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An analysis of the factors determining crime in England and Wales: A quantile regression approach

Siddhartha Bandyopadhyay
Birmingham

Samrat Bhattacharya
PNC

Rudra Sensarma
Indian Institute of Management, Kozhikode

Abstract

We analyze the impact of policing and socio-economic variables on crime in England and Wales during 1992-2007 using the quantile regression model which enables us to analyze different points of the crime distribution. The quantile regression model allows us to analyze whether or not the factors that affect crime do so in the same way for high and low crime areas. By using data from 43 police force areas, we examine how the effect of real earnings, unemployment, crime detection rate, income inequality and proportion of young people varies across high and low crime areas. Six crime categories are examined – burglary, theft and handling, fraud and forgery, violence against the person, robbery, and sexual assault. We find statistically significant differences in the impact of explanatory variables on various types of crime for low and high crime areas. For example, higher detection rate reduces crime but the effect is stronger in low crime areas. Further, we find opposing effects of earnings and unemployment across high and low crime areas which may explain why recessions may have no impact on crime or even lower it.

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Contact: Siddhartha Bandyopadhyay - s.bandyopadhyay@bham.ac.uk, Samrat Bhattacharya - bhattacharya.12@gmail.com, Rudra Sensarma - rsensarma@gmail.com.
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1. Introduction

Following the theoretical work of Becker (1968) which views crime as a rational activity which responds to changes in costs and benefits, several studies have empirically analyzed the various determinants of crime rate (see e.g. Doyle et. al 1999, Gould et. al 2002 for the US and Witt et. al 1998, 1999; Carmichael and Ward 2000, 2001; Han et. al 2013 for the U.K.). These studies have shown that both measures of policing (such as detection rate) and various socio-economic factors such as unemployment, income, inequality and proportion of young people in the population can explain variations in crime rates. By estimating linear regression models, all these papers essentially study the effects of the mean levels of explanatory variables on the mean level of crime. However, theory does not provide any guide as to why we should restrict ourselves to analyzing the mean effects only. We argue that it is actually informative to analyze the entire crime distribution instead of just the mean level. This is important because the way in which a factor such as income or unemployment or detection rate affects crime rates can be different in high crime and low crime areas. If that is the case, this has important implications for policy which may have to be tailored differently for high crime and low crime areas. Indeed, as argued by Pease (2010), understanding the distribution of crime is necessary for effective policing. Further, analyzing the way socio economic and policing factors affect crime differently across high and low crime regions may provide us an understanding of the apparent paradox that crime does not necessarily increase in a recession. Indeed, there seems to be evidence that overall crime may have decreased with the current recession in the U.K.[1]

To the best of our knowledge, *our paper is the first to analyze the determinants of crime at different points of the crime distribution.* To achieve this we use a quantile regression estimation technique (Koenker, 2005) using panel data on crime and various explanatory factors in England and Wales for the period 1992-2007 at the Police Force Area level. Using this estimation technique, we are able to examine how the factors that are important in explaining crime differ in impact across high and low crime areas. There is a growing literature which uses quantile techniques in applied work e.g. to analyze the determinants of wages (Buchinsky, 1994), school performance (Eide and Showalter, 1997), health (O'Donnell et al. 2009) and stock returns (Chuang et al. 2009). However, the only crime related applications we are aware of are Britt (2009) who looks at how various characteristics (such as race or offense severity) affect sentence length across various quantiles of the distribution of sentences and Freeborn and Hartman (2012) who look at the same issue within the federal prison system.

Using quantile regression analysis, we find significant differences in impact of our explanatory variables on crime rates across different points of the crime rate distribution. For example, our results show that unemployment increases crime but its impact is usually strongest in high crime areas, suggesting that a targeted unemployment policy in high crime regions may be more beneficial. The impact of detection, while successful in lowering crime across all crime regions, is far stronger in low crime areas than high crime areas suggesting the possibility that where crime is high, the deterrent effect of detection is lower. Further, crime is higher when earnings increase, which indicates that income increases lead to greater opportunities for crime and it is strongest for high crime areas. The impact of inequality on crime is more nuanced. In low crime areas, inequality is associated with increased crime, but this is not necessarily the case in high crime areas. This, perhaps, suggests that in high crime societies, the added criminal opportunities arising from wage disparity are offset by potential victims taking added precautions against

[1] See http://www.bbc.co.uk/news/10645702. It appears that overall crime has fallen by as much as 9% in England and Wales in 2009-10 compared to the previous year and this trend continued with the latest recorded figure showing a drop of 15% making it one of the biggest year to tear drops, see http://www.theguardian.com/uk-news/2014/apr/24/crime-rate-england-wales-falls-lowest-level-33-years.

criminals. The different effects of earnings, unemployment, detection and inequality across high and low crime regions are usually ignored when one simply looks at the average impact of policing and socio-economic factors on crime but which we can pick up in our quantile regressions.

It is useful to review the expected impact of the policing and socio economic variables on crime as well as briefly look at what existing studies have found in this regard. If people rationally weigh the costs and benefits of crime then detection increases should lower crime and empirical studies which directly include detection rate do find such an effect (e.g. Doyle et. al, 1999, Han et. al, 2013). The impact of socio economic variables is more complex. Unemployment should increase crime because it leads to a lower opportunity cost of crime. Countering that, some have argued (Cantor and Land, 1985, Chiricos, 1987, and Smith et. al, 1992) that this may lower crime as people stay at home and thus give fewer opportunities for burglary as well as being robbed. Most of the major recent empirical studies however find that the net effect of unemployment is positive (e.g. Witt et al., 1999, Doyle et al., 1999, Gould et al., 2002).

