi_2}{\partial n_{cr}} \to n_{cr} = \left(\frac{w_{cr} - \rho}{p_2 B_0 \eta} \right)^{\frac{1}{\eta - 1}} \tag{15}$$

To solve the model, we have to add the clearing conditions as follows:

$$n_{lf} + n_{el} + n_{cr} + l = 1 \tag{16}$$

$$c_1 = y_1 \quad \text{and} \quad c_2 = y_2 \tag{17) \& (18}$$

Solving for the system equations above, we get the values for the different labor force participation and other elements based on the assigned parameters, which are shown in the **Appendix**. As a result, one of this model's predictions is that to increase the number of police officers and thereby control criminal activity, the government needs to raise tax rates. This depreciates the rate of return and wages in the normal good market and, consequently, appreciates the rate of return and wages in the crime market, attracting more individuals to the illegal market versus the legal one. Thus, in real-world data, we should see the slight drop-offs, from the legal market as individuals who are officially unemployed still need to

[5] **Figure A1** shows the sales tax impacts on the market forces.

provide for their families[6]. This implies that these individuals have been hired for work in an illegal market. However, the total production of the crime good drops when the normal good production is intensified, compared to the crime good. Consequently, the relative price of crime to normal good decreases while the relative wages increase.

8. Discussion

McCollister et al. (2010) claim that the social cost per crime is $29,000 in the US. Considering ten million crimes that have happened yearly over the past two decades, the long-term annual loss in the whole economy caused by criminal activities is more than $290 billion; thus, reducing crime rates by 1% can save more than $3 billion every year (Farhidi & Mawi, 2022). Having this back of the envelop calculation gives us an insight on how much should we spend in controlling crimes, and alternatively legalizing a few activities could potentially free funds to invest in other sensitive social crisis. Within that in mind, the results show that there is no significant and robust relationship between the increasing the number of the police officers and the reduction in criminal activities (**Figure 4**). Therefore, we need to search and invest in alternative methods—rather than the conventional approaches which were focused on raising the police budget—to reduce and control such social tragedy.

Freeman (1996) states that the total number of men under the supervision of the criminal justice system in the United States (whether incarcerated, probated, or paroled) is equivalent to seven percent of the entire workforce. This is ten times higher than in other Western European countries. Many of those sentenced to prison eventually return to society with their labor market opportunities and skills reduced and their criminal abilities and opportunities appreciated. They also

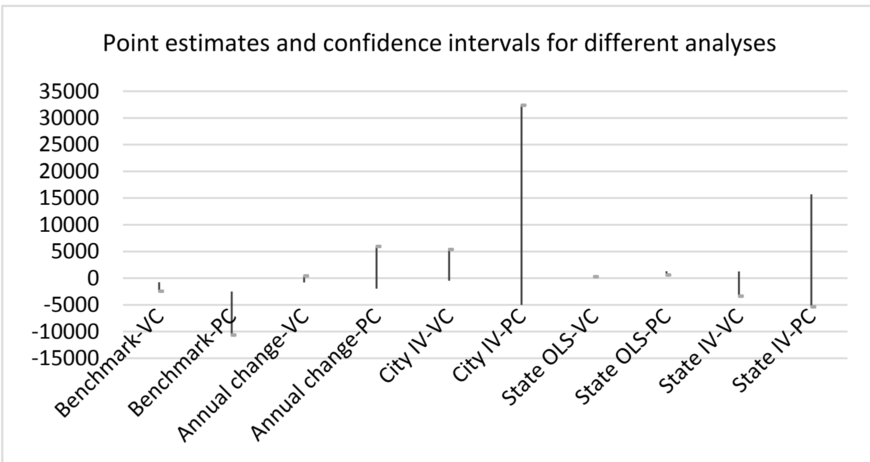

Figure 4. Summary of the findings based on four different analyses: Impact of increasing law enforcement per capita on the crime rates. Violent crime—VC, Property crime—PC.

