Asymmetric Effects and Hysteresis in Crime Rates: Evidence from the United States

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November, 2013

PRELIMINARY - COMMENTS APPRECIATED

Abstract

This paper empirically investigates the existence of hysteresis in crime rates. This is the first empirical study to consider the existence of asymmetric effects on crime from variations in the probability of punishment and in the opportunity cost of crime. I investigate whether positive variations on variables associated to those factors, respectively police officers and average level of income, are statistically different from negative variations. Using US crime data at the state level between 1977 and 2010, I find that police force size and real average income of unskilled workers have asymmetric effects on most types of crimes. The absolute value of the average impact of positive variations in those variables on property and violent crime rates are statistically smaller than the absolute value of the average effect of negative variations. These effects are robust under several specifications. A closer inspection of the data reveals a relatively monotonic negative relationship between wages and property crime rates, as well as negative variations in police and most crime rates. However, the relationships between positive variations in law enforcement size and most crime rates are non-linear. The magnitude of the observed asymmetries supports the hypothesis of hysteresis in crime, and suggests that no theoretical or empirical analysis would be complete without careful consideration of that important feature in the relationships between crime, police and legal income. These results corroborate the argument that policy makers should be more inclined to set pre-emptive policies rather than mitigating measures.

Key words: Criminality, Hysteresis, Asymmetric effects.

JEL Classification: K42, D90, D83.

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1 Introduction

This paper empirically examines the predictions in Loureiro (2013b) that the processes governing criminal behaviour are inherently permeated by hysteresis and, consequently, the absolute value of the magnitude of the impact of variables such as the probability of punishment and income on crime rates will depend on whether the variations of those determinant variables are positive or negative.

It is shown that if criminal activity is associated with intrinsic sunk costs and learning, then the cost of leaving a criminal career is higher than entering it and there is hysteresis at the individual level, where the crime decision in a given period is determined not only by the current expected costs and benefits entailed by the illicit act, but it is also affected by criminal decisions taken in the past.

If there is hysteresis at the individual level, the aggregation of all crime decisions of the agents will render hysteresis in crime rates. For any sufficiently large society, the smallest reduction in the probability of punishment will make some individuals at the margin between committing a crime or not to choose the illegal option. A subsequent increase in the probability of punishment, will make some of the new criminals to stop committing crimes, but some individuals will prefer to continue in the criminal career, even if the probability of punishment is exactly the same as the original one.

Therefore, hysteresis in crime rates emerges from the aggregation of individual crime decisions that display the hysteresis effect and can be understood as a path-dependent process, where the current level of crime depends not only on the current levels of variables like the number of police officers and income, but also whether their levels in the previous periods were below or above the current levels. If there is hysteresis in crime, policies aiming to reduce crime rates will have a diminished impact when compared to the impact where individuals with a criminal past will behave similarly to individuals without a criminal past.

Loureiro (2013b) concluded that there is hysteresis in crime rates for at least two of the factors that affect them: probability of punishment and legal income, where the latter captures the opportunity cost of crime.

One important consequence of hysteresis is that the effect on an outcome variable from positive exogenous variations in the determining variables has a different magnitude from negative variations. That asymmetric effect is clearer in a situation in which the crime reduction policy in a given period is simply a reversal of a deterioration of one determinant of crime. A concrete example would be a situation where part of the police officers in a city are dismissed in a given year, resulting in a escalation in crime. If all sacked police officers are readmitted in the following year in an attempt to restore the original crime levels and hysteresis is present in the criminal behavior, that policy will result in a lower crime rate, but higher than the original one. [1]

That prediction is empirically investigated by analysing US crime data at the state level between 1977 and 2010, using police force size as a proxy for the probability of punishment[2] and real average income of unskilled workers as the opportunity cost of crime.[3] It is, to my knowledge, the first paper to consider the existence of asymmetric effects of variations in the probability of punishment and in the opportunity cost of crime.

I find that two of the main determinants of crime - police force size and real average income of unskilled workers - have significant asymmetric effects on most types of crimes. The average impact of positive variations in the income of unskilled workers on property crime rates are statistically smaller than the absolute value of the average effect of negative variations. That asymmetry is also observed for the law enforcement variable in both property and violent crime.

The results are robust under several models and specifications. As will be discussed, no theoretical or empirical analysis would be complete without careful consideration of that important feature of the relationships between crime, police and legal income.

In the following section, I present the empirical literature of the economics of crime focused on the impact of the probability of punishment and legal wages on crime. The data used in the present analysis is discussed in section 3, while the empirical framework is presented in section 4. This is followed by the results in section 5 and a nonparametric analysis in section 6. Section 7 concludes.

2 Related Literature

2.1 Hysteresis and Asymmetric Effects in Crime

The economics of crime literature is fairly extensive as economists play a prominent role in the pursuit to establish causality of socioeconomic variables on aggregate crime measures.

[1]Note that this a simplifying example to convey the concept of hysteresis in crime rates. It is very unlikely that a negative variation will be followed by a positive value with the exact same size in absolute terms. However, if crime decision is indeed permeated by hysteresis, crime rates will also display the hysteresis property, even in the case of the absolute value of increases/decreases are different, provided that increase are not much larger than the decreases in absolute terms.

[2]From the Uniform Crime Reports - UCR Crime data compiled by the Federal Bureau of Investigation - FBI and Annual Survey of State and Local Government Employment and Census of Governments.

[3]From the Current Population Survey - CPS

Polinsky and Shavell (2007) and Dills, Miron, and Summers (2008) provide a relatively recent overview of contributions provided by economists since Becker's seminal paper. However, only very recently have the study of persistence and asymmetric cycles been the primary focus of a study in the empirical crime literature. The first authors (and to date, the only ones) to explicitly test for the existence of asymmetric cycles in crimes rates were Mocan and Bali (2010). The authors compare the effects on crime rates of positive and negative variations on unemployment rates and obtain statistical evidence for the existence of asymmetries in that relationship.

Hysteresis and asymmetric effects have also been the objects of empirical studies in other areas in economics, especially in unemployment.[4] Because variables like unemployment and inflation are closely connected with GDP cycles, those studies frequently refer to this analysis as asymmetric cycles.

2.2 Effect of the Probability of Punishment on Crime

The relationship between police and crime is one of the classical examples of the pernicious effects of simultaneity on the interpretation of correlations. Even though a larger police force is expected to increase the probability of punishment and consequently reduce crime rates, the empirically observed relationship could be largely dominated by the positive response of the policy maker to the higher levels of crime in the previous periods.[5]

Ehrlich (1973) provided the first empirical analysis in the economics of crime in which the author was also the first to empirically estimate the relationship between the probability of punishment (proxied by the per capita expenditure on police) and crime. However, only almost a quarter of a century later, was the relevant issue of simultaneity between police and crime rates the main focus of a research paper.

The first paper to use a panel data set in order to mitigate the crucial problem of unobserved heterogeneity to estimate the impact of deterrence variables on crime was Cornwell and Trumbull (1994), that made use of an offense ratio of face-to-face crimes to non-face-

[4]For a recent survey on hysteresis in unemployment, see O'Shaughnessy (2011).

[5]One alternative perspective is to examine the impact on crime of exogenous variations on the level of harshness of the penalties, rather than probability of punishment, since, as seen in Loureiro (2013b), there is a trade-off between those variables. However, due to the fact that it would involve the use of very restricted data and that there is little variation in the severity of punishment across areas and over time, it is empirically challenging to examine impacts of variations in the severity of punishment on crime. A rare empirical study on this issue is Lee and McCrary (2009), that explores the discontinuous increase in the severity of punishment for individuals at the age of 18. They find that a negative, but very small impact of harsher penalties on criminal behaviour. That result corroborates the hypothesis of hysteresis in crime from a different perspective.

to-face crimes and tax revenues per capita. Levitt (1997) uses electoral cycles in the police expenditures to identify the impact of police on crimes. However, McCrary (2002) points out some coding errors in Levitt (1997) and showed that Levitt's results were not statistically significant, and police would not have any effect on crime with the instrumental variables based on electoral cycles. Levitt (2002) provides a reply by using the number of firefighters as an instrument for police force and finds significant effects of police on crime rates. Lin (2009) uses state tax rates as an instrumental variable for local police numbers. Evans and Owens (2007) and Worrall and Kovandzic (2010) instrument police levels with two types of federal law enforcement grants.

Corman and Mocan (2000) get around the use of instrumental variables by using monthly data and exploring the fact that the training of a police officer takes at least six months to identify the impact of police on crime rates in New York City. Unfortunately, that approach is not possible for a nationwide estimation in the US, since, although monthly crime data is available at many levels of aggregation since the first years of the Uniform Crime Reports - UCR, compiled by the Federal Bureau of Investigation - FBI, the number of police officers are aggregated by year. Buonanno and Mastrobuoni (2012) circumvent the endogeneity issues by exploring a centralised and lengthy process to hire police officers in Italy.

Di Tella and Schargrodsky (2004) and Draca, Machin, and Witt (2011) are two prominent studies that exploit natural experiments (terrorist attacks, followed by sharp increase in the police force in the affect city) to detect the impact of police on crime rates.

Chalfin and McCrary (2013) show that all previous analyses suffer from severe and unexpected measurement error in the data on the size of the police force. This measurement error, rather than the simultaneity between police and crime, is the main source of upwards bias in the police-crime nexus. Supported by thorough anecdotal evidence, public administration and political economy studies, the authors make a very compelling case for the relative exogeneity of the law enforcement variable as the response from policy makers in the short term is extremely limited and is, to a great extent, idiosyncratic. The authors find a consistent estimator without measurement error by using data on the number of police from the Annual Survey of Government (ASG) as an instrument for the standard UCR data on police. Their estimates are five times larger in absolute value when compared to the estimates that do not correct for the measurement error.

2.3 Effect of Income on Crime

Economic theory predicts that labour income has a negative effect on crime as it encapsulates the opportunity cost of the criminal career.[6] Nevertheless, many empirical studies that analyse the impact of income on crime rates find ambiguous signs for the associated coefficients.[7] One of the reasons is related to the fact that the usual measure of income is the overall income in a location, such as GDP per capita, which captures the labour market expected benefits, but also the expected gain from criminal activity.

Another problem associated with the use of income measures of an area, rather then the individual in the empirical crime equation is the possibility that the associated coefficient is also capturing the higher propensity to report crime of richer areas, as pointed out by Soares (2004) and Soares and Naritomi (2010).

It is a stylised fact in the crime literature that most crimes are committed by young men. Gould, Weinberg, and Mustard (2002) explore that fact and analyse the impact of wages of unskilled men on crime rates using a panel data set of US counties. The authors show that the long-run trend in crime rates can be better explained by the long-run trend in wages of unskilled men rather than by the trend in unemployment.[8]

It can be argued that level of income is an endogenous variable in the crime equation if areas with high crime rates receive less investment and have less job opportunities when compared to areas with lower crimes rates. That is less likely to happen at the state level. However, if that was still the case, it was more likely that this bias would be stronger in violent crimes than property crimes. However, the fact that none of the coefficients associated to violent crime are statistically significant provides little support for the hypothesis of simultaneity between income levels and crime in the present analysis.

Another possibility in this direction is that individuals with better job prospects in terms of wages, emigrate from areas with high levels of crime. Cullen and Levitt (1999) show that every additional reported crime is associated with one-person person decline in a average city with at least 100,000 inhabitants in the US. However, most migration occurred within the same Metropolitan Statistical Area (MSA). As the great majority of the MSAs in the US are within one state, it is less likely that such effect occur at the state level.

Doyle, Ahmed, and Horn (1999) and Gould, Weinberg, and Mustard (2002) show that

[6] One alternative perspective to capture the opportunity cost of crime, particularly for developing countries, is to examine poverty rates. Loureiro (2013a) provides a recent example of that approach.

[7] For a survey on the studies that analyse labour market outcomes on crime, see Mustard (2010).

[8] Freeman (1996) provides an inquiry about the reasons that make young unskilled men more prone to commit crimes.

OLS and GMM estimates do not vary significantly, suggesting that endogeneity of income is not a concern in the crime equation.

3 Data

I analyse data from the 50 US states between 1977 and 2010. Six crime categories are used. Three types of property crime: burglary, larceny and motor vehicle theft; and three types of violent crime: murder, aggravated assault and forcible rape. All crime variables are calculated in terms of rates per 100,000 inhabitants. These data are obtained from the Uniform Crime Reports - UCR Crime data compiled by the Federal Bureau of Investigation - FBI, and obtained from the Inter-university Consortium for Political and Social Research - ICPSR, which also provides data on police officers per 100,000 inhabitants.

A usual concern with respect to crime data is the existence of measurement error in crime rates, especially underreporting. This problem can be greatly mitigated by the use of panel data techniques that control for unobserved heterogeneity. Any measurement error in the dependent variable not captured by this approach will only affect the standard errors of the coefficients, reducing the probability of rejecting the null of no relationship.