Like unemployment, the effects of earnings on crime can be ambiguous. While earnings may be expected to lower crime by increasing the gains from not committing crime, it also increases the opportunity for committing crime – higher wages lead to more wealth to steal. Further, as pointed out by Machin and Meghir (2004), the impact of wages on crime would be strongest in low wage deciles as they are the people who at the margin may take to crime. A decrease in wages of upper deciles as usually happens in a recession for instance is unlikely to make the higher earners who have lost jobs take to crime while lowering the opportunities to steal for potential criminals. Hence average wage changes may even increase crime (as in Han et. al, 2013). Inequality may again reinforce the incentive to commit crime: increases in prosperity of one sector increases the value of things to steal while decreases in wages may lower the opportunity cost of crime. Both of these effects increase economic crimes while growing inequality may aggravate social conflict and increase violent crime as well. Against that is the fact that potential victims can take added precautions which can lower crime (Lott and Mustard, 1997 and Ayres and Levitt, 1998 show that self protection by carrying concealed weapons and LoJacks respectively lower crime) and so the net impact of inequality may again be negative.

To summarize, for most of the socio-economic variables, the expected effect on crime could go either way because of the opposing influences of various factors and therefore their net impact, particularly their differential impact in areas with different crime levels remains an empirical question. The rest of the paper proceeds as follows. In Section 2 we outline the estimation methodology and describe the data. Section 3 discusses our main findings and Section 4 concludes.

2. Estimation Methodology and Data

We estimate the following specification that allows crime rate to be determined by policing and various socio-economic factors considered in previous studies:

$$\text{Crime}_{it} = \beta_0 + \beta_1 \text{ Detection}_{it-1} + \beta_2 \text{ Unemployment}_{it-1} + \beta_3 \text{ Earnings}_{it-1} + \beta_4 \text{Inequality}_{it-1} + \beta_5 \text{Proportion of young people}_{it-1} + \varepsilon_{it} \quad (1)$$

where i represents the cross-sectional unit of observation, t represents time and ε_{it} is the error term. The explanatory variables are taken with a period's lags to allow some time before they can have an effect on crime. While we believe that this lagged specification and not a contemporaneous relation is the appropriate specification, it also makes the explanatory factors pre-determined, reducing endogeneity problems arising from reverse causality (see also our discussion in section 3 using IV techniques for robustness). In a contemporaneous specification crime in an area could influence, for instance, the detection rate but it is less likely that crime will significantly affect past detection rate. Further, as a robustness check a specification with higher order lags are also used which produces similar results.

Previous studies have used least squares regression methods to estimate the above relationship which amounts to estimating the conditional mean of crime rate. However we are interested in studying the entire conditional distribution of crime rate. Therefore we employ the quantile regression method (Koenker, 2005) which is a widely used estimation technique when it comes to examining the impact of explanatory variables at different points of the distribution of the dependent variable. Following Koenker (2005), we can write the quantile regression as:

$Crime_{it} = X_{it-1}\beta_\theta + \varepsilon_{\theta it}$ and $Quant(Crime_{it} \mid X_{it-1}) = X_{it-1}\beta_\theta$

where X_{it-1} is a vector of the explanatory variables (with one period lags) as specified in equation (1), β_θ is a vector of the parameters and $Quant(Crime_{it} \mid X_{it-1})$ is the θ^{th} quantile of $Crime_{it}$ given X_{it-1}. The coefficients of the θ^{th} quantile are estimated by solving the following as a linear programming problem:

$$\min_{\beta \in R^k} \sum \rho_\theta (Crime_{it} - X_{it-1}\beta_\theta)$$

where ρ_θ (.) is a check function defined as $\rho_\theta(\varepsilon) = \theta\varepsilon$ if $\varepsilon \geq 0$, and $\rho_\theta(\varepsilon) = (\theta\text{-}1)\varepsilon$ if $\varepsilon < 0$. In case of the median ($\theta = 0.50$), the estimation amounts to minimizing the sum of equally weighted (absolute) deviations from the median whereas in case of all other quantiles, the deviations are asymmetrically weighted. For instance in case of the 25th quantile ($\theta = 0.25$), the positive residuals carry less weight (0.25 weight) than the negative residuals (0.75 weight) so that 75% of the observations lie above the fitted regression line and 25% lie below. Other than allowing us to study the marginal effects across the distribution (which becomes important if the tail behaviour is different from the mean especially in the presence of heteroscedasticity), the quantile regression is also robust to the presence of outliers. We report detailed results from quantile regressions for the 25th, 50th and 75th quantiles, i.e. for $\theta = 0.25$, 0.50 and 0.75 and graphically show the coefficients for a higher number of quantiles. Once the coefficients are estimated, standard errors are generated by 250 bootstrap replications to avoid imposing distributional assumptions which is also one of the advantages of estimating a quantile regression.

We include individual year dummies to account for year effects as well as 9 regional dummies to capture unobserved regional heterogeneity.[2] All the variables except dummies are taken in logarithms.

[2] Regions are the top tier of sub-national administration in England. We include dummies for Wales and the following nine English regions (one dummy less to avoid the dummy variable trap): East Midlands, East England, London, North East England, North West England, South East England, South West England, West Midlands, and Yorkshire and the Humber. PFAs belonging to the same region are expected to have similar features of criminal activity (due to criminal mobility and displacement effects within a region). The mapping of regions to PFAs is available on request.

We employ data for 43 Police Force Areas (PFAs) in England and Wales for the period 1992-2007.[3] We consider **crime rate** (number of offences per 1000 population) for three types of property crime, burglary, theft and handling, fraud and forgery; and three types of violent crime, violence against the person, robbery and sexual offences. The data are available at the PFA level from the Home office publications *Criminal Statistics* and *Crime in England and Wales.*

A host of independent variables are included in the analyses as proxies for the benefits and costs of committing crimes. These include earnings, unemployment rate, detection rate, inequality and proportion of young people in the population.

Unemployment rate is defined as the ratio of the number of unemployment benefits claimants to the number of people in the workforce. The data source is *Nomis,* the official labour market statistics of the *Office for National Statistics*. As in the case of earnings, the data is aggregated at the PFA level from the local authority level.

Earnings are measured by the deflated average weekly earnings for all industries. The data on weekly earnings are available at the local authority level from *Annual Survey of Hours and Earnings* provided by the *Office for National Statistics*. Earnings are then aggregated at the PFA level from the local authority level by mapping the geographical boundaries covered by local authorities and the PFAs.