[6]Legalizing illicit activities and boosting up the prices might have an adverse effect on other types of crimes since affording the first type cost more money. It may encourage an individual to commit a crime to provide it.

face more obstacles in potential employment than others, which increases their likelihood of working in the crime market. Therefore, part of the resources and efforts that have been invested in decreasing the crime rates are effectively depleted over time. Therefore, there is no evidence showing the cost effectiveness of raising police funds to successfully control crimes and rehabilitations.

One of the feasible and possible approaches to reverse the outcomes above is that the government could legalize some particular criminal activities. They could also modify the specific thresholds of being a criminal—such as the legal level blood alcohol content—which would lead to a reduction in conviction and sentencing. There are some ways to reduce the pecuniary return in the crime markets, such as reducing the amount of cash in circulation (Wright et al., 2014). While increasing the risk of being recognized and captured by the police is one way, promoting competition by legalizing some activities is another—such as particular drugs and prostitution; New Zealand among other were able to achieve this goal successfully. Imposing higher tax rates on those activities, creates a self-reduction mechanism to control the crime market. This tax increase6 on illegal markets would allow the government to lower taxes on the normal market. They could thereby provide more opportunities for individuals to find better jobs with higher wages in those legal markets. As a result, because of the low return on criminal activity, businesses would then have the incentive to abandon illegal practices.

9. Conclusion

In this study, I propose an empirical model to verify the relationships between the drivers of crime. Relying on the strength of the results, I conclude that the financing and equipping law enforcement employees has had a positive but not significant impact on both property and violent crime rates over the past decade, although the results are not conclusive. One explanation for such a conclusion is that increasing the number of police officers may decrease the aggregate crime rates by raising the probability of getting caught. However, providing the resources for hiring more police officers may impose a higher rate of taxes on the legal market, leading to a reduction in the employment rate and a depreciation of the rate of return in those legal markets. Therefore, more individuals—specifically those who are unemployed—are attracted to the illegal market; thus, the latter effect outweighs the first one. This conclusion is supported by a recent panel study which shows a strong link between poverty and inequality-as the roots—and the criminal activities (Anser et al., 2020). Whereas, Kovandzic et al. (2016) derive different conclusion based on the natural experiment between Newark and Jersey City where they find that reduction in the number of the police officers due to the recession led to the higher crime rates. While this result only support the internal validity of such relationship, but other studies are skeptical on the external validity and generalization of such findings.

I also developed a new structural model in the crime literature as a complement to the existing analysis. Increasing the number of police officers can decrease the aggregate crime rates by raising the probability of getting caught. However, providing the resources for hiring more police officers imposes a higher rate of taxes on the legal market, which leads to a reduction in the employment rate and a depreciation of the rate of return in those traditional markets (compared to criminal markets). Therefore, more individuals—specifically those who are unemployed—are attracted to the illegal market; thus, the latter effect outweighs the first one. A feasible approach to decrease the criminal activities would be to decriminalize illicit activities that do not have negative impact on the society due to extensive research and experiments such as some drugs and prostitution. In addition, investing in infrastructure, creating, and supporting affordable job and housing, and providing basic healthcare for the lowest income percentile of the society would be a wise choice rather than increasing the funding for law enforcement to control the crime. Besides, impose higher taxes on certain drugs and the solicitation of prostitution could create fund for the societal infrastructure investments. In this case, the government can cut tax rates on existing legal markets, thereby allowing them to employ and produce more.

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Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

References

Anser, M. K., Yousaf, Z., Nassani, A. A., Alotaibi, S. M., Kabbani, A., & Zaman, K. (2020). Dynamic Linkages between Poverty, Inequality, Crime, and Social Expenditures in a Panel of 16 Countries: Two-Step GMM Estimates. *Journal of Economic Structures, 9,* 1-25. https://doi.org/10.1186/s40008-020-00220-6

Becker, G. S. (1968). Crime and Punishment: An Economic Approach. In N. G. Fielding, A. Clarke, & R. Witt (Eds.), *The Economic Dimensions of Crime* (pp. 13-68). Palgrave Macmillan. https://doi.org/10.1007/978-1-349-62853-7_2