A more pernicious problem is related to measurement error of one of the explanatory variables.[9] The studies in the empirical literature of the economics of crime displayed no concern about the existence of measurement error in the explanatory variables in the crime equation. Chalfin and McCrary (2013) show the great deal of measurement error in the police force rates obtained from the UCR data. There are two sources of measurement error in the law enforcement variable generally used in the literature: 1. Misclassification in what constitutes a sworn police officer; 2. Underestimation of the population size used in the calculation in the police officers rate, especially in the years prior to the census.

I tackle one of the sources of measurement error by correcting the population used in both UCR and ASG data sets by nonparametric smoothing. This issue is especially crucial in the present study, as it explore the positive and negative variations in the police officers rate.

Because the theoretical sign of the coefficient associated to police is negative, the measurement error in the police variable will cause the estimated coefficient to be overestimated, increasing the probability of the type II error.

[9] If it is the classical measurement error problem, the estimate of the coefficient will suffer from attenuation bias. See Fuller (1987), Hausman (2001) and Wooldridge (2002).

I also used the number of police officers from the Annual Survey of State and Local Government Employment and Census of Governments - hereafter ASG data - run by the US Census Bureau. The data for federal and state employees are the actual numbers, however, as the local government statistics are based on a sample of local governments, and the same reasons that can lead to measurement error in the UCR data are also present, the variable from this source is also noisy.

Because the police data from the UCR and ASG data in each year are a snapshot of October,[10] I follow the usual procedure in the literature to use the measures for the previous year in all regressions. In addition, because the years included in the analysis are restricted only by the CPS data (before 1977, some states are not in the sample), I can keep the 34 years by using police data in 1976.

I generate the average real income of young males without college and the other control variables by using microdata from the Current Population Survey - CPS, provided by the Bureau of Labor Statistics and which I retrieved from Integrated Public Use Microdata Series - IPUMS.[11] Details on the extraction and organisation of the data is outlined in the appendix 8.1.

3.1 Descriptive Statistics and Trends in Crime Rates, Police Force and Wages

Figure 3.1 shows the trends for the proportion of police officers by 100,000 inhabitants, real total income for unskilled workers and for the overall population in the United States between 1977 and 2010. There is a sustained increase in the three variables over the period, with exceptions given by a pronounced decrease in law enforcement in the beginning of the 80s and a significant decline in the total real income after the economic crisis in 2008. A closer look at the police variable reveals the short term cyclicality of this variable, first pointed out by Levitt (1997).[12]

[10] After 1997 the month was March in the ASG data. I include a dummy variable to account for that fact in the regressions involving the two measures.

[11] King, Ruggles, Alexander, Flood, Genadek, Schroeder, Trampe, and Vick (2012)

[12] Figure 3.1 suggests that the variables are non-stationary. Preliminary panel data tests that account for heterogeneity in the autoregressive coefficient of the Dickey-Fuller regression, cross-section dependence and level shifts reject the hypothesis of unit roots for police, income and crime rates. Additionally, most series for the individual states are trend-stationary (stationary after the trend is accounted for) and this result is even stronger when at least one structural break is allowed.

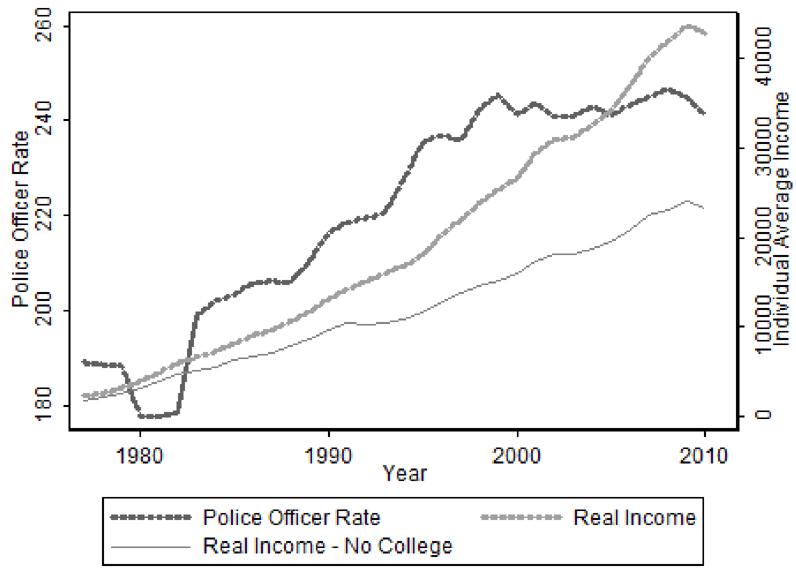


Figure 3.1: Police Rate and Overall Average Income and Unskilled Workers Income - USA - 1977-2010

Data Source: UCR/FBI and CPS.

Figures 3.2a and 3.2b display crime rates and clearance rates[13] for respectively property and violent crimes in the US between 1970 and 2010. There is an unequivocal turn in the trend of both types of crimes that does not coadunate with clearance rates over the period.

Table 3.1 provides the descriptive statistics for the variables under analysis for the 50 US states between 1977 and 2010.[14] The first part of the table presents the statistics related to crime rates. It is clear that larcenies correspond to the bulk of property crimes in the US, whereas aggravated assaults represents the great majority of crimes registered as violent.

It is also possible to observe that the two alternative measures of police force, data from the UCR/FBI and the ASG have similar means and standard deviations. That is also captured by the scatter plot between the two measures in figure 8.7 in the appendix. It is clear that police and population data from both the UCR and the ASG have very similar distributions, but there is still significant noise in the measurement of those variables in both sources.

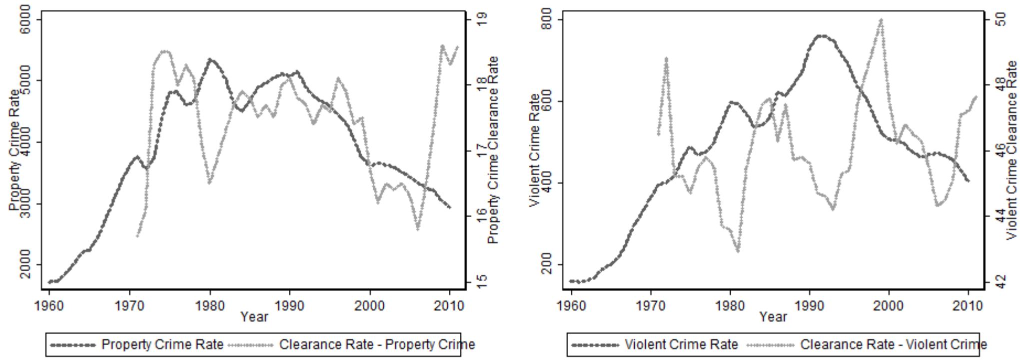
Another important aspect regarding the UCR police variable, the reference measure of law enforcement in this paper, regards the fraction of observations across the states and over the years that had positive variations. Table 3.1 shows that approximately 61% of the states/years had positive variations in police in the period under consideration. That is confirmed by figure 3.3a which shows the distribution of variations in police force for the uncorrected data. Figure 3.3b displays the same information for the corrected data, which has a very similar pattern. As expected, the variations are concentrated around the smallest values. The variations in the police force can also be observed in figure 3.5 which displays the law enforcement sizes for all states between 1977 and 2010.

Also from table 3.1, it is possible to observe that the level of income of unskilled workers was larger, when compared to the previous year in 89% of the cases. This fact can also be observed from figure 3.6. Even tough the number of negative variations is relatively small, figures 3.4a and 3.4b shows that the variations for both the income of unskilled workers and all workers were larger in absolute terms than the ones observed for police.

The spatial distribution across the continental states of the variables discussed in this section are displayed in appendix 8.2.

[13] Clearance rates refer to the proportion of crimes that are solved by the arrest of the perpetrator.

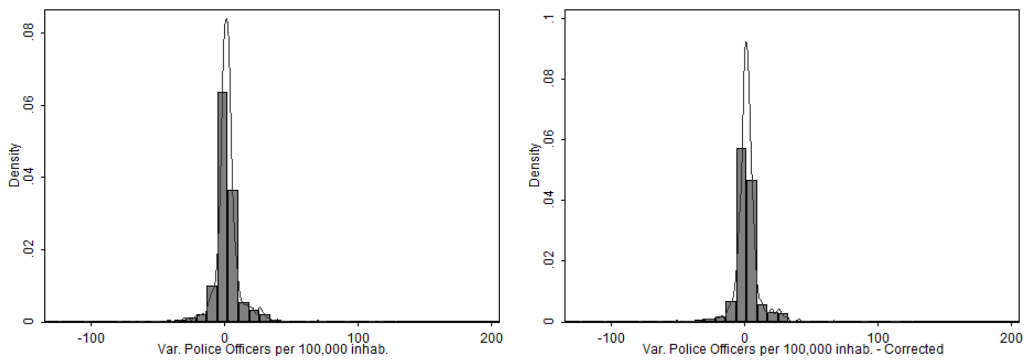
[14] Washington DC is excluded from the sample for constituting a classical outlier in the analysis, since its law enforcement size is considerably larger than all other states.



(a) Property Crime (b) Violent Crime

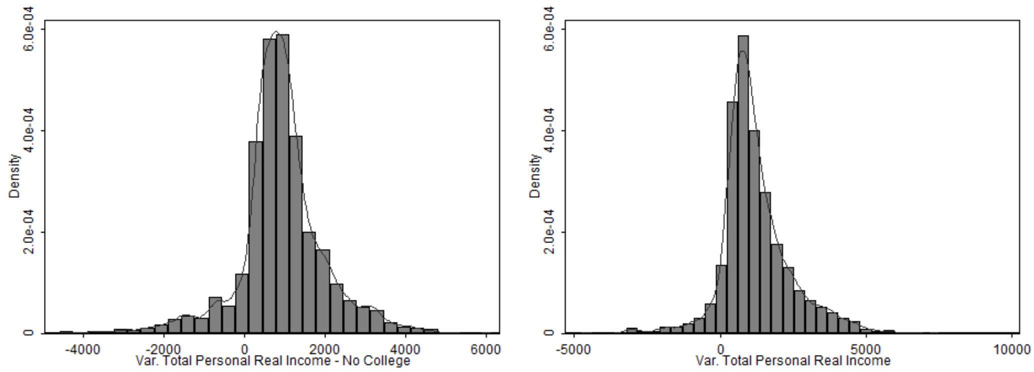
Figure 3.2: Crime rates and Clearance Rates - USA - 1970-2010

Data Source: UCR/FBI.



(a) ΔPolice (b) ΔPolice Corrected

Figure 3.3: Histograms and Kernel Densities (Epanechnikov): Police



(a) ΔIncome - No College (b) Δ Income

Figure 3.4: Histograms and Kernel Densities (Epanechnikov): Income
Data Source: CPS.

Table 3.1: Descriptive Statistics - States

	N	**mean**	**sd**	**min**	**max**
Property Crime Rate	1700	4089.4	1177.44	1705.3	7996
Burglary Rate	1700	985.22	414.26	292.3	2906.7
Larceny Rate	1700	2723.07	725.48	1235.6	5106.1
Motor Vehicle Theft Rate	1700	381.11	204.62	70.5	1157.7
Violent Crime Rate	1700	450.61	228.27	47	1244.3
Murder Rate	1700	6.13	3.53	0.2	20.3
Aggravated Assault Rate	1700	278.79	146.62	31.3	785.7
Forcible Rape Rate	1700	34.45	13.54	7.3	102.2
Police Officers rate - UCR	1700	205.68	54.9	68.84	434.24
Police Officers per - ASG	1700	203.85	42.6	122.40	403.08
Variation in UCR Police > 0	1700	0.61	0.49	0	1
Total Real Income	1700	19041.11	12954.5	1686.25	56685.22
Total Real Income - No College	1700	15823.39	9540.4	1686.25	41398.51
Variation in Income - No College > 0	1700	0.89	0.31	0	1
Unemployment Rate	1700	0.06	0.02	0.02	0.19
Unemployment Rate - No College	1700	0.07	0.02	0.02	0.19
Perc. Urban Area	1700	0.61	0.26	0	1
Fraction of Female Headed HH	1700	0.27	0.03	0.11	0.36
Perc. of Young Males	1700	0.09	0.01	0.05	0.15
Total Real Income of HH	1700	43366.54	29683.26	3994.7	142940.75
Population - CPS	1700	5.08E+06	5.55E+06	365149	3.57E+07
Population - UCR	1700	5.29E+06	5.82E+06	410986	3.73E+07
Population - ASG	1700	5.22E+06	5.70E+06	402000	3.73E+07

Notes: All monetary variables adjusted by CPI in 2010. *Data Source*: UCR/FBI/ASG/CPS.