Detection rate is measured by the proportion of recorded offences that have been "cleared up". The "cleared up" offences refer to those cases in which the offenders have been identified and given a caution, fined or charged by the police. Therefore, the detection rate is included in the analyses as proxy for the probability of apprehension. Like the crime rate data, the detection rates at PFA level are obtained from the Home office publications *Criminal Statistics* and *Crime in England and Wales.*

Inequality is measured by the inter-quartile range and calculated by taking the difference in earnings in the upper 25th and lower 25th quantiles. Like the earnings data, the source of the inequality data is the *Annual Survey of Hours and Earnings* and the data are aggregated at the PFA level from the local authority level.

Proportion of **young** people is defined as the ratio of the number of young people aged between 15 and 24 years to the entire population. The data source is the mid-year estimated population by age groups obtained from the *Office for National Statistics.* The number of people aged between 15 and 24 years has been calculated by aggregating two original age groups available in the data source — 15-19 and 20-24. The data are available at local authority level and have been aggregated at the PFA level.

Table 1 shows some basic features of the data. Among the crime rates, property crimes seem to be more frequent than the violent crimes with the highest average rate shown by theft and handling followed by burglary. Among violent crimes, violence against the person has the highest average rate. Interestingly the average detection rates seem to be higher for most violent crimes than the property crimes. The tests of normality show that all the crime rates are non-

[3] There have been some changes in the counting rules for the crime rates since 1 April, 1998. First, the crime rates and relevant statistics have been documented according to the financial year system, which starts from 1st of April and ends on 31st of March the following year, rather than the normal calendar year. Second, the definitions of some types of crime have been broadened and thus their crime rates have exhibited upward shifts since 1998. We have also run separate regressions by splitting the sample into pre 1998 and post 1998. The separate estimates we obtain do not qualitatively change our main results.

normal which supports our choice of quantile regression to study the entire distributions instead of relying on the means.[4]

3. Results

The detailed results from regressing crime rates for the six crime types on the different explanatory factors are reported in tables 2a (for property crimes) and 3a (for violent crimes) for the three quartiles (the 25th quantile i.e. q25, the 50th quantile or median i.e. q50 and the 75th quantile i.e. q75) while figures 1-5 plot the magnitudes of the coefficients of the explanatory variables across deciles (i.e. q10 to q90). Tests of equality of coefficients from the q25 and q75 are presented in tables 2b (for property crimes) and 3b (for violent crimes).

The impact of unemployment on crime is positive for every crime category as seen in tables 2a and 3a, with its impact being strongest in high crime areas. For example, a 1% increase in unemployment increases theft and handling by 0.28% in the low crime regions but by 0.46% in the high crime regions. Similarly, a 1% increase in unemployment increases robbery by 0.46% in the low crime regions but by 0.72% in high crime regions. However the coefficients in the higher quantiles are significantly different from the coefficients in the lower quantiles only for theft and handling and robbery (see tables 2b and 3b). This is consistent with the inverse relationship most seen in the empirical literature.

Moving on to the role of earnings, table 2a shows that the coefficient of earnings is positive and statistically significant for all types of property crime but the effect is stronger for higher quantiles than for lower quantiles. Table 2b shows that the coefficients in the higher quantiles (q75) are significantly different from the coefficients in the lower quantiles (q25) for theft and handling and fraud and forgery but not for burglary. Table 3a shows similar results i.e. the impact of earnings is positive and increasing as we move from lower to higher quantiles. In this case the coefficients of earnings in the higher quantiles are significantly different from the coefficients in the lower quantiles for all the three types of violent crime (see table 3b). Overall the results seem to indicate that crime rates are higher in more prosperous areas and the marginal effect of an increase in earnings is stronger in the high crime areas than in low crime areas. This suggests that in a high crime area, criminals find it easier to commit crime and therefore the effect of an increase in crime opportunity (following an increase in earnings) is strongest in those areas. To illustrate a 1% increase in earnings increases theft and handling by 0.87% in low crime areas but the impact is over four times stronger in high crime areas with the commensurate increase in crime rate being 3.46%. This is consistent with Han et. al (2013).

The above findings seem to suggest that a deterioration of economic conditions may work in opposite directions i.e. lower earnings may reduce crime while higher unemployment may increase crime. The opposing effects of earnings and unemployment give rise to a possible explanation for why crime actually fell during the current recession. While income levels fell reducing the opportunities for crime, it is less likely that the laid off office workers (who were typically impacted by the recession as evidenced by fall in inequality during the recession) would take to crime. Therefore the crime reducing effect of lower earnings may have been stronger than the crime increasing effect of unemployment, particularly in high crime areas where these effects are the strongest.

[4] Mata and Machado (1996) note that quantile regression is robust to departures from normality such as long tails and outliers.

The coefficient of detection rate is negative (as posited in the literature) and significant across all quantiles (with the exception of violence against the person where the coefficient is significant only in the median regression) but the absolute value of the coefficients is highest in low crime areas. This implies that the marginal effect of 'clearing up' is stronger in low crime areas. For example, a 1 % increase in detection lowers theft and handling by 0.54% in low crime areas and this is about four times stronger that its impact in high crime areas where the drop is only 0.13%. However the coefficients are significantly different across the lower and upper quantiles for three of the six types of crime viz. Theft and handling, fraud and forgery and sexual offences. Further, detection and crime are inversely related for 5 out of 6 crime categories. Stigma effects may explain why the threat of detection may be less in high crime areas where being arrested by the police is common.

The relationship between inequality and crime is somewhat more complicated. The impact of inequality on crime is significant (except for fraud and forgery and robbery) but changes signs as we move from lower to higher quantiles. The role of inequality in increasing crime is strongest in the lower quantiles while surprisingly (with the exception of fraud and forgery), increasing inequality actually lowers crime in the higher quantiles. We hypothesize that if income inequality increases in high crime areas, potential victims might be taking more anticipatory precautions. This may lead to lower crime in spite of rising inequalities in the high crime areas.