Bound, J., Jaeger, D. A., & Baker, R. M. (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,* 443-450. https://doi.org/10.1080/01621459.1995.10476536

Buonanno, P. (2006). Crime and Labour Market Opportunities in Italy (1993-2002). *Labour, 20,* 601-624. https://doi.org/10.1111/j.1467-9914.2006.00346.x

Buonanno, P., & Leonida, L. (2009). Non-Market Effects of Education on Crime: Evidence from Italian Regions. *Economics of Education Review, 28,* 11-17. https://doi.org/10.1016/j.econedurev.2007.09.012

Bursik, R. J. (1988). Social Disorganization and Theories of Crime and Delinquency: Problems and Prospects. *Criminology, 26,* 519-552.

https://doi.org/10.1111/j.1745-9125.1988.tb00854.x

Byrne, J. M., & Sampson, R. J. (Eds.). (1986). *The Social Ecology of Crime*. Springer-Verlag. https://doi.org/10.1007/978-1-4613-8606-3

Chaiken, J. M., & Chaiken, M. R. (1983). Trends and Targets. *The Wilson Quarterly, 7,* 103-130.

Chalfin, A., & Raphael, S. (2011). Work and Crime. In M. Tonry (Ed.), *Oxford Handbook on Crime and Criminal Justice* (pp. 444-476). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780195395082.013.0015

Chang, J. J., Lu, H. C., & Chen, M. (2005). Organized Crime or Individual Crime? Endogenous Size of a Criminal Organization and the Optimal Law Enforcement. *Economic Inquiry, 43,* 661-675. https://doi.org/10.1093/ei/cbi046

Chiricos, T. G. (1987). Rates of Crime and Unemployment: An Analysis of Aggregate Research Evidence. *Social Problems, 34,* 187-212. https://doi.org/10.2307/800715

Di Tella, R., & Schargrodsky, E. (2004). Do Police Reduce Crime? Estimates Using the Allocation of Police Forces after a Terrorist Attack. *American Economic Review, 94,* 115-133. https://doi.org/10.1257/000282804322970733

Draca, M., Koutmeridis, T., & Machin, S. (2019). The Changing Returns to Crime: Do Criminals Respond to Prices? *The Review of Economic Studies, 86,* 1228-1257. https://doi.org/10.1093/restud/rdy004

Draca, M., Machin, S., & Witt, R. (2011). Panic on the Streets of London: Police, Crime, and the July 2005 Terror Attacks. *American Economic Review, 101,* 2157-2181. https://doi.org/10.1257/aer.101.5.2157

Ehrlich, I. (1973). Participation in Illegitimate Activities: A Theoretical and Empirical Investigation. *Journal of Political Economy, 81,* 521-565. https://doi.org/10.1086/260058

Ehrlich, I. (1975). On the Relation between Education and Crime. In F. T. Juster (Ed.), *Education, Income, and Human Behavior* (pp. 313-338). National Bureau of Economic Research.

Elliott, D. S. (1994). Longitudinal Research in Criminology: Promise and Practice. In E. G. M. Weitekamp, & H. J. Kerner (Eds.), *Cross-National Longitudinal Research on Human Development and Criminal Behavior* (pp. 189-201). Springer. https://doi.org/10.1007/978-94-011-0864-5_9

Evans, W., & Owens, E. (2007). COPS and Crime. *Journal of Public Economics, 91,* 181-201. https://doi.org/10.1016/j.jpubeco.2006.05.014

Fajnzylber, P., Lederman, D., & Loayza, N. (2002). What Causes Violent Crime? *European Economic Review, 46,* 1323-1357. https://doi.org/10.1016/S0014-2921(01)00096-4

Farhidi, F. (2018). *Essays in Environmental and Energy Economics*. GSU Scholarworks.