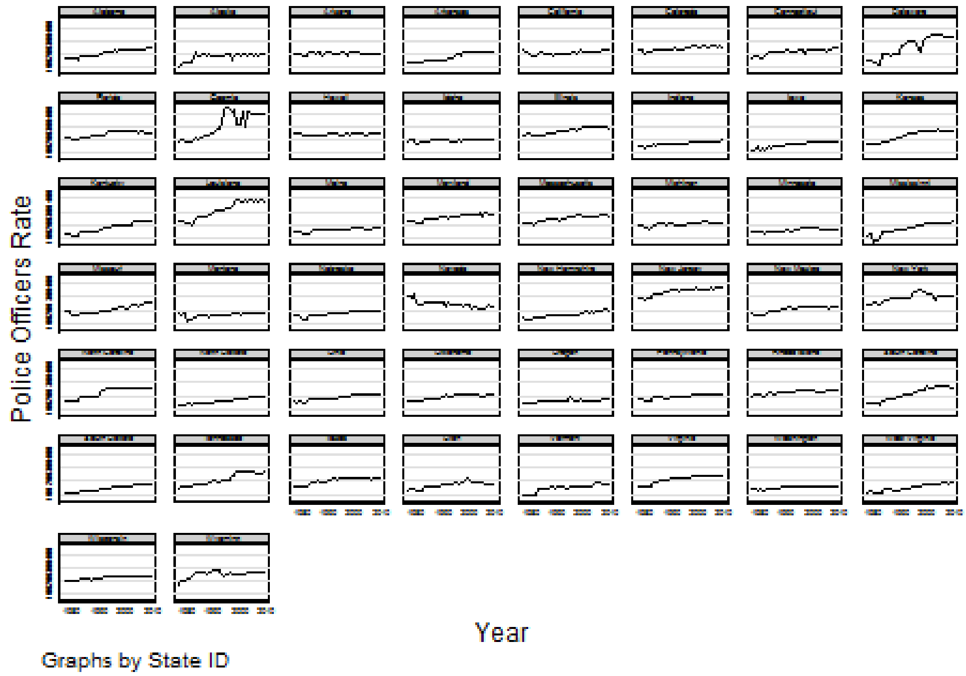


Figure 3.5: Police Rate by State

Data Source: UCR/FBI.

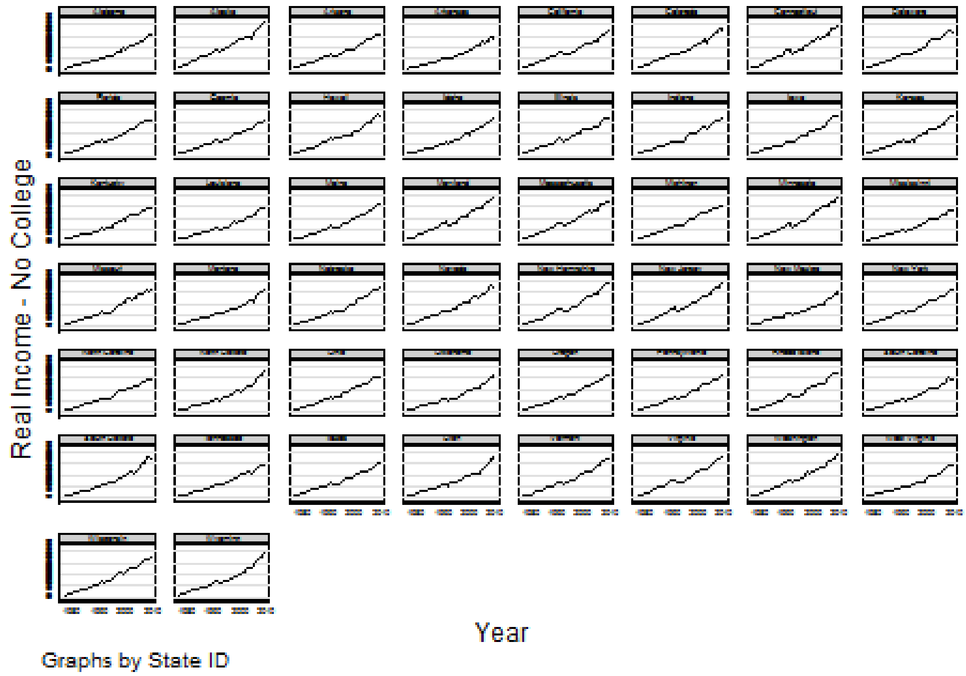


Figure 3.6: Real Income - Unskilled Workers by State

Data Source: CPS.

4 Empirical Framework

I focus attention on two variables susceptible to public policy and that potentially affect crime rates: income levels and number of police officers, with the last variable being potentially endogenous. However, as discussed in section 2, the uncoordinated efforts of overlapping police agencies make this variable relatively exogenous, especially at the state level. As in Chalfin and McCrary (2013), I focus attention at another source of endogeneity: measurement error of the police variable.[15] The other variables present in the theoretic model of crime and relevant to the decision of the individual at the margin are either controlled by observable variables or assumed to vary across states (but constant over time) and captured by the fixed effects, such as the severity of the punishment. Other variables that are not explicitly considered in the theoretical economic model, but can also affect crime, like the urbanization rate and fraction of young males are also included in the regressions.

I start by investigating the existence of asymmetric effects in variations of wages. As it will be seen in the next subsection, a similar approach is not feasible for the police variable as it would require the availability of two different instruments for each direction of variation. To examine the hypothesis of asymmetric cycles in the number of police officers, I will split the sample in two sub-samples, according to the predominance of positive or negative variations in the police force.

4.1 Random Coefficients Model

I initially estimate the following equation:[16]

$$Crime_{it} = \psi_i + \lambda_t + \mathbf{x}_{it}'\beta + \gamma Police_{it-1} + \delta_0 + \delta_1 Income_{it}^{+} + \delta_2 Income_{it}^{-} + \epsilon_{it} \tag{4.1}$$

where

$$\delta_0 = \begin{cases} 1 & if\ \Delta Income_{it} \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{4.2}$$

[15]The third possible source of endogeneity is omitted variable problem. That is a less likely possibility in the present analysis after controlling for several relevant variables and state and fixed effects.

[16]This is similar to the procedure adopted by Mocan and Bali (2010), that analyses the asymmetric effects of unemployment. However, the authors do not relax the assumption of a common intercept and as it will be seen, that is crucial to the analysis of asymmetric effects of wages and police force.

$$Income^{+}_{it} = \begin{cases} Income_{it} & if\ \Delta Income_{it} \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{4.3}$$

$$Income^{-}_{it} = \begin{cases} Income_{it} & if\ \Delta Income_{it} < 0 \\ 0 & \text{otherwise} \end{cases} \tag{4.4}$$

$Crime_{it}$ denotes one of the crime rates described in the previous section, $Police_{it-1}$ is the proportion of police officers relative to the state population in the previous period, $Income_{it}$ is the average real[17] income level for unskilled workers, $\mathbf{x}'_{it}$ is a vector of socioeconomic variables and ψ_i and λ_t are respectively state and year fixed effects. [18]

If individuals get locked in crime and there is hysteresis in the relationship between crime and income, a test of the hypothesis that $|\delta_1| = |\delta_2|$ must be rejected. However, note that the converse is not necessarily true. It must be emphasized that the detection of asymmetric effects is only indicative of the existence hysteresis in crime rates.

Additionally, note that the inclusion of the term δ_0 as defined by equation 4.2 relaxes the assumption of common intercepts for positive and negative changes. If this coefficient is not included, a linear specification might not reject the null hypothesis of homogeneous slopes for positive and negative variations, even if this is the case in the data.[19] As it will be seen in the following section, the assumption of heterogenous intercepts for positive and negative changes in the wage rate is crucial to correctly specify equation 4.1.

One would be worried about multicolinearity problem arising from the fact of estimating $Income^{+}$ and $Income^{-}$ in the same equation. That would be the case in a cross-sectional analysis, but the use of panel data dilute this problem.

4.2 Sample Split

An important implicit assumption under the specification given by equations 4.1-4.4 is that all other coefficients and state and time fixed effects are common to both states

[17] Deflated using the CPI with base in 2000.

[18] Baltagi, Matyas, and Sevestre (2008) show that an over-specification of the error components model (estimate a two-way model when the true model is one-way) provides consistent estimates, whereas under-specification of the error components model (estimate a one-way model when the true model is two-way) generates inconsistent estimates.

[19] To some extent, this is equivalent to the situation of a simple linear regression where the intercept is not specified when the data display an association that does not depart from the origin. In the case of where the true relationship is positive and has a positive intercept, the omission of the intercept in the regression will lead to an overestimation of the coefficient and potentially to an incorrect non-rejection of the null of no relationship.

with predominantly positive variations and states with predominantly negative variations. To check the robustness of the results, I split the sample according to the predominance of positive variations (number of positive variations above the average). [20] Because the threshold here is known, the inference is based on the standard distributions.[21] The empirical model is then given by the following equations:

$$Crime_{it} = \psi_{1i} + \lambda_{1t} + \mathbf{x}'_{it}\beta_1 + \gamma_1 Police_{it-1} + \delta_1 Income_{it} + \epsilon_{1it}, \text{ if } i \in \Gamma \tag{4.5}$$

$$Crime_{it} = \psi_{2i} + \lambda_{2t} + \mathbf{x}'_{it}\beta_2 + \gamma_2 Police_{it-1} + \delta_2 Income_{it} + \epsilon_{2it}, \text{ if } i \notin \Gamma \tag{4.6}$$

where Γ is the set of states with positive variations in income above the average.

That model allows to use the instrumental variable approach[22] to estimate the heterogeneity of negative and positive variations in police force using the same instrument:

$$Crime_{it} = \phi_{1i} + \lambda_{1t} + \mathbf{x}'_{it}\beta_1 + \theta_1 Police_{it-1} + \varrho_1 Income_{it} + \mu_{1it}, \text{ if } i \in \Omega \tag{4.7}$$

$$Crime_{it} = \phi_{2i} + \lambda_{2t} + \mathbf{x}'_{it}\beta_2 + \theta_2 Police_{it-1} + \varrho_2 Income_{it} + \mu_{2it}, \text{ if } i \notin \Omega \tag{4.8}$$

where Ω is the set of states with positive variations in police above the average.

To simplify the analysis, I exclude the police variable from equations 4.5 and 4.6 in the estimations presented in section 5.

4.3 Measurement Error in Police and IV Estimation

As recently emphasised by Chalfin and McCrary (2013), there is considerable measurement error in the law enforcement variable caused by misclassification and underestimation of the population size, especially in years prior to the census. That measurement error would lead to the attenuation bias, which in the present case would be an upward bias.

The authors claim that measurement error, rather than the simultaneity between police and crime would the main source of upwards bias in the relationship between police and crime. They claim that the police variable would be relatively exogenous, since the response from policy makers in the short term is extremely limited. That argument is even more compelling

[20] Chan (1993) shows that this type of estimator is strongly consistent.
[21] To see the properties of sample splitting and threshold estimators, see Hansen (1999) and Hansen (2000).
[22] Caner and Hansen (2004) show that if the threshold is exogenous, the IV/GMM estimator is consistent, but not necessarily efficient.

for state level data as the police department efforts are combinations of overlapping and uncoordinated local police agencies.

In order to tackle the measurement error in the police officers rates, I will follow Chalfin and McCrary (2013) and instrument the UCR/FBI law enforcement measure with the ASG measure. This procedure in which a noisy measure of police is used as an instrument for another measure of police will provide consistent estimates, conditional on the fact that the assumptions in the classical measurement error model hold.

4.3.1 Classical Measurement Error Model

Consider a crime equation with all variables and time and fixed effects netted out, apart from the correctly measured police size $Police_{it}^{*}$:

$$Crime_{it} = \eta_0 + \eta_1 Police_{it}^{*} + \epsilon_{it} \tag{4.9}$$

and $E(Police_{it}^{*}\epsilon_{it}) = 0$. However, if $Police_{it}^{*}$ is not observed, and all that can be observed is a noisy measure of police, $Police_{it}$, and the corresponding measurement error is given by:

$$e_{it} = Police_{it} - Police_{it}^{*} \tag{4.10}$$

It is assumed that $E(e_{it}) = 0$ and since $E(Police_{it}^{*}\epsilon_{it}) = 0$ as well as $E(Police_{it}\epsilon_{it}) = 0$, we have that $E(e_{it}\epsilon_{it}) = 0$.

A crucial assumption is that:

$$E(e_{it}Police_{it}^{*}) = 0 \tag{4.11}$$

Equation 4.11 is the classical errors-in-variables (CEV)[23]

The OLS estimation of the crime equation with the noisy police variable will yield:

$$\begin{aligned} Crime_{it} &= \gamma_0 + \gamma_1(Police_{it} - e_{it}) + \epsilon_{it} \\ &= \gamma_0 + \gamma_1 Police_{it} + \kappa_{it} \end{aligned} \tag{4.12}$$

with $\kappa_{it} = \epsilon_{it} - \gamma_1 e_{it}$ and consequently $E(Police_{it} \cdot \kappa_{it}) \neq 0$

If condition 4.11 holds, then $E(e_{it}Police_{it}) = E(e_{it}Police_{it}^{*}) + E(e_{it}^{2}) = \sigma_e^2$ and

$$plim(\hat{\gamma_1}) = \gamma_1\left(\frac{\sigma^2_{Police^*}}{\sigma^2_{Police^*} + \sigma^2_e}\right) = \gamma_1\frac{\sigma^2_{Police^*}}{\sigma^2_{Police}} \neq \gamma_1 \tag{4.13}$$

[23]For details, see Wooldridge (2002).

for $\sigma^2_{Police^*} \neq \sigma^2_{Police}$.