In line with the literature, young people are positively associated with increases in four types of crime viz. Burglary, theft and handling, violence against the person and robbery but the impact does not vary monotonically across quantiles. Also, the coefficients are not significantly different for low and high crime areas in the case of burglary and robbery.

Figures 1-5 show the magnitude of coefficients of the main explanatory variables across finer points in the crime rate distributions. The behaviour of the coefficients across the deciles are consistent with the reported detailed results for quartiles and clearly show that the effects are far from uniform across the distributions as would be the case if a linear regression approach were followed.

Finally, it should be noted that our correction for endogeneity using lagged independent variables is imperfect as crime and detection may be both correlated with an unobservable third factor e.g. tolerance for crime. It is usual to use instrumental variable (IV) techniques wherever possible to correct this (see Levitt, 1997). However, quantile techniques using IV are not well developed. We have however used a recently developed Stata programme (available at http://faculty.chicagobooth.edu/christian.hansen/research/ivqrstata.zip) which allows for IV quantile regression[5]. We report the results in the appendix. We use police expenditure per police officer to instrument for detection. The instrument chosen has been used in the literature (see Machin and Meghir, 2004) and justified on the basis that police expenditure in the UK is determined by a police funding formula and does not directly depend on crime. As can be seen in the Appendix, our main results are robust to the use of this IV.

4. Conclusion

Our quantile regression approach allows us to identify how the relationship between crime and various law enforcement and socio economic factors varies with the level of crime. Instead of a 'one size fits all' approach, the quantile approach enables us to study the determinants of crime

[5] This is based on their pioneering work on IV Quantile regressions (see Chernozhukov, and Hansen, 2005) and the Stata code is supplied by Do Wan Kwak.

across different points of the distribution of crime rate. It suggests that policing is most effective in low crime areas. The varying effect of detection is perhaps not so surprising; crime in some areas may be high precisely because people are less responsive to the fear of being caught. This might well be because of what people loosely call a 'culture of crime'. In a high crime area being apprehended may not carry the same stigma as in a low crime area and thus the deterrent effect of detection is lower[6]. There might also be multiple equilibria as suggested earlier. Wage increases are associated with higher crime with the effect being most marked in high crime areas. This suggests that the short run impact of wage changes may not only increase crime, it will do so most strongly in high crime areas.

Further, unemployment is positively associated with crime but its impact is highest in high crime areas. Thus, employment opportunities in crime prone areas have an especially ameliorating impact on crime suggesting the need for focussing on employment expansion policies in high crime regions. There is suggestive evidence that workfare programmes are very effective at tackling crime in Denmark (see Fallese, Geerdsen, Imai and Tranaes, 2010 and the discussion in the Civitas blog http://www.civitas.org.uk/wordpress/2011/01/11/unemployment-workfare-and-crime/). This may well be a policy to break the cycle of unemployment and crime that may be affecting high crime areas. The impact of wage inequality on crime also varies significantly across quantiles and in fact at higher quantiles can even decrease crime. We have offered one explanation for this in terms of increased victim precaution but the impact of inequality on crime deserves more investigation.

The combined effect of opposing factors may well explain why crime and recession do not have a clear relationship. In high crime but prosperous areas wages decline during a recession thereby lowering crime possibly because there are less opportunities for crime. Our quantile regression results suggest that this 'diminishing opportunities' effect would indeed be stronger in the high crime areas. Further, the typical residents in such high wage areas who are affected by the recession are unlikely to switch to crime when they become unemployed i.e. the typical laid off office worker is unlikely to take to, say, burglaries.[7] While there are countervailing effects in that higher unemployment increases crime, it may still not be strong enough to offset the fact that lowered wages reduce opportunities for crime. Hence, understanding the opposing forces at work across different crime regions enables us to reconcile the paradox of rising unemployment and falling crime even when the impact of increased unemployment holding wage constant increases crime.[8] Thus, more research on decomposing the way different regions are affected by crime will greatly enhance our understanding of the determinants of crime. Trickett et. al. (1995) analyze regional differences in crime pattern and Tseloni and Pease (2005) focus on inequalities in the distribution of people who become victims of crime. Looking at how the distribution of incidence of crime changed with the distribution of policing and socio economic factors across regions over time suggests a fruitful area of future research.

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[6] Of course, the impact of stigma on crime is more complicated. Increased stigma can actually increase recidivism so the net impact of an increase in stigma may not be negative (see Funk, 2004)

[7] For a different explanation of the ambiguous relationship between crime and recession which looks at the dynamic incentives to commit crime across business cycles, see Bagchi and Bandyopadhyay (2010).

[8] This paradox is seen not just in the U.K. as mentioned but in the U.S. as well for the current recession. See, http://www.nytimes.com/2011/05/24/us/24crime.html?_r=2&hp