Farhidi, F., & Mawi, Z. (2022). Is It Costly to Transition from Fossil Fuel Energy: A Trade-Off Analysis. *Energies, 15,* Article 7873. https://doi.org/10.3390/en15217873

Freeman, R. B. (1987). The Relation of Criminal Activity to Black Youth Employment. *The Review of Black Political Economy, 16,* 99-107. https://doi.org/10.1007/BF02900926

Freeman, R. B. (1994). Crime and the Labor Market. In J. Q. Wilson, & J. Petersilia (Eds.), *Crime* (pp. 191-224). Institute for Contemporary Studies.

Freeman, R. B. (1996). *Why Do So Many Young American Men Commit Crimes and What Might We Do About it?* No. w5451, National Bureau of Economic Research. https://doi.org/10.3386/w5451

Freeman, R. B. (1999). The Economics of Crime. In *Handbook of Labor Economics* (Vol.

3, pp. 3529-3571). Elsevier. https://doi.org/10.1016/S1573-4463(99)30043-2

Garoupa, N. (2007). Optimal Law Enforcement and Criminal Organization. *Journal of Economic Behavior & Organization, 63,* 461-474. https://doi.org/10.1016/j.jebo.2004.04.010

Glaeser, E. L., & Sacerdote, B. (1999). Why Is There More Crime in Cities? *Journal of Political Economy, 107,* S225. https://doi.org/10.1086/250109

Glaeser, E., Sacerdote, B., & Scheinkman, J. (1996). Crime and Social Interactions. *Quarterly Journal of Economics, 111,* 507-548. https://doi.org/10.2307/2946686

Gould, E. D., Weinberg, B. A., & Mustard, D. B. (2002). Crime Rates and Local Labor Market Opportunities in the United States: 1979-1997. *Review of Economics and Statistics, 84,* 45-61. https://doi.org/10.1162/003465302317331919

Grogger, J. (1998). Market Wages and Youth Crime. *Journal of Labor Economics, 16,* 756-791. https://doi.org/10.1086/209905

Grogger, J. T. (1994). *Criminal Opportunities, Youth Crime and Young Men's Labor Supply.* Department of Economics, University of California.

Hansen, K., & Machin, S. (2002). Spatial Crime Patterns and the Introduction of the UK Minimum Wage. *Oxford Bulletin of Economics and Statistics, 64,* 677-697. https://doi.org/10.1111/1468-0084.64.s.6

Imai, K., Keele, L., & Tingley, D. (2010). A General Approach to Causal Mediation Analysis. *Psychological Methods, 15,* 309-334. https://doi.org/10.1037/a0020761

Jacobs, J. (1961). *The Life and Death of Great American Cities.* Random House.

Kelaher, R., & Sarafidis, V. (2011). *Crime and Punishment Revisited.* MPRA Discussion Paper 28213, University Munich.

Kornhauser, R. R. (1978). *Social Sources of Delinquency: An Appraisal of Analytic Models.* University of Chicago Press.

Kovandzic, T. V., Schaffer, M. E., Vieraitis, L. M., Orrick, E. A., & Piquero, A. R. (2016). Police, Crime and the Problem of Weak Instruments: Revisiting the "More Police, Less Crime" Thesis. *Journal of Quantitative Criminology, 32,* 133-158. https://doi.org/10.1007/s10940-015-9257-6

Land, K. C., McCall, P. L., & Cohen, L. E. (1990). Structural Covariates of Homicide Rates: Are There Any Invariances across Time and Social Space? *American Journal of Sociology, 95,* 922-963. https://doi.org/10.1086/229381

Lee, D. S. Y. (1993). *An Empirical Investigation of the Economic Incentives for Criminal Behavior.* Harvard University.

Lee, D. S., & McCrary, J. (2009). *The Deterrence Effect of Prison: Dynamic Theory and Evidence.* Industrial Relations Section, Princeton University.