4.3.2 IV Solution

With the use of another independent and noisy measure of police $Police^b_{it}$ and respective measurement error given by:

$$u_{it} = Police^b_{it} - Police^*_{it} \tag{4.14}$$

with $E(u_{it}) = 0$ and similarly to the previous imperfect measure of police the following conditions hold:

$$\begin{aligned} &E(Police_{it}\epsilon_{it}) = 0 \\ &E(u_{it}Police^*_{it}) = 0 \\ &E(u_{it}\epsilon_{it}) = 0 \\ &E(u_{it}e_{it}) = 0 \end{aligned} \tag{4.15}$$

$Police^b_{it}$ is an appropriate instrument to $Police_{it}$ since the conditions above imply that:

$$\begin{array}{lcllcl} E(Police^b_{it}\epsilon_{it}) & = & E(Police^*_{it}\epsilon_{it}) + E(u_{it}\epsilon_{it}) & & = & 0 \\ E(Police^b_{it}Police_{it}) & = & E(Police^*_{it}Police_{it}) + E(u_{it}Police_{it}) & & & \\ & = & E(Police^*_{it}Police_{it}) + 0 & & > & 0 \end{array} \tag{4.16}$$

which are respectively the conditions of exclusion and relevance for the instrument.

5 Results

This section presents the estimates of the models specified in the previous section. All regressions control for state and year effects and for the variables discussed in the data section.[24] The standard errors are clustered at the state level and all coefficients are standardised. All regressions with instruments reject the null of weak instruments and underidentification.[25]

Table 5.1 provides the estimates for the baseline model with respect to the level of income of unskilled workers.[26] Tables with the same approach where the overall level of income is used are presented in the appendix.

A higher level of income for unskilled workers has a negative impact on property crime, burglary and larceny, with an increase in one standard deviation in income contributing to reduce those crimes by respectively 0.84, 0.76 and 0.87 deviations. Those are very large magnitudes if one considers the size of the standard deviations of those variables. There is no statistically significant effect on motor vehicle theft or any violent crime.

The fact that impact of income is only observed on property crimes is in line with the empirical literature that find some evidence in this direction. This is also an expected result from the theoretical perspective, as the effect of the level of wages would play a role as an opportunity cost of crime in the less serious crimes.

[24]The year effects capture the trends and common shocks such as changes in federal legislation and efficiency of the police to deter crime. The models were estimated with First Differences as well, yielding similar coefficients to the Fixed effects estimates.

[25]The tests are respectively the Cragg-Donald Wald F statistic and the Kleibergen-Paap rank LM statistic.

[26]In order to simplify the analysis, I exclude the police variable from the estimations focused on the impact of income on crime.

Table 5.1: Crime Equations - States - Unskilled Workers Total Income - Baseline

	Property	Burglary	Larceny	MVT	Violent	Murder	Assault	Rape
Unskilled Workers								
Total Income	-0.85***	-0.77***	-0.90***	-0.18	-0.00	0.30**	0.07	0.05
	(0.22)	(0.22)	(0.23)	(0.25)	(0.13)	(0.10)	(0.17)	(0.28)
Constant	-1.21***	-0.54	-1.57***	-0.34	-0.33	0.47**	-0.36	-0.33
	(0.34)	(0.34)	(0.34)	(0.34)	(0.20)	(0.16)	(0.27)	(0.40)
State Effects?	yes	yes	yes	yes	yes	yes	yes	yes
Time Effects?	yes	yes	yes	yes	yes	yes	yes	yes
Observations	1700	1700	1700	1700	1700	1700	1700	1700
R^2	0.63	0.71	0.58	0.34	0.35	0.48	0.34	0.26

Notes: Standardised coefficients. Weighted by population in 2010. Standard errors robust to heteroscedasticity and clustering on state in parentheses. p-values for the test for unobserved state, time and two-way effects, respectively: 0.0000 ; 0.0000; 0.0000 in all regressions.
Regressions controlled for the Proportion of black people,
Proportion of population between 15-19, 20-24, 25-29, 30-34 and 35-39 years old
Urbanization, Proportion of one-parent households and Unemployment rate.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$ *Data Source*: UCR/FBI/CPS.

5.1 Random Coefficients Model

Tables 5.2 and 5.3 present the estimates of the empirical models presented at section 4.1 with respect to the level of income of unskilled workers. Tables with the same approach where the overall level of income is used are presented in the appendix.

Table 5.2 shows the results of the estimation of equation 4.1 with $\delta_0 = 0$.[27] There is no evidence of asymmetries between positive and negative variation with a common intercept.[28] However, as discussed in Loureiro (2013b), if there is a hysteresis loop in the relationship, it would be nonlinear. For a sample of observed values within a relatively short range of income values, the assumption of linearity is fairly reasonable, but the assumption of common intercept is very restrictive.[29]

That assumption is relaxed in the estimation presented in Table 5.3. There are asymmetric effects on positive and negative variations in wages for all property crime rates, apart from motor vehicle theft. Reductions of one standard deviation in the level of income of unskilled workers increase those crime rates by approximately one standard deviation. Increases in those variables produce a decrease in crime rates, however, that reduction is significantly smaller in absolute value than the ones observed when wages increase.

As in the previous approach, the impact of income is only observed on property crimes. It is also important to note that the estimated coefficients are now all larger then the ones observed when the assumption of common slopes and intercepts for positive and negative variations on income is implicitly assumed.

[27] I also exclude the police variable from the estimations focused on the impact of income on crime, in order to simplify the analysis and the exposition of the results.

[28] When testing the hypothesis of asymmetric effects, I use the more conservative two-sided test rather then the one-sided test, since the latter is more powerful to reject the null than the former.

[29] That assumption was present in Mocan and Bali (2010) in their analysis using unemployment.

Table 5.2: Crime Equations - States - Unskilled Workers Total Income - Asymmetric Effects - Common Intercept

	Property	Burglary	Larceny	MVT	Violent	Murder	Assault	Rape
Unskilled Workers								
Total Income (Negative Δ)	-0.50	-0.31	-0.69*	0.11	0.14	0.80***	0.12	0.21
	(0.34)	(0.36)	(0.33)	(0.42)	(0.27)	(0.23)	(0.29)	(0.35)
Unskilled Workers								
Total Income (Positive Δ)	-0.50	-0.33	-0.66*	0.10	0.12	0.75***	0.11	0.21
	(0.32)	(0.34)	(0.31)	(0.39)	(0.25)	(0.21)	(0.27)	(0.33)
State Effects?	yes	yes	yes	yes	yes	yes	yes	yes
Time Effects?	yes	yes	yes	yes	yes	yes	yes	yes
Observations	1700	1700	1700	1700	1700	1700	1700	1700
R^2	0.67	0.76	0.60	0.48	0.55	0.66	0.56	0.35
Positive Δ=Negative Δ test	1.01	0.79	0.84	2.67	2.87	1.53	4.03	0.37
p-value	0.31	0.77	0.36	0.10	0.09	0.22	0.05	0.54

Notes: Standardised coefficients. Weighted by population in 2010. Standard errors robust to heteroscedasticity and clustering on state in parentheses. p-values for the test for unobserved state, time and two-way effects, respectively: 0.0000 ; 0.0000; 0.0000 in all regressions.
Regressions controlled for the proportion of population between 15-19, 20-24, 25-29, 30-34 and 35-39 years old, Urbanization, Proportion of one-parent households and Unemployment rate.
*** p<0.01, ** p<0.05, * p<0.1 *Data Source*: UCR/FBI/CPS.

Table 5.3: Crime Equations - States - Unskilled Workers Total Income - Asymmetric Effects

	Property	Burglary	Larceny	MVT	Violent	Murder	Assault	Rape
Unskilled Workers								
Total Income (Negative Δ)	-1.03***	-0.94***	-1.05***	-0.38	0.01	0.33*	0.14	-0.07
	(0.26)	(0.24)	(0.28)	(0.30)	(0.16)	(0.12)	(0.21)	(0.32)
Unskilled Workers								
Total Income (Positive Δ)	-0.88***	-0.79**	-0.92***	-0.29	0.00	0.34**	0.08	0.03
	(0.24)	(0.23)	(0.25)	(0.29)	(0.15)	(0.11)	(0.20)	(0.29)
Positive Δ Unskilled Workers								
Total Income =1	-0.27*	-0.32**	-0.21*	-0.18	0.02	-0.08	0.15	-0.22
	(0.11)	(0.11)	(0.10)	(0.15)	(0.08)	(0.06)	(0.10)	(0.20)
Constant	-1.01**	-0.25	-1.43***	-0.28	-0.33	0.59**	-0.46	-0.18
	(0.37)	(0.38)	(0.38)	(0.42)	(0.24)	(0.18)	(0.31)	(0.47)
State Effects?	yes	yes	yes	yes	yes	yes	yes	yes
Time Effects?	yes	yes	yes	yes	yes	yes	yes	yes
Observations	1700	1700	1700	1700	1700	1700	1700	1700
R^2	0.62	0.71	0.57	0.26	0.34	0.47	0.34	0.25
Positive Δ=Negative Δ test	8.88	10.96	7.95	1.84	0.26	0.34	2.78	1.10
p-value	0.00	0.00	0.00	0.18	0.61	0.55	0.10	0.29

Notes: Standardised coefficients. Weighted by population in 2010. Standard errors robust to heteroscedasticity and clustering on state in parentheses. p-values for the test for unobserved state, time and two-way effects, respectively: 0.0000 ; 0.0000; 0.0000 in all regressions.
Regressions controlled for the proportion of population between 15-19, 20-24, 25-29, 30-34 and 35-39 years old, Urbanization, Proportion of one-parent households and Unemployment rate.
*** p<0.01, ** p<0.05, * p<0.1 *Data Source*: UCR/FBI/CPS.

5.2 Sample Split

In this section I estimate the empirical models proposed in section 4.2, correcting for measurement error in the police force variable. Table 5.4 present the estimates for asymmetric variations in wages.[30] The results are qualitative similar to the previous approach, indicating strong asymmetric effects for all property crime rates, apart from motor vehicle theft. Nevertheless, the asymmetries are sharper than the ones observed in the random coefficients approach, under the assumption of homogeneous effects.

I now turn the focus to test the existence of asymmetric effects of police on crime. As a benchmark, the first part of table 5.5 presents the estimates without the correction for the measurement error in the population and police force sizes, whereas the second part display the results when both issues are tackled according to the strategy specified in section 4.3.

Table 5.6 present the estimates for asymmetric variations in police size. The asymmetric effects are even sharper than the ones observed for wages. There are asymmetric effects on positive and negative variations in the number of police officers for all crime rates, except larceny and rape. Reductions of one standard deviation in the police force size increase those crime rates produce increases in crime rates with varying magnitudes in terms of standard deviations. The largest effect is observed for motor vehicle theft, where reducing the police presence can increase crime rates by 2.59 standard deviations. More strikingly, increases in the number of police officers produce a decrease only in murder rates, with reduction being significantly smaller in absolute value than the ones observed in a police increase. All the other crime rates are either not statistically sensible to positive variations in police or positively affected by increase in police in the short run. That suggests that there still simultaneity between police and crime. Nevertheless, there is no reason to believe that this asymmetric effects would not persist if that issue is taken into account.

Table 5.7 present a robustness check. The results are robust to alternative estimation strategies, especially in terms of the sign of the coefficients. The conclusions of the test for the differences of the coefficients in this table are very similar to the ones in the previous analysis and therefore omitted. The results are robust across the alternative estimation procedures.

The first part of the table shows the estimates when the District of Columbia (DC) is included in the sample (initially excluded for having a level of police much higher than all US states). Asymmetric effects are also found with this approach. However, unlike the estimates

[30] As in previous section, I exclude the police variable from the estimations focused on the impact of income on crime.

where DC is not included, the effects from police are intensified and the asymmetries are more evident. Additionally, unlike the previous approach, Larceny has a negative impact from negative variations in police.

It can also be seen from table 5.7 that the results are not greatly altered when other approaches are used: excluding all the other covariates; excluding very small variations in police; excluding all states with population size below the 25th percentile and when the regressions are not weighted by the population size of each state.

However, as suggested in Loureiro (2013b), the relationship between crime rates and its main determinants is more likely to be non-linear rather than linear as assumed in the preceding analysis.