References

1. Ayres, I and S. Levitt (1999) "Measuring Positive Externalities from Unobservable Victim Precaution: An Empirical Analysis of Lojack" *The Quarterly Journal of Economics*, 113 (1), 43-77.
2. Bagchi, A and Bandyopadhyay, S. (2010) "Workplace Deviance and the Business Cycle", Discussion paper, University of Birmingham.
3. Billger, S M. and Goel, R. (2009) "Do existing corruption levels matter in controlling corruption?: Cross-country quantile regression estimates," *Journal of Development Economics*, 90(2), 299-305.
4. Britt, C. (2009) "Modeling the Distribution of Sentence Length Decisions Under a Guidelines System: An Application of Quantile Regression Models," *Journal of Quantitative Criminology*, 25(4), 341-370.
5. Buchinsky, M. (1994) "Changes in the U.S. Wage Structure 1963-1987: Application of Quantile Regression", *Econometrica* 62(2), 405-58.
6. Burdett, K, R .Lagos, and R. Wright, (2003), "Crime, Inequality, and Unemployment", *American Economic Review,* 93 (5), 1764-1777.
7. Cantor, D and Land, K. (1985) "Unemployment and Crime Rates in the Post-World War II United States: A Theoretical and Empirical Analysis", *American Sociological Review*, 50 (3), 317-332.
8. Carmichael, F. and Ward, R. (2000) "Youth Unemployment and Crime in the English Regions and Wales", *Applied Economics*, 32(5), 559-571.
9. Chernozhukov, V. and Hansen, C. 2005, "An IV Model of Quantile Treatment Effects", *Econometrica*, 73(1), 245-261
10. Chiricos. T. (1987) "Rates of Crime and Unemployment: An Analysis of Aggregate Research Evidence", *Social Problems,* 34,187-212.
11. Chuang, C, Kuan, C and Lin, H. (2009) "Causality in quantiles and dynamic stock return-volume relations," *Journal of Banking & Finance*, 33(7), 1351-1360.
12. Doyle, J M., Ahmed, Ahmed, E and Horn, R. (1999) "The Effects of Labor Markets and Income Inequality on Crime: Evidence from Panel Data", *Southern Economic Journal,* 65(4), 717-738.
13. Freeborn, B.A. and Hartman, M.E. (2010) "Racial and Ethnic Disparities in Federal Sentencing: A Quantile Regression Approach", 5th Annual Conference on Empirical Legal Studies Paper.
14. Funk, P. (2004) "On the Effective Use of Stigma as a Crime-deterrent", *European Economic Review*, 48(4), 715-728.
15. Eide, E and Showalter, M. (1998) "The effect of school quality on student performance:

16. A quantile regression approach", *Economics Letters* 58(3), 345–350.

17. Fallesen, P, Geerdsen, L Imai, S and Tranaes, T, (2010) "The Effect of Workfare Policy on Crime", Discussion paper, Queen's University.

18. Gould, Eric D., Weinberg, Bruce A. and Mustard, David B. (2002) "Crime Rates and Local Labor Market Opportunities in the United States: 1979-1997", *The Review of Economics and Statistics*, 84(1): 45-61.

19. Han, L., Bandyopadhyay, S. and Bhattacharya, S. (2013) "Determinants of Violent and Property Crimes in England and Wales: A Panel Data Analysis", *Applied Economics,* 45(34): 4820-4830.

20. Koenker, R. (2005) Quantile Regression, Cambridge University Press: Cambridge.

21. Levitt, S. (1997) "Using Electoral Cycles in Police Hiring to Estimate the Effect of Police on Crime", *American Economic Review,* 1997, 87(3): 270-90

22. Lott, J and Mustard, D. (1997) "Crime, Deterrence, and Right-to-Carry Concealed Handguns", *The Journal of Legal Studies*, 26(1), 1-68.

23. Machin, S and Meghir, C. (2004) "Crime and Economic Incentives", Journal of Human Resources, 39(4), 958-79.

24. Mata, M and Machado, J.A.F. (1996) "Firm start-up size: A conditional quantile approach", *European Economic Review* 40(6), 1305-1323.

25. Pease, K. (2012) "Crime Concentration and Police Work", The Sage handbook of Criminological Research Methods.

26. Smith, M., Devine, J. and Sheley, J. (1992) "Crime and unemployment: Effects across age and race categories", *Sociological Perspectives*, 35(4), 551-72.

27. Trickett, A., Ellingworth, D, Hope, T. and Pease, K. (1995) "Crime victimization in the eighties: Changes in area and regional inequality", *British Journal of Criminology,* 35 (3), 343-359.

28. Tseloni, A, and Pease, K. (2005) "Population Inequality: The Case of Repeat Crime Victimization", *International Review of Victimization*, 12(1), 75-90.

29. Witt, R., Clarke, A. and Fielding, N. (1998) "Crime, Earnings Inequality and Unemployment in England and Wales", *Applied Economics Letters*, 5(4), 265-267.

30. Witt, R., Clarke, A. and Fielding, N. (1999) "Crime and Economic Activity: A Panel Data Approach", *The British Journal of Criminology*, 39(3), 391-400.

Table 1: Descriptive Statistics

Dependent Variables

Crime Type	Mean	Std Dev	Min	Max	Normality
Burglary	18.76	14.35	4.07	16.83	0.62(0.00)
Theft and Handling	55.31	101.48	13.18	89.04	0.23(0.00)
Fraud and Forgery	6.34	18.51	1.01	19.85	0.20(0.00)
Violence against person	11.83	13.50	1.88	13.04	0.51(0.00)
Robbery	1.06	1.33	0.05	11.92	0.63(0.00)
Sexual Offenses	0.83	0.72	0.28	8.07	0.44(0.00)

Independent variables

Explanatory Variable	Mean	Std Dev	Min	Max	Normality
Unemployment rate	3.97	2.35	0.61	11.52	0.91(0.00)
Earnings	399.16	109.78	242.70	1081.30	0.85(0.00)
Detection Rate – Burglary	18.08	8.03	7	56	0.89(0.00)
Detection Rate – Theft and Handling	22.39	7.01	8	54	0.92(0.00)
Detection Rate – Fraud and Forgery	44.52	16.14	9	98	0.98(0.00)
Detection Rate - Violence against person	69.68	15.78	24	97	0.96(0.00)
Detection Rate – Robbery	30.94	12.23	10	96	0.90(0.00)
Detection Rate – Sexual Offenses	60.30	23.04	20	124	0.93(0.00)
Inequality (Inter-quartile range)	0.71	0.05	0.57	0.88	0.99(0.00)
Proportion of young people	12.31	1.14	8.11	15.41	0.99(0.00)

Note: Normality refers to the W-statistics from the Shapiro-Wilk test of normality. The figures in parentheses are p-values (null hypothesis is of normality).