Levitt, S. D. (1996). The Effect of Prison Population Size on Crime Rates: Evidence from Prison Overcrowding Litigation. *Quarterly Journal of Economics, 111,* 319-351. https://doi.org/10.2307/2946681

Levitt, S. D. (2002). Using Electoral Cycles in Police Hiring to Estimate the Effect of Police on Crime: Reply. *American Economic Review, 92,* 1244-1250. https://doi.org/10.1257/00028280260344777

Levitt, S. D. (2004). Understanding Why Crime Fell in the 1990s: Four Factors That Explain the Decline and Six That Do Not. *Journal of Economic Perspectives, 18,* 163-190. https://doi.org/10.1257/089533004773563485

Levitt, S. D., & Venkatesh, S. A. (2000). An Economic Analysis of a Drug-Selling Gang's Finances. *The Quarterly Journal of Economics, 115,* 755-789.

https://doi.org/10.1162/003355300554908

Levy, B. L., Phillips, N. E., & Sampson, R. J. (2020). Triple Disadvantage: Neighborhood Networks of Everyday Urban Mobility and Violence in US Cities. *American Sociological Review, 85,* 925-956. https://doi.org/10.1177/0003122420972323

Lin, M.-J. (2009). More Police, Less Crime: Evidence from U.S. State Data. *International Review of Law and Economics, 29,* 73-80. https://doi.org/10.1016/j.irle.2008.12.003

Lochner, L. (1999). *Education, Work, and Crime: Theory and Evidence*. Rochester Center for Economic Research Working Paper No. 465. https://doi.org/10.2139/ssrn.208291

Lochner, L. (2004). Education, Work, and Crime: A Human Capital Approach. *International Economic Review, 45,* 811-843. https://doi.org/10.3386/w10478

Lowenkamp, C. T., Cullen, F. T., & Pratt, T. C. (2003). Replicating Sampson and Groves's Test of Social Disorganization Theory: Revisiting a Criminological Classic. *Journal of Research in Crime and Delinquency, 40,* 351-373. https://doi.org/10.1177/0022427803256077

Machin, S., & Meghir, C. (2004). Crime and Economic Incentives. *Journal of Human Resources, 39,* 958-979. https://doi.org/10.2307/3559034

Mansour, A., Marceau, N., & Mongrain, S. (2006). Gangs and Crime Deterrence. *Journal of Law, Economics, and Organization, 22,* 315-339. https://doi.org/10.1093/jleo/ewj015

Marselli, R., & Vannini, M. (1997). Estimating a Crime Equation in the Presence of Organized Crime: Evidence from Italy. *International Review of Law and Economics, 17,* 89-113. https://doi.org/10.1016/S0144-8188(96)00060-9

Marvell, T. B., & Moody, C. E. (1996). Specification Problems, Police Levels, and Crime Rates. *Criminology, 34,* 609-646. https://doi.org/10.1111/j.1745-9125.1996.tb01221.x

McCollister, K. E., French, M. T., & Fang, H. (2010). The Cost of Crime to Society: New Crime-Specific Estimates for Policy and Program Evaluation. *Drug and Alcohol Dependence, 108,* 98-109. https://doi.org/10.1016/j.drugalcdep.2009.12.002

McDonald, J. F., & McMillen, D. P. (2010). *Urban Economics and Real Estate: Theory and Policy*. John Wiley & Sons. https://doi.org/10.1017/CBO9781107587991

Morgan, S. L., & Winship, C. (2014). *Counterfactuals and Causal Inference*. Cambridge University Press.

Neanidis, K. C., & Papadopoulou, V. (2013). Crime, Fertility, and Economic Growth: Theory and Evidence. *Journal of Economic Behavior & Organization, 91,* 101-121. https://doi.org/10.1016/j.jebo.2013.04.007

Neanidis, K. C., & Rana, M. P. (2014). *Crime versus Organized Crime in Italy: Do their Drivers Differ?* CGBCR.

Paternoster, R. (2010). How Much Do We Really Know about Criminal Deterrence? *The Journal of Criminal Law and Criminology, 100,* 765-824.