Table 5.4: Crime Equations - States - Unskilled Workers Total Income - Split Sample

	Property	Burglary	Larceny	MVT	Violent	Murder	Assault	Rape
Unskilled Workers								
Total Income (Negative Δ)	-1.23***	-1.14***	-1.25***	-0.39***	-0.12	0.16**	0.05	-0.44**
	(0.12)	(0.12)	(0.13)	(0.11)	(0.07)	(0.06)	(0.09)	(0.17)
Constant	-1.93***	-1.26***	-2.19***	-0.86***	-0.49***	0.14	-0.27	-0.88**
	(0.19)	(0.20)	(0.21)	(0.18)	(0.11)	(0.09)	(0.15)	(0.27)
State Effects?	yes	yes	yes	yes	yes	yes	yes	yes
Time Effects?	yes	yes	yes	yes	yes	yes	yes	yes
Observations	816	816	816	816	816	816	816	816
R^2	0.636	0.702	0.582	0.211	0.307	0.488	0.262	0.280
Unskilled Workers								
Total Income (Positive Δ)	-0.44***	-0.33**	-0.48***	-0.19	0.10	0.53***	0.05	0.65***
	(0.12)	(0.12)	(0.12)	(0.16)	(0.09)	(0.06)	(0.10)	(0.13)
Constant	-0.48*	0.28	-0.90***	-0.13	-0.18	0.88***	-0.49**	0.38
	(0.20)	(0.19)	(0.20)	(0.26)	(0.15)	(0.10)	(0.17)	(0.22)
State Effects?	yes	yes	yes	yes	yes	yes	yes	yes
Time Effects?	yes	yes	yes	yes	yes	yes	yes	yes
Observations	884	884	884	884	884	884	884	884
R^2	0.621	0.742	0.546	0.310	0.361	0.493	0.385	0.237
Positive Δ=Negative Δ test	4.63	14.29	4.48	40.92	9.98	2.29	0.19	0.78
p-value	0.0316	0.0002	0.0244	0.0000	0.0016	0.1303	0.6628	0.3760

Notes: Standardised coefficients. Weighted by population in 2010. Standard errors robust to heteroscedasticity and clustering on state in parentheses. p-values for the test for unobserved state, time and two-way effects, respectively: 0.0000 ; 0.0000; 0.0000 in all regressions.
Regressions controlled for the proportion of population between 15-19, 20-24, 25-29, 30-34 and 35-39 years old, Urbanization, Proportion of one-parent households and Unemployment rate.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$ *Data Source*: UCR/FBI/ASG/CPS.

Table 5.5: Crime Equations - States - Police & Total Income - OLS & IV

OLS	Property	Burglary	Larceny	MVT	Violent	Murder	Assault	Rape
Police	0.47*	0.37	0.63**	-0.21	0.00	-0.16*	0.11	0.01
	(0.26)	(0.26)	(0.26)	(0.21)	(0.16)	(0.09)	(0.16)	(0.20)
Total Income	-1.01***	-0.85***	-0.93***	-0.79*	-0.48***	0.23***	-0.41**	-0.53**
	(0.22)	(0.18)	(0.21)	(0.40)	(0.18)	(0.07)	(0.20)	(0.26)
State Effects?	yes	yes	yes	yes	yes	yes	yes	yes
Time Effects?	yes	yes	yes	yes	yes	yes	yes	yes
Observations	1700	1700	1700	1700	1700	1700	1700	1700
R^2	0.791	0.856	0.742	0.510	0.606	0.726	0.580	0.621
IV & Population Correction	Property	Burglary	Larceny	MVT	Violent	Murder	Assault	Rape
Police	0.51**	0.15	1.10***	-1.12***	-0.43**	-0.67***	-0.21	0.57***
	(0.21)	(0.22)	(0.20)	(0.27)	(0.17)	(0.12)	(0.13)	(0.14)
Total Income	-0.86***	-0.75***	-0.72***	-0.88***	-0.54***	0.12***	-0.46***	-0.37***
	(0.09)	(0.09)	(0.09)	(0.14)	(0.07)	(0.04)	(0.08)	(0.09)
State Effects?	yes	yes	yes	yes	yes	yes	yes	yes
Time Effects?	yes	yes	yes	yes	yes	yes	yes	yes
Observations	1700	1700	1700	1700	1700	1700	1700	1700
R^2	0.796	0.851	0.735	0.462	0.601	0.654	0.566	0.583

Notes: Standardised coefficients. Weighted by population in 2010. Standard errors robust to heteroscedasticity and clustering on state in parentheses. p-values for the test for unobserved state, time and two-way effects, respectively: 0.0000 ; 0.0000; 0.0000 in all regressions.
Regressions controlled for the proportion of population between 15-19, 20-24, 25-29, 30-34 and 35-39 years old, Urbanization, Proportion of one-parent households and Unemployment rate.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$ *Data Source*: UCR/FBI/ASG/CPS.

Table 5.6: Crime Equations - States - Police - Split Sample - IV & Population Correction

	Property	Burglary	Larceny	MVT	Violent	Murder	Assault	Rape
Police (Negative Δ)	-0.35	-0.55*	-0.54**	-2.59***	-1.74***	-0.71***	-1.37***	0.62**
	(0.28)	(0.30)	(0.25)	(0.47)	(0.31)	(0.16)	(0.25)	(0.23)
Total Income	-0.42***	-0.45***	-0.34**	-0.30	-0.01	0.19***	-0.07	0.03
	(0.14)	(0.13)	(0.14)	(0.22)	(0.13)	(0.06)	(0.12)	(0.13)
State Effects?	yes	yes	yes	yes	yes	yes	yes	yes
Time Effects?	yes	yes	yes	yes	yes	yes	yes	yes
Observations	714	714	714	714	714	714	714	714
R^2	0.865	0.902	0.829	0.514	0.616	0.725	0.623	0.659
Police (Positive Δ)	1.44***	0.86***	1.67***	0.64*	0.20	-0.54***	0.02	0.58**
	(0.29)	(0.23)	(0.30)	(0.28)	(0.14)	(0.11)	(0.19)	(0.21)
Total Income	-0.88***	-0.85***	-0.76***	-0.67***	-0.40***	-0.04	-0.19*	-0.81***
	(0.15)	(0.13)	(0.14)	(0.18)	(0.08)	(0.05)	(0.09)	(0.13)
State Effects?	yes	yes	yes	yes	yes	yes	yes	yes
Time Effects?	yes	yes	yes	yes	yes	yes	yes	yes
Observations	986	986	986	986	986	986	809866	986
R^2	0.646	0.788	0.544	0.552	0.615	0.772	0.500	0.459
Positive Δ=Negative Δ test	3.13	6.42	0.22	9.38	3.73	9.61	12.09	2.24
p-value	0.0767	0.0113	0.6376	0.0022	0.0534	0.0019	0.0005	0.1341

Notes: Standardised coefficients. Weighted by population in 2010. Standard errors robust to heteroscedasticity and clustering on state in parentheses. p-values for the test for unobserved state, time and two-way effects, respectively: 0.0000 ; 0.0000; 0.0000 in all regressions.
Regressions controlled for the proportion of population between 15-19, 20-24, 25-29, 30-34 and 35-39 years old, Urbanization, Proportion of one-parent households and Unemployment rate.
*** p<0.01, ** p<0.05, * p<0.1   *Data Source*: UCR/FBI/ASG/CPS.

Table 5.7: Crime Equations - States - Police - Split Sample - Robustness Check

	Property	Burglary	Larceny	MVT	Violent	Murder	Assault	Rape
Include DC								
Police (Negative Δ)	-1.29***	-1.89***	0.25	-4.18***	-2.24***	-2.06***	-1.06***	0.51*
Police (Positive Δ)	1.19***	0.65**	1.37***	0.67**	0.50*	0.53	0.61*	-0.07
No covariates								
Police (Negative Δ)	-0.94**	-1.26***	0.44	-4.13***	-2.05***	-2.04***	-0.99***	0.40
Police (Positive Δ)	1.31***	0.77***	1.48***	0.78***	0.24*	-0.31***	0.17	0.22
Exclude $\lvert\Delta police\rvert < 1$								
Police (Negative Δ)	-1.00**	-1.63***	0.40	-3.61***	-1.94***	-1.81***	-0.87***	0.52
Police (Positive Δ)	0.99**	0.45*	1.24**	0.40*	0.14	-0.33**	0.17	-0.05
Exclude pop. $<$ 25 perc.								
Police (Negative Δ)	-1.29***	-1.91***	0.22	-4.13***	-2.16***	-2.09***	-0.95***	0.59*
Police (Positive Δ)	0.98***	0.55**	1.22**	0.35	0.13	-0.29**	0.08	0.11
No population weights								
Police (Negative Δ)	-0.43	-1.04***	1.12**	-3.99***	-1.73***	-0.80***	-1.27***	1.22*
Police (Positive Δ)	1.08***	0.51***	1.30***	0.58***	0.06	-0.36***	0.09	-0.21

Notes: Standardised coefficients. Standard errors robust to heteroscedasticity
and clustering on state in parentheses. p-values for the test for unobserved state, time and two-way effects,
respectively: 0.0000 ; 0.0000; 0.0000 in all regressions.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$ *Data Source*: UCR/FBI/ASG/CPS.

6 Semiparametric Estimation

All the analyses in the previous sections, and indeed all longitudinal studies in the crime literature, assumed linearity of the investigated relationships and all coefficient comparisons were in terms of the means. In order to test if those assumptions were very restrictive I estimate the asymmetric effects of positive and negative variations in wages and police on crime nonparametrically.

That also allows to reconcile the observed asymmetric effects with the concept of hysteresis, by taking into account the shape of the relationships over the observed support of both wages and police and the theoretical possible values of those variables. If there is hysteresis the confidence intervals for the negative and positive variations relationships should not overlap in at least a significant part of the independent variable.

In the nonparametric approach, I keep the same structure of the previous sections controlling linearly for the state/time effects, covariates and instrument. For that reason the procedure in this section is effectively a semiparametric estimation.

The models discussed in section 4.2 can be now restated as semiparametric single index models:

$$Crime_{it} = \varphi_1(\psi_{1i} + \lambda_{1t} + \mathbf{x}'_{it}\beta_1 + \gamma_1 Police_{it-1} + \delta_1 Income_{it}) + \epsilon_{1it} \text{ if } i \in \Gamma \tag{6.1}$$

$$Crime_{it} = \varphi_2(\psi_{2i} + \lambda_{2t} + \mathbf{x}'_{it}\beta_2 + \gamma_2 Police_{it-1} + \delta_2 Income_{it}) + \epsilon_{2it} \text{ if } i \notin \Gamma \tag{6.2}$$

$$Crime_{it} = \varphi_3(\phi_{1i} + \lambda_{1t} + \mathbf{x}'_{it}\beta_1 + \theta_1 Police_{it-1} + \varrho_1 Income_{it}) + \mu_{1it} \text{ if } i \in \Omega \tag{6.3}$$

$$Crime_{it} = \varphi_4(\phi_{2i} + \lambda_{2t} + \mathbf{x}'_{it}\beta_2 + \theta_2 Police_{it-1} + \varrho_2 Income_{it}) + \mu_{2it} \text{ if } i \notin \Omega \tag{6.4}$$

where Γ is the set of states with positive variations in income above the average, Ω is the set of states with positive variations in police above the average and $\varphi_k,\ k = \{1, 2, 3, 4\}$ are estimated nonparametrically.[31]

As in the parametric estimation, I simplify the analysis by excluding the police variable from the estimations of equations 6.1 and 6.2.

I use the the Lowess estimator - Locally Weighted Scatterplot Smoothing that uses the tricubic kernel:

$$K(z) = \frac{70}{81}(1 - |z|^3)^3 \times \mathbf{1}(|z| < 1). \tag{6.5}$$

One of its advantages lies on the fact that, unlike most nonparametric estimators based on other kernel functions, it is a robust estimator against outliers.[32] Because the results of nonparametrically estimated models are much more sensible to the bandwidth choice, rather than the kernel choice, even for the Lowess estimator, I test the robustness of the estimates for different values of bandwidth.

In order to implement the semiparametric single index models for panel data, I partial out the control variables and the fixed and time effects where the residuals, rather than the variables in levels are used in order to account for state and year effects, in addition to all control variables and the instrument used in the previous section.

Equations 6.1-6.4 are then rewritten as:

$$Resid(Crime_{it}) = \varphi_1(\delta_1 Resid(Income_{it})) + \varepsilon_{1it} \text{ if } i \in \Gamma \tag{6.6}$$

$$Resid(Crime_{it}) = \varphi_2(\delta_2 Resid(Income_{it})) + \varepsilon_{2it} \text{ if } i \notin \Gamma \tag{6.7}$$

$$Resid(Crime_{it}) = \varphi_3(\theta_1 Resid(Police_{it-1})) + \zeta_{1it} \text{ if } i \in \Omega \tag{6.8}$$

$$Resid(Crime_{it}) = \varphi_4(\theta_2 Resid(Police_{it-1})) + \zeta_{2it} \text{ if } i \notin \Omega \tag{6.9}$$

The Frisch-Waugh-Lovell theorem ensures that the estimated coefficients δ_1, δ_2, θ_1 and θ_1 in equations 6.1-6.4 are identical to the ones in equations 6.6-6.9.[33]

Figures 6.1 and 6.2 show the nonparametric estimates using the Lowess estimator with 0.5 bandwidth. The results are qualitatively unaltered for a different variations of levels of

[31] For the properties of the semiparametric single index model, see Ichimura (1993), that established the estimator.