Table 2a: Quantile regression results for determinants of property crimes

	Burglary			Theft and handling			Fraud and forgery		
	q25	q50	q75	q25	q50	q75	q25	q50	q75
Unemp	0.4122*	0.3807*	0.5113*	0.2823*	0.3095*	0.4633*	0.0527	0.0811	0.0252
	(.0694)	(.0926)	(.0736)	(.0402)	(.0501)	(.0623)	(.0525)	(.0852)	(.0837)
Earnings	1.7010*	1.4098*	2.0533*	0.8669*	1.1117*	3.4570*	1.7188*	2.3756*	3.6161*
	(.3397)	(.6133)	(.2818)	(.2759)	(.4828)	(.8066)	(.3194)	(.6165)	(.206)
Detection	-0.3436*	-0.3144*	-0.2850*	-0.5455*	-0.3094*	-0.1369+	-0.3478*	-0.1844*	-0.0560
	(.0642)	(.0928)	(.0535)	(.0709)	(.0729)	(.0746)	(.0573)	(.0754)	(.0556)
Inequality	0.7535*	-0.0563	-1.1706*	0.3812	0.1847	-1.2828*	-0.1279	-0.0475	-0.5741
	(.2922)	(.4876)	(.513)	(.2621)	(.291)	(.5201)	(.4104)	(.5713)	(.5568)
Young	0.9167*	1.2407*	0.4818	0.9597*	0.8644*	0.0291	0.2992	0.1140	-0.5430+
	(.2746)	(.4218)	(.3134)	(.1449)	(.2223)	(.2887)	(.2242)	(.3923)	(.3113)
Intercept	1.9792*	2.1419*	3.8205	5.1985*	4.5758*	3.7057*	3.2290	2.1161	2.0755+
	(.6729)	(1.0051)	(.9747)	(.5917)	(.5467)	(.8021)	(.7597)	(.9654)	(1.0996)
Pseudo-R2	0.4529	0.4206	0.4871	0.4198	0.4007	0.4343	0.4885	0.4724	0.5165
# obs.	643	643	643	643	643	643	643	643	643

Note: All independent variables are lagged by one year; year and region dummies are included; numbers in parentheses are boot-strapped standard errors; * and + indicate statistically significant coefficients at 5% and 10% levels.

Table 2b: Tests of equality of coefficients across quantiles (H0: q25=q75) for property crimes

	Burglary	Theft and handling	Fraud and forgery
Unemp			
F-stat	1.33	8.46	0.09
p-value	0.25	0.00	0.76
Earnings			
F-stat	1.34	13.99	39.54
p-value	0.25	0.00	0.00
Detection			
F-stat	0.79	21.97	19.85
p-value	0.37	0.00	0.00
Inequality			
F-stat	13.62	8.53	0.60
p-value	0.00	0.00	0.44
Young			
F-stat	1.78	12.38	5.81
p-value	0.18	0.00	0.02

Table 3a: Quantile regression results for determinants of violent crimes

	Violence against the person			Robbery			Sexual offences		
	q25	q50	q75	q25	q50	q75	q25	q50	q75
Unemp	0.2356*	0.2825*	0.3165*	0.4674*	0.5392*	0.7263*	0.1658*	0.2237*	0.2429*
	(.0555)	(.0582)	(.0716)	(.0822)	(.0806)	(.097)	(.0596)	(.0515)	(.0541)
Earnings	0.4725+	0.8398*	2.1046*	2.8647*	3.1159*	3.3291*	0.2677	0.9299*	1.9271*
	(.2914)	(.4012)	(.4113)	(.2382)	(.2159)	(.1563)	(.227)	(.2789)	(.2325)
Detection	-0.1045	-0.1739*	-0.0884	-1.1266*	-1.103*	-0.9926*	-0.4784*	-0.3316*	-0.2064*
	(.0832)	(.0858)	(.1095)	(.0849)	(.0919)	(.1001)	(.0931)	(.078)	(.0668)
Inequality	0.3842	-0.8997*	-1.5723*	0.7203	0.2322	-0.7717	0.6133+	0.2055	-0.8485
	(.3545)	(.471)	(.5594)	(.5134)	(.5794)	(.5664)	(.3804)	(.4604)	(.4199)
Young	0.7378*	0.3105	-0.3968	2.4835*	2.9277*	2.4844*	0.3089	0.1139	-0.1286
	(.2765)	(.2532)	(.2503)	(.2637)	(.2827)	(.3407)	(.2839)	(.2636)	(.2362)
Intercept	4.6119*	6.4989*	6.7305*	-4.1811*	-5.3376*	-4.0728*	4.2468*	3.633*	3.2379*
	(.7877)	(.7338)	(.8229)	(1.0054)	(1.0428)	(1.1299)	(.8999)	(.7229)	(.733)
Pseudo-R2	0.6648	0.6492	0.5839	0.5952	0.6118	0.6304	0.4289	0.4513	0.4663
# obs.	643	643	643	643	643	643	643	643	643

Note: All independent variables are lagged by one year; year and region dummies are included; numbers in parentheses are boot-strapped standard errors; * and + indicate statistically significant coefficients at 5% and 10% levels.

Table 3b: Tests of equality of coefficients across quantiles (H0: q25=q75) for violent crimes

	Violence against the person	Robbery	Sexual Offences
Unemp			
F-stat	1.02	4.97	1.45
p-value	0.31	0.03	0.23
Earnings			
F-stat	22.44	3.00	47.30
p-value	0.00	0.08	0.00
Detection			
F-stat	0.02	1.53	9.16
p-value	0.90	0.22	0.00
Inequality			
F-stat	13.40	5.30	9.32
p-value	0.00	0.02	0.00
Young			
F-stat	14.55	0.00	2.09
p-value	0.00	1.00	0.15