Piza, E. L., & Chillar, V. F. (2021). The Effect of Police Layoffs on Crime: A Natural Experiment Involving New Jersey's Two Largest Cities. *Justice Evaluation Journal, 4,* 176-196. https://doi.org/10.1080/24751979.2020.1858697

Raphael, S., & Winter-Ebmer, R. (2001). Identifying the Effect of Unemployment on Crime. *Journal of Law and Economics, 44,* 259-284. https://doi.org/10.1086/320275

Sampson, R. J., & Groves, W. B. (1989). Community Structure and Crime: Testing Social-Disorganization Theory. *American Journal of Sociology, 94,* 774-802. https://doi.org/10.1086/229068

Shaw, C. R., & McKay, H. D. (1969). Juvenile Delinquency and Urban Areas (Revised ed.). University of Chicago Press.

Shelley, L. I. (1981). *Crime and Modernization: The Impact of Industrialization and Urbanization on Crime*. Southern Illinois University Press.

Shichor, D., Decker, D. L., & O'Brien, R. M. (1980). The Relationship of Criminal Victimization, Police per Capita and Population Density in Twenty-Six Cities. *Journal of Criminal Justice, 8,* 309-316. https://doi.org/10.1016/0047-2352(80)90042-2

Sun, I. Y., Triplett, R., & Gainey, R. R. (2004). Neighborhood Characteristics and Crime: A Test of Sampson and Groves' Model of Social Disorganization. *Western Criminology Review, 5,* 1-16.

Taylor, J. B. (1978). *Econometric Models of Criminal Behavior: A Review*. North-Holland Publishing.

Veysey, B. M., & Messner, S. F. (1999). Further Testing of Social Disorganization Theory: An Elaboration of Sampson and Groves's Community Structure and Crime. *Journal of Research in Crime and Delinquency, 36,* 156-174. https://doi.org/10.1177/0022427899036002002

Viscusi, W. K. (1986). The Risks and Rewards of Criminal Activity: A Comprehensive Test of Criminal Deterrence. *Journal of Labor Economics, 4,* 317-340. https://doi.org/10.1086/298113

Wilson, J. Q., & Petersilia, J. (Eds.) (2010). *Crime and Public Policy*. Oxford University Press.

Wirth, L. (1938). Urbanism as a Way of Life. *American Journal of Sociology, 44,* 1-24. https://doi.org/10.1086/217913

Witte, A. D., & Tauchen, H. (1994). *Work and Crime: An Exploration Using Panel Data*. No. w4794, National Bureau of Economic Research. https://doi.org/10.3386/w4794

Wright, R., Tekin, E., Topalli, V., McClellan, C., Dickinson, T., & Rosenfeld, R. (2014). *Less Cash, Less Crime: Evidence from the Electronic Benefit Transfer Program*. No. w19996, National Bureau of Economic Research. https://doi.org/10.3386/w19996

Appendix

In order to solve the above system equations, we need to relax the leisure constraint as an any arbitrary constant, let's say $l = k : 0.3$.

Solving for the equations, while relaxing for the price of the numeraire ($\left(\frac{p_2}{p_1}\right) = p_2$) we get:

$$c_2 = c_1\left(\frac{1-\alpha}{\alpha p_2}\right) \tag{19}$$

$$\frac{\gamma}{n_{cr}} = -\frac{\beta}{l} + w_{cr}\left(\frac{1-\alpha}{p_2}\right)\alpha c_1^{\alpha} c_2^{-\alpha} \tag{20}$$

$$w_{lf} = \delta(1-t)A_0 n_{el}^{\delta-1} \tag{21}$$

$$w_{cr} = \left(p_2 B_0 \eta\right) n_{cr}^{\eta-1} + \rho \tag{22}$$

Sub back the above Equation (16) for c_1, c_2 and w_{cr} we get:

$$\frac{\gamma}{n_{cr}} = -\frac{\beta}{l} + \left(p_2 B_0 \eta n_{cr}^{\eta-1} + \rho\right)\left(\frac{1-\alpha}{p_2}\right)^{1-\alpha} \alpha^{\alpha} \tag{23}$$