[32] For details, see Fan and Gijbels (1996) and Cameron and Trivedi (2005).

[33] See Frisch and Waugh (1933) and Lovell (2008).

bandwidth and presented in the appendix.

Figure 6.1 provides a clear evidence of asymmetric effects for property crime rates. The degree of asymmetry is particularly strong for higher values of wages and nonexistent for lower levels of the distribution. This result is consistent with the hypothesis of hysteresis that predicts a larger gap between directions of variations as we move away from lower values of the independent variable.

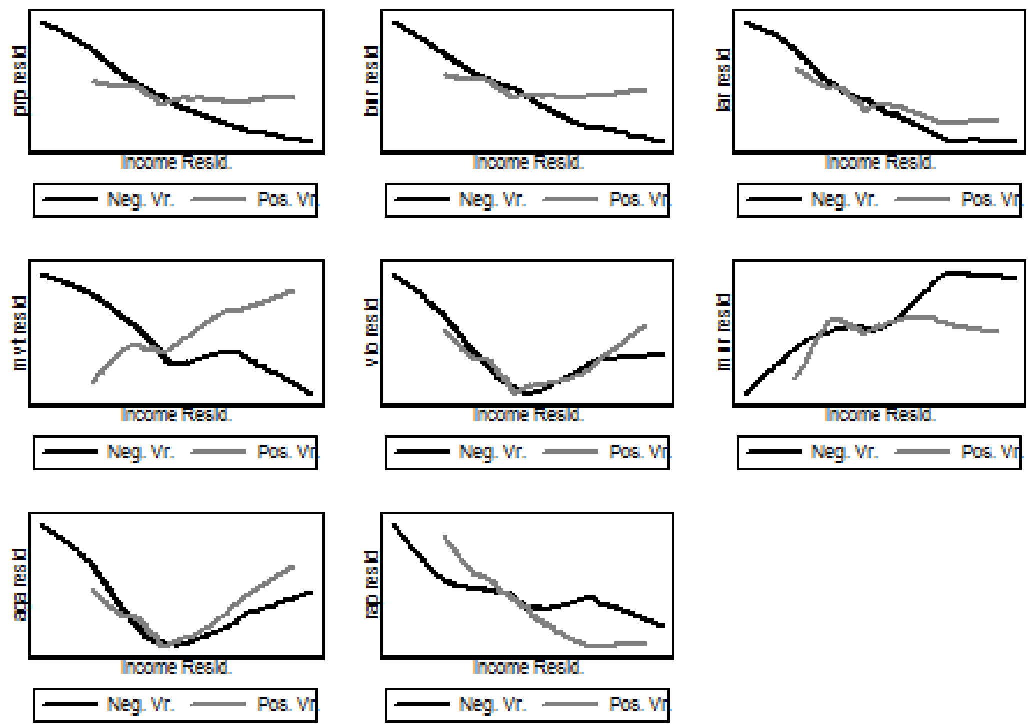


Figure 6.1: Positive vs Negative Variation in Wages - Lowess estimator - Bandwidth=0.5
Data Source: UCR/FBI/ASG/CPS.

Figure 6.2 displays the lowess estimates for the residuals of the IV regressions for the different crime rates and the police size. The results are similar to the ones observed for wages, but with the evidence of asymmetric effects present for all types of crimes. One important conclusion that can be taken form figure 6.2 is that all crime rates are negatively associated to police when this variable is fairly monotonically decreasing, but the relationship is highly nonlinear for positive variations.

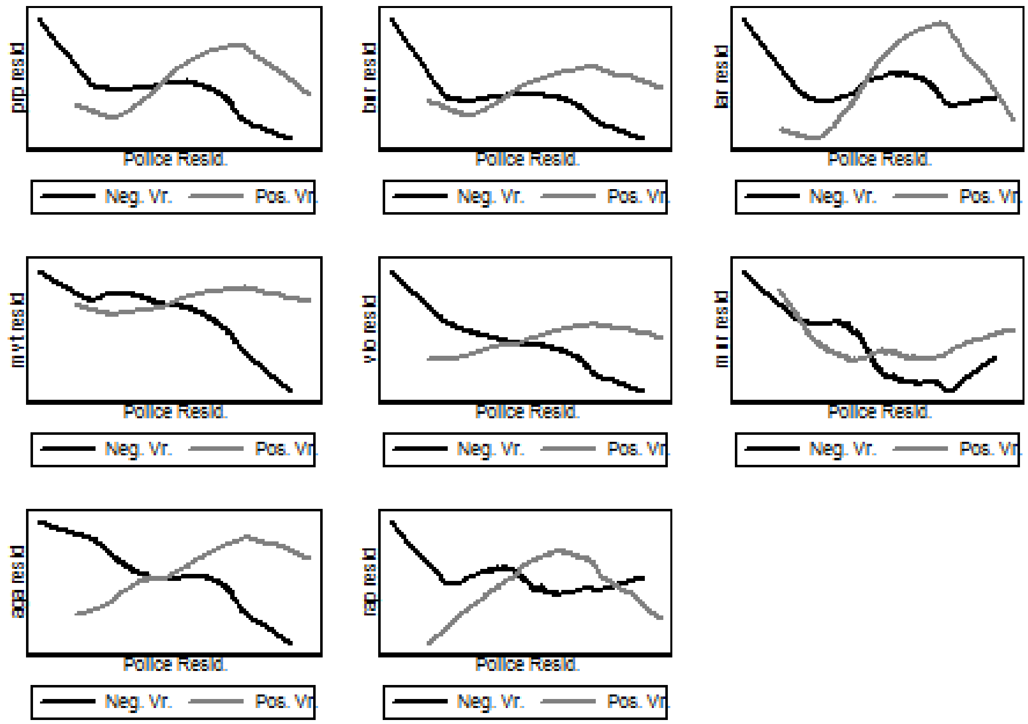


Figure 6.2: Positive vs Negative Variation in Police - Lowess estimator - Bandwidth=0.5
Data Source: UCR/FBI/ASG/CPS.

It is also important to note from 6.2 that the positive coefficients associated to positive variations in police officers obtained in the linear specification of the previous section were crucially stemming from increases when the size of the police force were smaller than the average in the sample. For higher numbers of police officers, those relationships are all negative, except to murder, but the slopes are still significantly larger in absolute value when compared to negative variations in police, respectively to each type of crime.

7 Conclusions

This paper estimates the asymmetric impact of police and income on property and violent crime rates in the US between 1997 and 2010. This is the first effort to capture these asymmetries and it is also the first to correct for the measurement error at a higher level of aggregation. Furthermore, this is also the first analysis to take into account the existence of nonlinearities in the main determinants of crime with longitudinal aggregate crime data.

There is evidence of asymmetric effects of positive and negative variations in the level of income for both unskilled workers and the general population for property crime rates. In general, reductions of one standard deviation in the level of real income of unskilled workers increase those crime rates by approximately one standard deviation. Increases in the levels of real income produce a decrease in crime rates, however, that reduction is significantly smaller in absolute value than the ones observed when real income increase.

Those asymmetric effects are also observed for positive and negative variations in the number of police officers for all crime rates, except larceny and rape. Reductions of one standard deviation in the size of the police force increase those crime rates by one to four standard deviations, depending on the type of crime. For some types crimes and under some specifications, increases in the police size produce a decrease is significantly smaller in absolute value than the ones observed when law enforcement increase. For most specifications and types of crime, police and crime are positively associated when only positive variations are considered. A closer inspection with a semiparametric estimation reveals that the slopes are positive only for lower levels of police officers and they are negative for higher levels, except to murder, but the slopes are still significantly larger in absolute value when compared to negative variations in police, respectively to each type of crime.

The magnitude of the asymmetries found in this paper supports the hypothesis of hysteresis in crime and suggests that no theoretical or empirical analysis would be complete without careful consideration of that important feature of the relationships between crime, police and legal income. These results are relevant for any empirical analysis of policies at crime reduction, but they are particularly important for evaluations of policies based on increases of police force size.

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8 Appendix

8.1 Extraction and Organisation of the Data

In this section I explain the details of extraction of the data from three used sources: Uniform Crime Reports - UCR, Current Population Survey - CPS and Annual Survey of State and Local Government Employment and Census of Governments - ASG.

8.1.1 UCR Data

The crime and police data are provided by the Federal Bureau of Investigation - FBI that runs the Uniform Crime Reports - UCR. Because the FBI webpage provide only the most recent years of data, I used the historical series archived by the Inter-university Consortium for Political and Social Research - ICPSR that dates back to 1966. However, years prior 1975 follow a very different methodology of organisation. And because the CPS data was not representative to all states before 1977, I restrict the sample between 1977 and 2010. This compilation of local government data provides a snapshot in October for the number of police personnel, disaggregated by police officers and administrative workers. To calculate the crime variables, I use the number of offenses that are available at monthly basis and are disaggregated by several categories of crime, where each category and each month is recorded in an individual variable. I group the data onto the crime types used in this paper by year. I use all main categories of crime: burglary, larceny, motor vehicle theft, murder, aggravated assault and forcible rape. I calculate the crime rates by dividing each crime variable by the respective population in each state and multiply by 100,000. A similar procedure is carried out to obtain the number of police officers by 100,000 inhabitants.

8.1.2 CPS Data

I use the data from the Current Population Survey - CPS, provided by the Bureau of Labor Statistics to construct most of the covariates in the estimated model, including the personal level of income. The microdata for the interviews carried out in march is available at the Integrated Public Use Microdata Series (IPUMS) website since 1962. However, the data is representative to all states only after 1977. The micro data is aggregated into sample-weighted variables by state for each year between 1977 and 2010.

8.1.3 ASG Data

In order to obtain the second measurement of police size, I also used the number of police officers from the Annual Survey of State and Local Government Employment and Census of Governments, U.S. Census Bureau. The data for federal and state employees are the actual numbers, however, as the local government statistics are based on a sample of local governments. As in the UCR data, the numbers refer to October of each year, but after 1997 the reference month was changed to March. As carried out in the UCR data, I calculate the number of police officers by 100,000 inhabitants by using the corrected population sizes provided by the dataset.

8.2 Maps

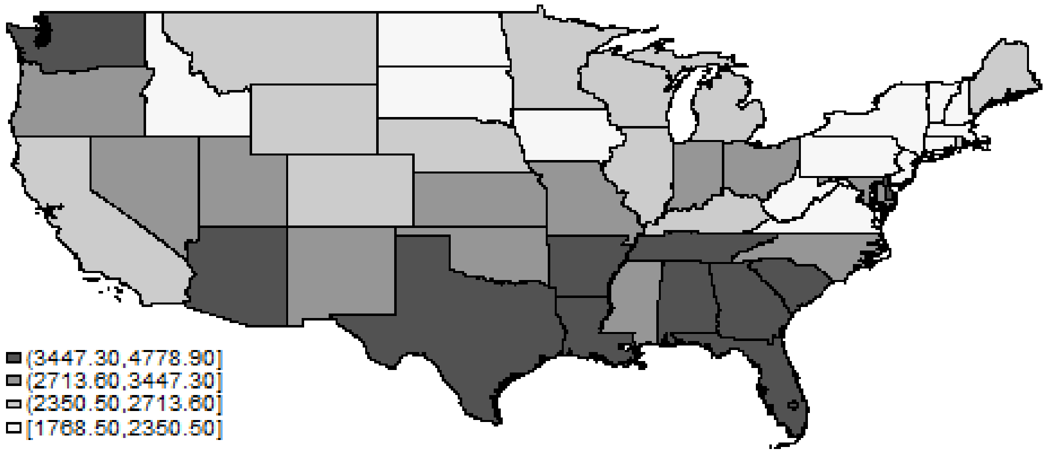

Figure 8.1: Property Crime Rates - States - 2010

Data Source: UCR/FBI.

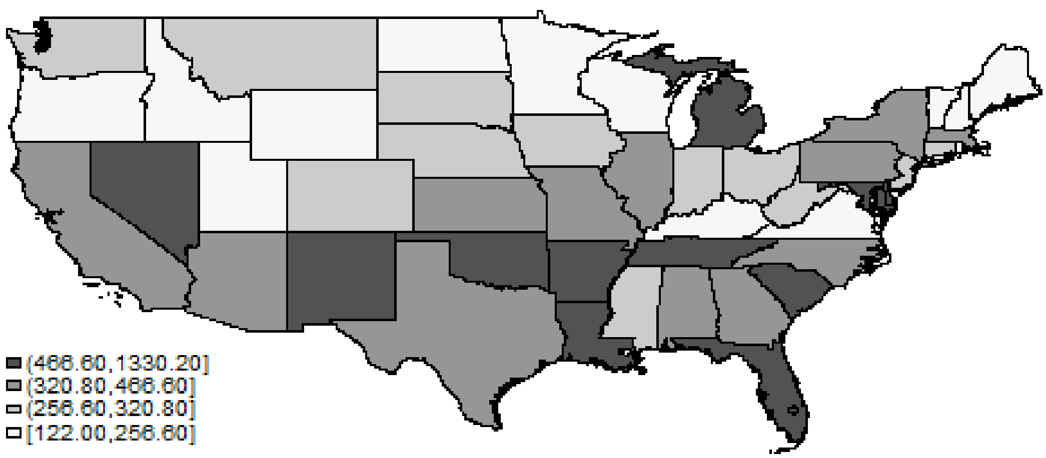

Figure 8.2: Violent Crime Rates - States - 2010

Data Source: UCR/FBI.