Figure 1: Impact of unemployment on 6 types of crime across deciles

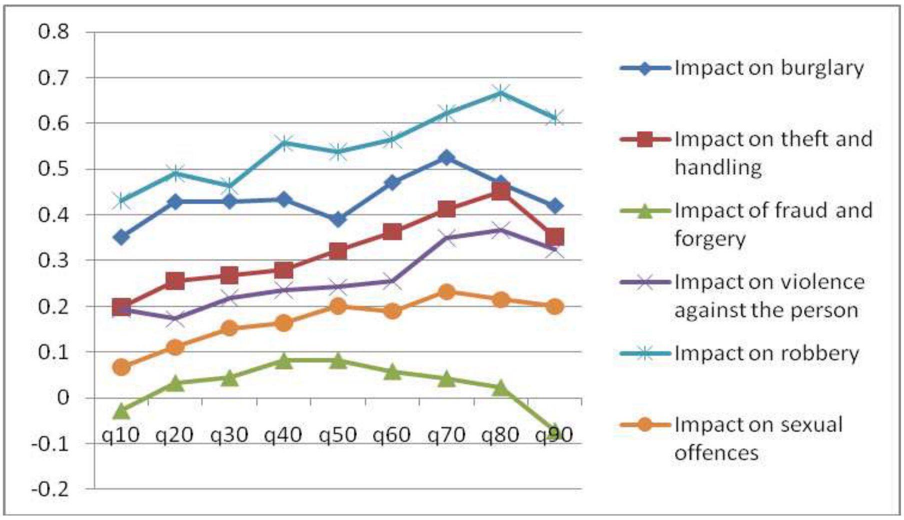


Figure 2: Impact of earnings on 6 types of crime across deciles

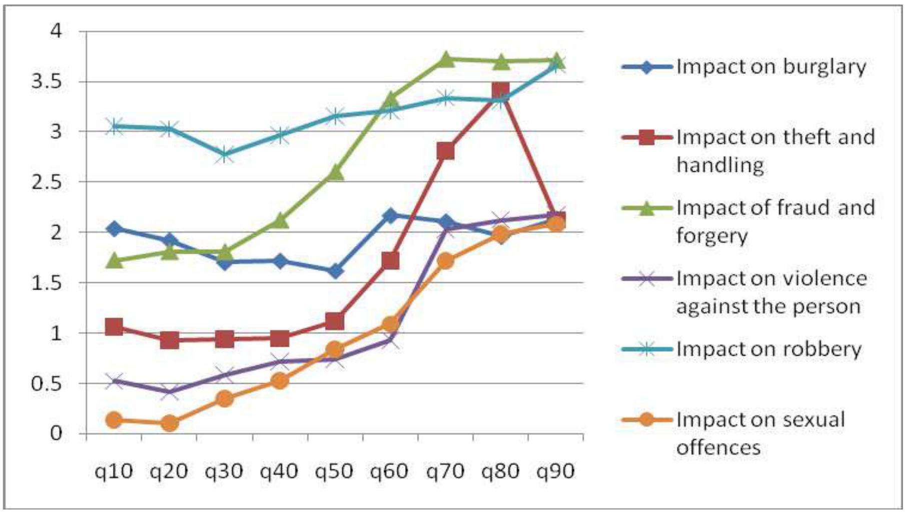


Figure 3: Impact of detection rate on 6 types of crime across deciles

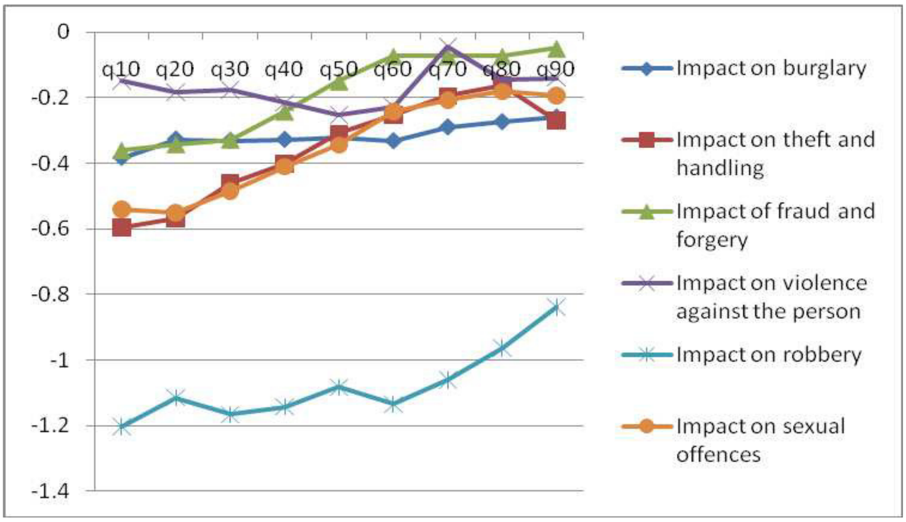


Figure 4: Impact of inequality on 6 types of crime across deciles

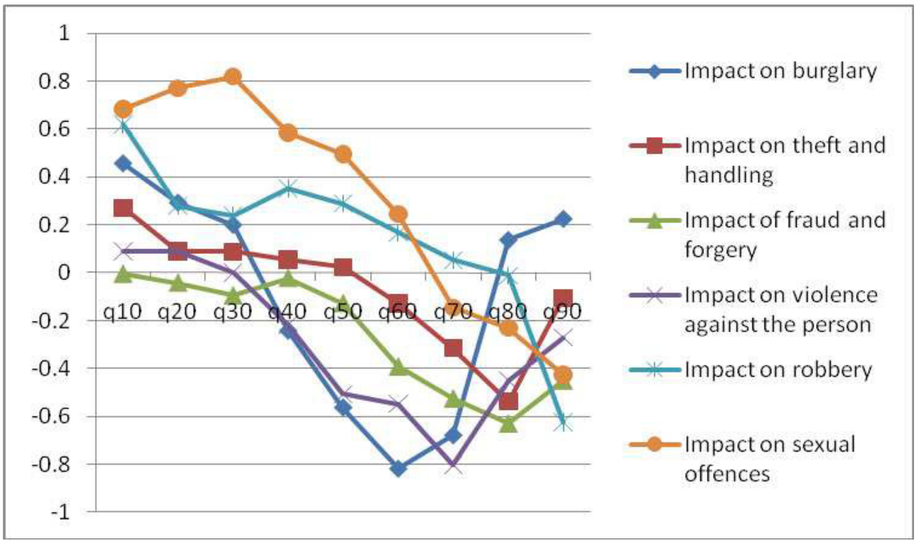
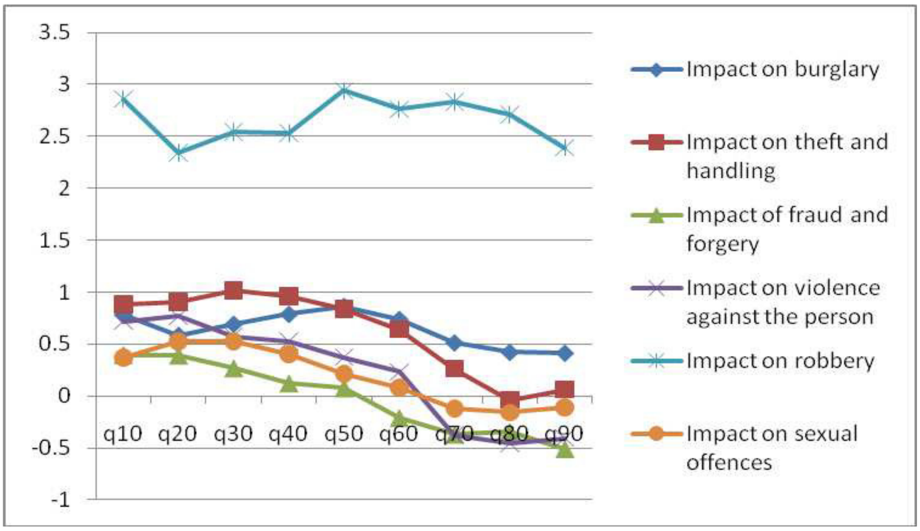


Figure 5: Impact of young people on 6 types of crime across deciles



Appendix: IV Quantile regression results using one lag of police expenditure

Table A-1: IV Quantile regression results for determinants of property crimes

	Burglary			Theft and handling			Fraud and forgery		
	q25	q50	q75	q25	q50	q75	q25	q50	q75
Detection	-0.9156	-0.5178	-1.0513	-0.8582	-0.3646	0.1925	0.2969	0.5265	0.1565
	(0.4006)	(0.2561)	(0.3846)	(0.5223)	(0.3582)	(0.4252)	(0.4303)	(0.3520)	(0.3896)
Unemployment	0.4078	0.4063	0.2785	0.2969	0.3298	0.3101	0.2855	0.4026	0.3177
	(0.1009)	(0.0645)	(0.0968)	(0.1315)	(0.0902)	(0.1071)	(0.1084)	(0.0886)	(0.0981)
Earnings	1.4402	2.5568	2.1248	0.5185	1.8415	1.2951	2.0851	3.8746	2.4479
	(0.3693)	(0.2361)	(0.3545)	(0.4815)	(0.3302)	(0.3920)	(0.3967)	(0.3245)	(0.3591)
Inequality	-0.5547	-1.3432	-1.1094	-0.3082	-1.0704	0.3278	-0.1520	-0.3942	0.3765
	(0.7978)	(0.5101)	(0.7659)	(1.0402)	(0.7134)	(0.8468)	(0.8570)	(0.7010)	(0.7759)
Young	0.9157	0.7920	0.7197	0.7789	0.7239	1.6008	1.6819	1.5499	1.1439
	(0.2990)	(0.1912)	(0.2871)	(0.3899)	(0.2674)	(0.3174)	(0.3212)	(0.2627)	(0.2908)