Using government budget condition and Equations (3) and (17)

$$n_{lf} = \frac{(1-t)n_{el}}{tA_0^{1-\delta}} \tag{24}$$

Sub back (20) in (9), we have:

$$n_{cr} = 1 - l - \left(\frac{(1-t) + tA_0^{1-\delta}}{tA_0^{1-\delta}}\right)n_{el} \tag{25}$$

Using production functions, market clearing conditions and (20), we get:

$$p_2 = \left(\frac{A_0(1-\alpha)}{B_0\alpha}\right)\left(\frac{(1-t)}{tA_0^{1-\delta}}\right)^{\delta} n_{el}^{\delta} n_{cr}^{\eta} \tag{26}$$

Sub back (21) and (22) into (19), we will get number of the law enforcement officers based on the parameters (which is a nonlinear function), then we can sub back into the previous equations and get the values for the variables:

$$n_{el} = \frac{\gamma l}{\beta z_1} + \frac{1-l}{z_1} - \frac{l\alpha^{\alpha}(1-\alpha)^{(1-\alpha)}(1-l-z_1 n_{el})\left((1-l-z_1 n_{el})^{\eta-1} B_0 \eta z_2 n_{el}^{\delta}(1-l-z_1 n_{el})^{\eta} + \rho\right)}{\beta z_1\left(z_2 n_{el}^{\delta}(1-l-z_1 n_{el})^{\eta}\right)^{1-\alpha}} \tag{27}$$

In which: $z_1 = \frac{(1-t) + tA_0^{1-\delta}}{tA_0^{1-\delta}}$, $z_2 = \left(\frac{A_0(1-\alpha)}{B_0\alpha}\right)\left(\frac{1-t}{tA_0^{1-\delta}}\right)^{\delta}$

In the last equation, as we can see, n_{el} is a function of itself, and to solve it I used MATLAB.

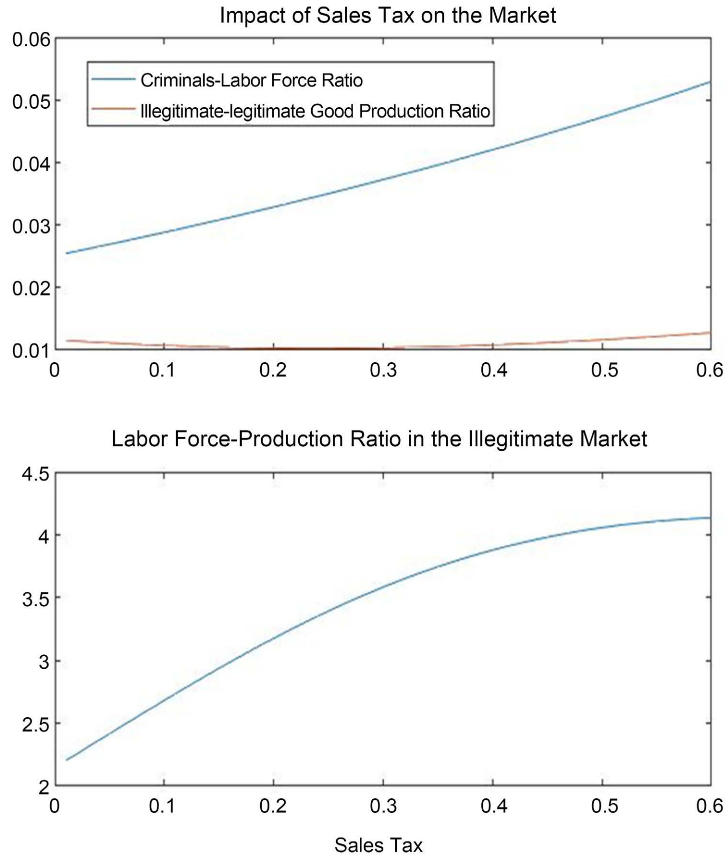

Figure A1. The top panel shows the impacts of the sales tax on labor force participation and production ratio in the economy; The lower panel shows the labor force-production ratio in the illegal market.