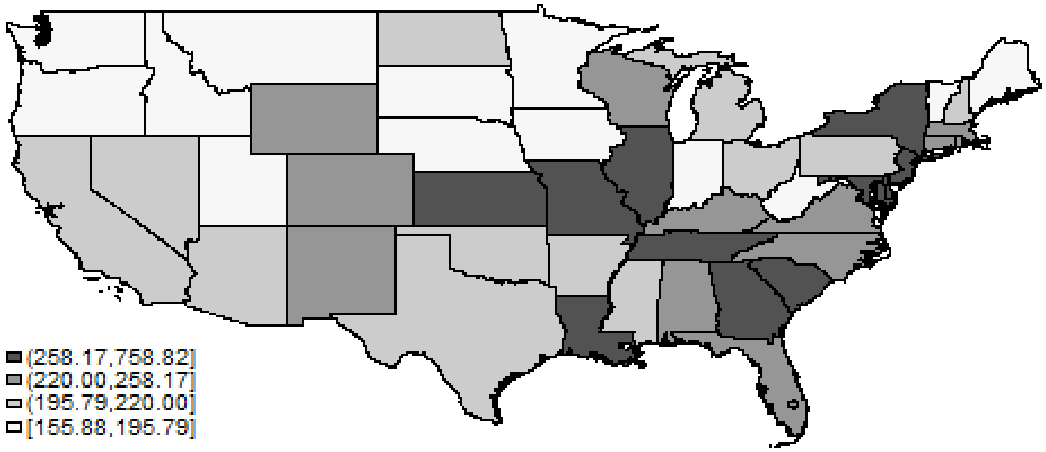

Figure 8.3: Police Officers per 100,000 inhab. - States - 2010

Data Source: UCR/FBI.

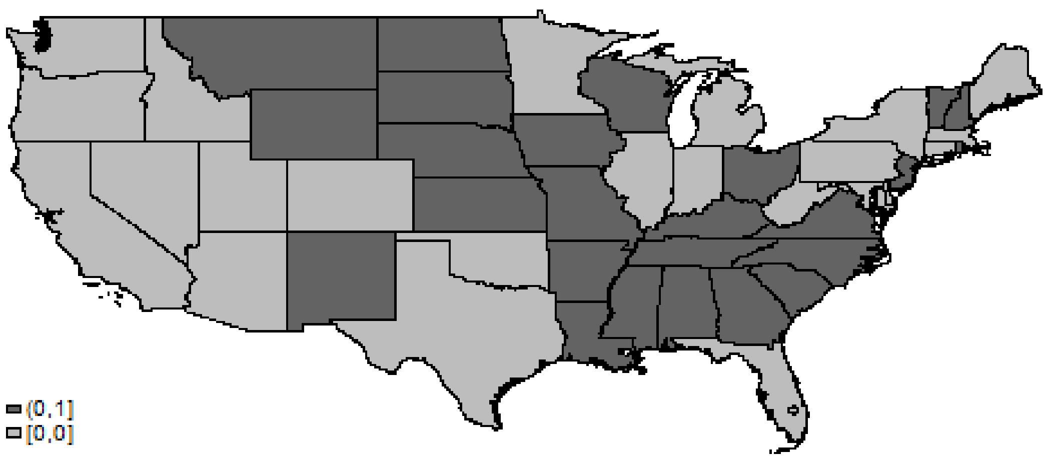

Figure 8.4: Positive Variations in Police Officers (pc) above Average in the 1977 - 2010 period - States

Data Source: UCR/FBI.

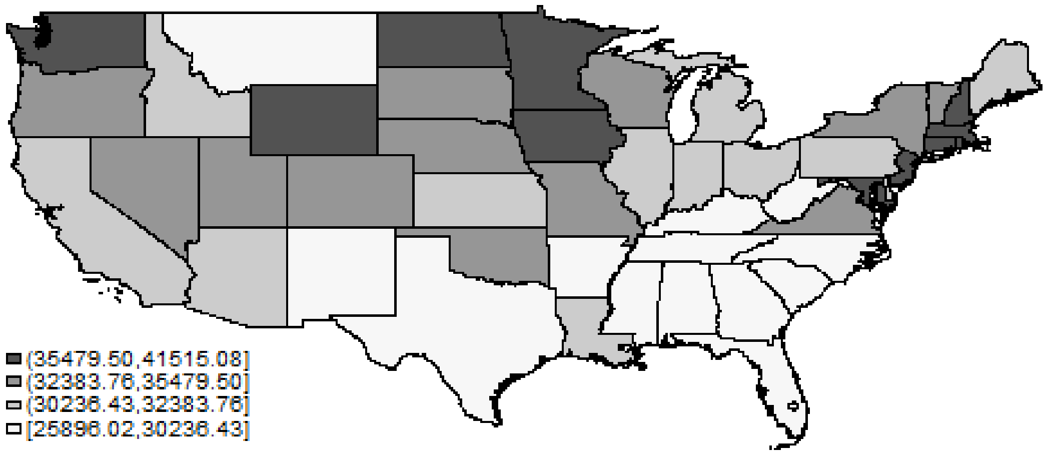

Figure 8.5: Real Income - Unskilled Workers - States - 2010

Data Source: CPS.

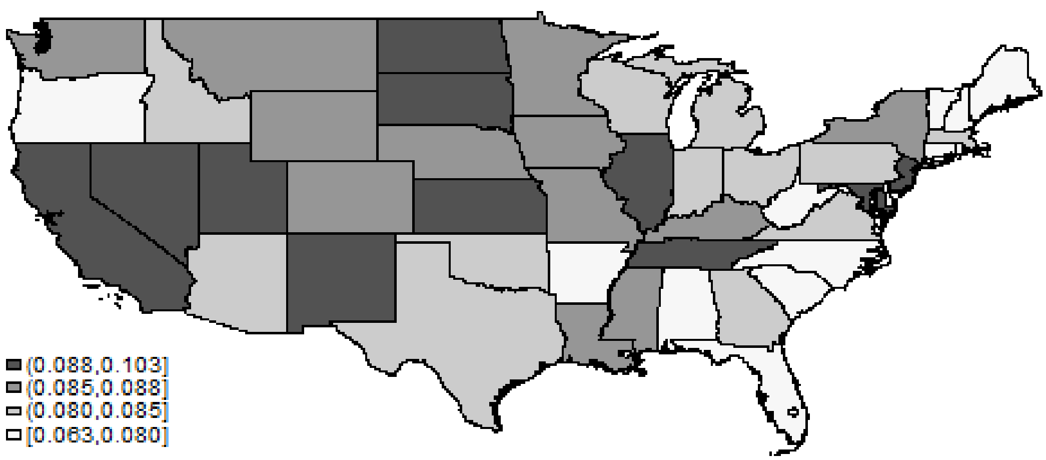

Figure 8.6: Young Male (%) - States - 2010

Data Source: CPS.

8.3 Additional Figures

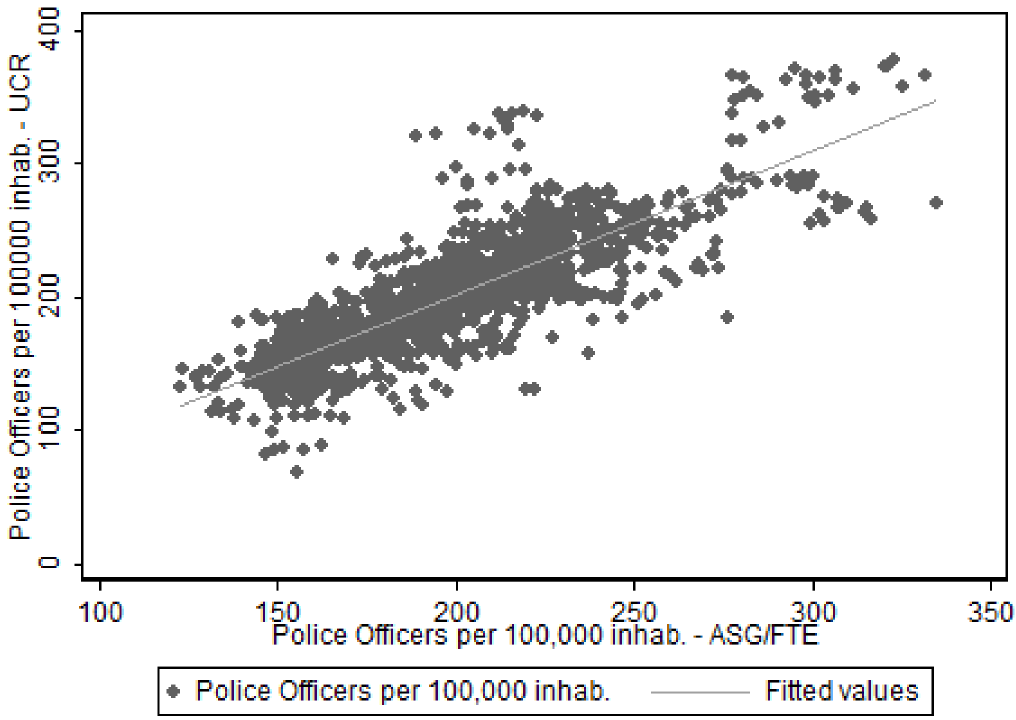

Figure 8.7: Police UCR vs Police ASG - US States - 1977 - 2010

Data Source: UCR/FBI/ASG.

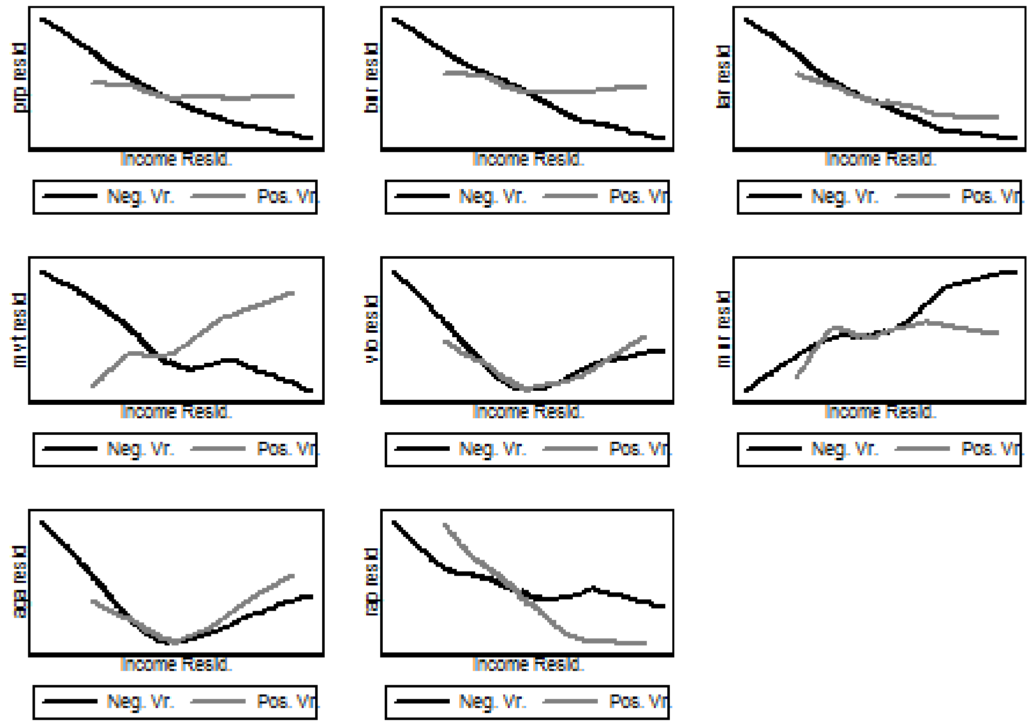

Figure 8.8: Positive vs Negative Variation in Wages - Lowess estimator - Bandwidth=0.8
Data Source: UCR/FBI/ASG/CPS.