Intercept	11.0802	13.7811	14.8617	9.9592	12.3930	6.3323	4.6329	8.5756	7.4006
	(1.4794)	(0.9459)	(1.4202)	(1.9288)	(1.3228)	(1.5703)	(1.5892)	(1.2998)	(1.4387)
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R2	0.0187	0.0373	0.0529	0.5947	0.0825	0.1542	0.4349	0.2404	0.0957
Number of obs.	591	591	591	591	591	591	591	591	591

Table A-2: IV Quantile regression results for determinants of violent crimes

	Violence against the person			Robbery			Sexual offences		
	q25	q50	q75	q25	q50	q75	q25	q50	q75
Detection	2.5888	3.0016	3.4018	-1.5976	-1.2029	-1.6274	5.7451	18.8513	12.4906
	(0.4743)	(0.4714)	(0.5763)	(0.4104)	(0.3370)	(0.4025)	(1.1812)	(3.2276)	(2.4167)
Unemployment	0.6520	0.5952	0.6917	0.6723	0.7690	0.6325	0.4356	-0.2470	0.3233
	(0.1195)	(0.1188)	(0.1452)	(0.1034)	(0.0849)	(0.1014)	(0.2976)	(0.8131)	(0.6088)
Earnings	0.9252	0.9416	0.5958	3.5605	3.7481	3.4309	2.7662	5.0154	1.7861
	(0.4372)	(0.4346)	(0.5313)	(0.3783)	(0.3107)	(0.3711)	(1.0890)	(2.9754)	(2.2279)
Inequality	-0.1622	-0.8295	-0.5704	-1.7014	-1.5121	-0.9155	-4.3376	-1.6871	0.6039
	(0.9445)	(0.9388)	(1.1477)	(0.8173)	(0.6712)	(0.8016)	(2.3525)	(6.4278)	(4.8130)
Young	1.3238	2.0880	2.7925	3.0179	3.0528	1.8774	3.5418	8.8807	7.4420
	(0.3540)	(0.3519)	(0.4302)	(0.3064)	(0.2516)	(0.3005)	(0.8818)	(2.4094)	(1.8041)
Intercept	-7.7273	-10.7597	-15.2991	10.2764	9.2654	13.2086	-21.8468	-88.6675	-65.2751
	(1.7514)	(1.7408)	(2.1281)	(1.5155)	(1.2446)	(1.4864)	(4.3621)	(11.9188)	(8.9245)
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R2	0.0002	0.0003	0.0272	0.2416	0.1235	0.0148	0.2567	0.0012	0.0581
Number of obs.	591	591	591	591	591	591	591	591	591