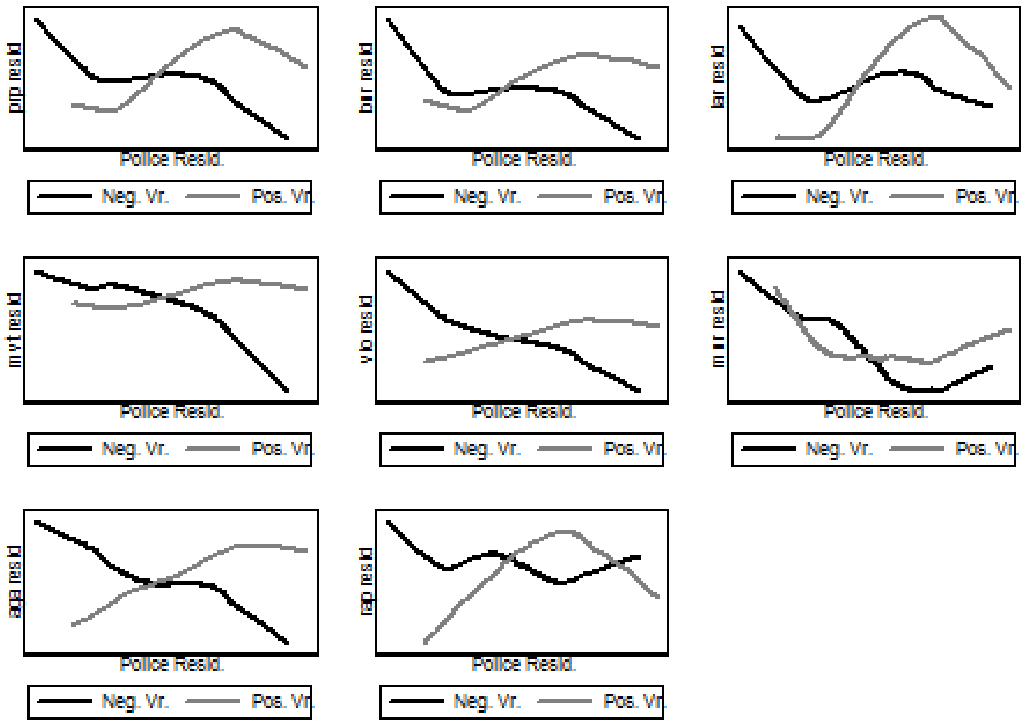

Figure 8.9: Positive vs Negative Variation in Police - Lowess estimator - Bandwidth=0.8
Data Source: UCR/FBI/ASG/CPS.

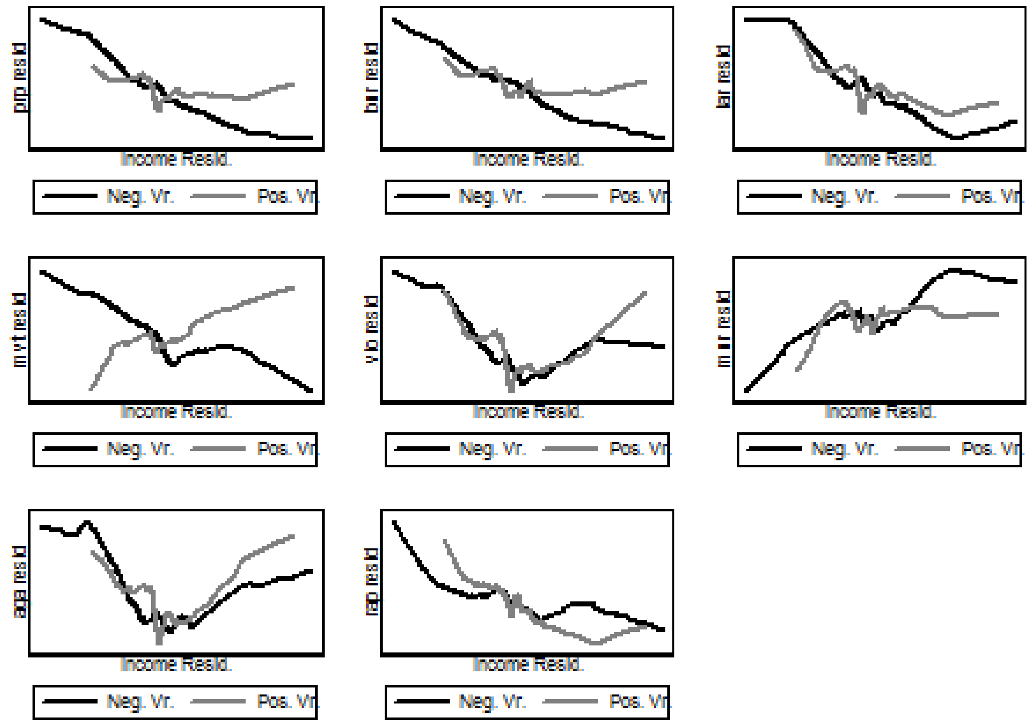

Figure 8.10: Positive vs Negative Variation in Wages - Lowess estimator - Bandwidth=0.2
Data Source: UCR/FBI/ASG/CPS.

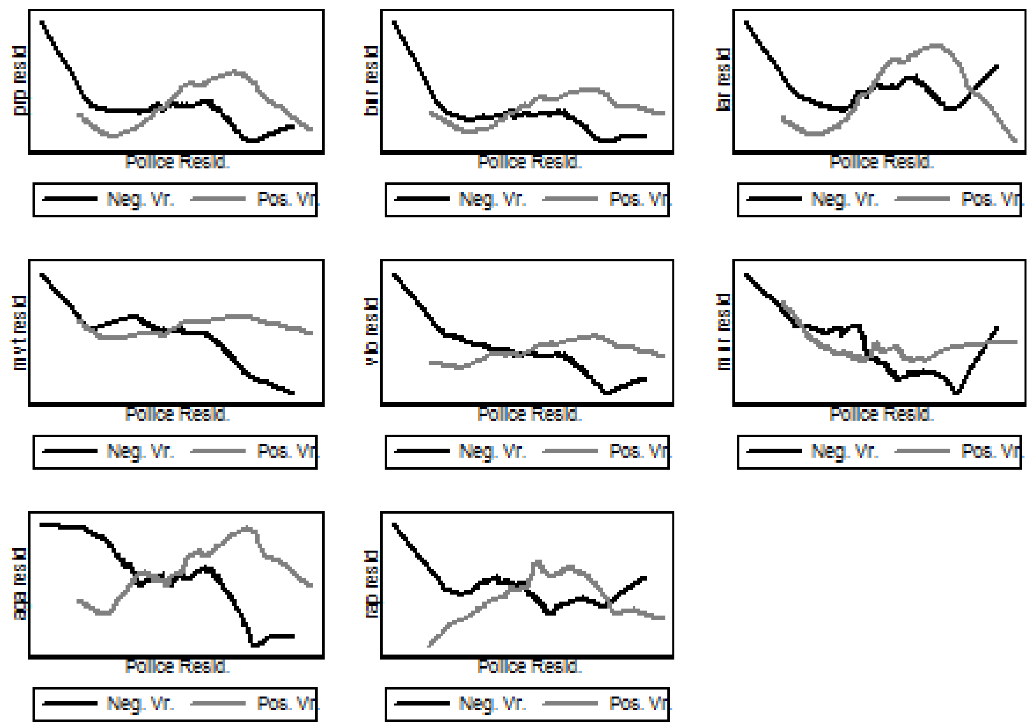

Figure 8.11: Positive vs Negative Variation in Police - Lowess estimator - Bandwidth=0.2
Data Source: UCR/FBI/ASG/CPS.

8.4 Additional Tables

Table 8.1: Crime Equations - States - Workers Total Income

	Property	Burglary	Larceny	MVT	Violent	Murder	Assault	Rape
Total Income	-1.21***	-1.00**	-1.16***	-0.86*	-0.48*	0.34	-0.37	-0.50
	(0.29)	(0.31)	(0.28)	(0.41)	(0.18)	(0.17)	(0.20)	(0.29)
Constant	-1.04**	-0.05	-1.33**	-1.13*	-0.63*	0.74***	-0.70*	-0.82*
	(0.36)	(0.38)	(0.39)	(0.53)	(0.24)	(0.20)	(0.30)	(0.39)
State Effects?	yes	yes	yes	yes	yes	yes	yes	yes
Time Effects?	yes	yes	yes	yes	yes	yes	yes	yes
Observations	1700	1700	1700	1700	1700	1700	1700	1700
R^2	0.70	0.78	0.63	0.50	0.57	0.62	0.57	0.36

Notes: Standardised coefficients. Weighted by population in 2010. Standard errors robust to heteroscedasticity and clustering on state in parentheses. p-values for the test for unobserved state, time and two-way effects, respectively: 0.0000 ; 0.0000; 0.0000 in all regressions.
Regressions controlled for the proportion of population between 15-19, 20-24, 25-29, 30-34 and 35-39 years old, Urbanization, Proportion of one-parent households and Unemployment rate.
*** p<0.01, ** p<0.05, * p<0.1 *Data Source*: UCR/FBI/CPS.

Table 8.2: Crime Equations - States - Total Income - Asymmetric Effects

	Property	Burglary	Larceny	MVT	Violent	Murder	Assault	Rape
Total Income (Negative Δ)	-1.34***	-1.12***	-1.25***	-1.04*	-0.52**	0.32	-0.38	-0.54
	(0.29)	(0.31)	(0.29)	(0.40)	(0.19)	(0.17)	(0.21)	(0.30)
Total Income (Positive Δ)	-1.19***	-0.97**	-1.15***	-0.84	-0.48*	0.36*	-0.39	-0.48
	(0.29)	(0.32)	(0.28)	(0.42)	(0.18)	(0.18)	(0.20)	(0.30)
Positive Δ								
Total Income =1	-0.33	-0.40	-0.19	-0.42*	0.00	-0.16	0.13	-0.19
	(0.21)	(0.20)	(0.21)	(0.20)	(0.12)	(0.10)	(0.13)	(0.19)
Constant	-0.71	0.36	-1.15*	-0.71	-0.65*	0.92**	-0.86**	-0.61
	(0.47)	(0.48)	(0.49)	(0.62)	(0.28)	(0.27)	(0.32)	(0.49)
State Effects?	yes	yes	yes	yes	yes	yes	yes	yes
Time Effects?	yes	yes	yes	yes	yes	yes	yes	yes
Observations	1700	1700	1700	1700	1700	1700	1700	1700
R^2	0.70	0.78	0.63	0.50	0.57	0.63	0.58	0.36
Positive Δ=Negative Δ test	3.99	4.69	1.76	7.92	0.48	2.05	0.60	0.65
p-value	0.05	0.03	0.18	0.00	0.48	0.15	0.80	0.42

Notes: Standardised coefficients. Weighted by population in 2010. Standard errors robust to heteroscedasticity and clustering on state in parentheses. p-values for the test for unobserved state, time and two-way effects, respectively: 0.0000 ; 0.0000; 0.0000 in all regressions.
Regressions controlled for the proportion of population between 15-19, 20-24, 25-29, 30-34 and 35-39 years old, Urbanization, Proportion of one-parent households and Unemployment rate.
*** p<0.01, ** p<0.05, * p<0.1 *Data Source*: UCR/FBI/CPS.

Table 8.3: Crime Equations - States - Total Income - Split Sample

	Property	Burglary	Larceny	MVT	Violent	Murder	Assault	Rape
Total Income (Negative Δ)	-2.10***	-1.90***	-2.06***	-1.02***	-0.59***	0.18**	-0.66***	-0.23
	(0.13)	(0.12)	(0.15)	(0.16)	(0.09)	(0.06)	(0.13)	(0.19)
Constant	-2.93***	-2.06***	-3.25***	-1.31***	-0.99***	0.32***	-1.12***	-0.65*
	(0.19)	(0.18)	(0.22)	(0.24)	(0.13)	(0.10)	(0.19)	(0.29)
State Effects?	yes	yes	yes	yes	yes	yes	yes	yes
Time Effects?	yes	yes	yes	yes	yes	yes	yes	yes
Observations	612	612	612	612	612	612	612	612
R^2	0.698	0.781	0.608	0.206	0.323	0.462	0.262	0.322
Total Income (Positive Δ)	-0.90***	-0.84***	-0.77***	-0.76***	-0.25***	0.21***	-0.11	-0.47***
	(0.09)	(0.09)	(0.09)	(0.11)	(0.06)	(0.05)	(0.07)	(0.11)
Constant	-1.04***	-0.40**	-1.16***	-1.07***	-0.67***	0.31***	-0.67***	-1.09***
	(0.14)	(0.14)	(0.14)	(0.18)	(0.10)	(0.08)	(0.12)	(0.18)
State Effects?	yes	yes	yes	yes	yes	yes	yes	yes
Time Effects?	yes	yes	yes	yes	yes	yes	yes	yes
Observations	1088	1088	1088	1088	1088	1088	1088	1088
R^2	0.673	0.750	0.621	0.328	0.370	0.447	0.377	0.229
Positive Δ=Negative Δ test	10.84	6.05	4.72	5.06	5.42	15.62	0.77	15.22
p-value	0.0035	0.0102	0.0300	0.0246	0.0200	0.0001	0.3811	0.0001

Notes: Standardised coefficients. Weighted by population in 2010. Standard errors robust to heteroscedasticity and clustering on state in parentheses. p-values for the test for unobserved state, time and two-way effects, respectively: 0.0000 ; 0.0000; 0.0000 in all regressions.
Regressions controlled for the proportion of population between 15-19, 20-24, 25-29, 30-34 and 35-39 years old, Urbanization, Proportion of one-parent households and Unemployment rate.
*** p<0.01, ** p<0.05, * p<0.1 *Data Source*: UCR/FBI/CPS.