EC331

Research in Applied Economics

The United Kingdom’s Focus on Learning – A Reason for the Ongoing Fall in Acquisitive Crime.

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Abstract

UK acquisitive crime has fallen by half since its peak in the mid-1990s. Even in the aftermath of the deepest recession the UK has faced since the Great Depression we can still feel safer now on the streets and in our homes than years ago. The aim of this paper is to assess whether a greater focus by government and the private sector on education and training has been a key driver of this trend. Our study develops a dynamic theoretical model which allows us to form hypotheses on the effects of human-capital formation on crime rates. The hypotheses are then tested using a fixed effects panel regression methodology, based on UK acquisitive crime data from the *Crime in England and Wales* series from 2004/5 to 2011/12. A dynamic specification using the difference GMM estimator is then estimated to examine whether crime inertia exists and also helps to assess the robustness of our fixed-effect results. The premier hypothesis of the paper is that higher levels of human-capital should have a reducing effect on rates of ‘blue-collar’ crime. Our results support this finding and show that the quality of education as well as the level of qualifications individuals achieve should help reduce blue-collar crime rates; however we don’t find the same crime-reducing effect of on-the-job training. We then discuss the implications of current UK education and training policy on crime and propose that the avoidance of regressive human-capital financing could help reduce crime.

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1. Introduction

Figures released in *Crime in England and Wales* (2014) showed UK crime rates have fallen to their lowest levels since 1980; burglary, which was considered the main crime issue in the 1990s, showed year-on-year decreases from roughly 900,000 offences to 500,000 between 2002/3 and 2011/12, even through the UK's severe recession. This general downward trend has been mirrored for most acquisitive crime categories in the past decade and is intriguing as the persistence of the trend through recession, has been at odds with the UK's history; for example, soaring crime rates in the Thatcher recession. One possible explanation is that although labour market opportunities have deteriorated since the recession, a continued focus on human-capital formation has made committing crime more costly in the long-term; for example, education spending as a percentage of national income has risen from 5.6% in 2004 to 7.6% in 2011 (IFS, 2010). In light of these trends, this paper empirically tests if efforts to improve the UK's human-capital have had a countervailing effect on 'blue-collar'[1] acquisitive crime rates.

Our assessment is carried out using the Buannano and Leonida (2004) rational choice model, which relates rational criminality to human-capital formation. Relatively little research has been conducted regarding effects of human-capital formation on crime, and particularly in the UK, with Machin et al. (2010) being the main exception. A potential reason is that previous literature has tended to use unemployment rates and wages as measures of the opportunity cost of crime. However this approach seems naïve given the potential long-lasting effects of incurring jail-time and acquiring a criminal-record. It seems more reasonable to also include long-term measures of earnings potential such as human-capital levels to proxy for the long-term component of opportunity cost.

[1] Low-skilled crime committed primarily by lower classes. We focus on: theft, burglary and robbery.

In terms of empirical methodology, the paper is most influenced by Han et al. (2009), particularly regarding the econometric strategy, the level of aggregation of UK data and the tackling of endogenous law-enforcement variables. However concerning specification the paper is similar to Buananno and Leonida (2009), given the authors tested their theoretical model using a panel data set for the 20 Italian regions from 1980-1995. The key finding of our paper is that improving both the quality and quantity of education, ceteris paribus, can reduce acquisitive crime rates. Therefore the UK's education system may have been a contributing factor to the fall in acquisitive crime.

The paper proceeds as follows: Section 2 reviews relevant literature. Section 3 develops the human-capital related crime model. Section 4 explains our empirical methodology. Section 5 describes our data. Section 6 presents and interprets our results and limitations. Section 7 discusses conclusions and policy implications.

2. Literature Review

Studies assessing the economic motives behind crime have been influenced by Becker's (1968) Rational Choice model, which portrays rational agents weighing costs and benefits of committing crimes and subsequently deciding whether to commit crime. Ehrlich (1975), however, was the first to theorise the relationship between human-capital and crime rates, focusing on education and training. Although he doesn't explicitly model human-capital formation he presents a time-allocation model of crime and explains how education may affect the variables. He postulated the following three hypotheses, which provide the basic theoretical justification for our empirical research:

1) Those with relatively low levels of education and training have a larger incentive to commit property crime, due to lower opportunity costs of committing crime and imprisonment.
2) Offenders probably start young as education and training don't increase returns of blue-collar crimes and because legitimate earnings for this age-group may be less than illegitimate rewards.

3) Those in school are less likely to engage in property crime than those not in school as they wouldn't view the opportunity cost of crime as current potential earnings, but as expected future returns on their investment in human-capital.

The interest in the relationship between human-capital and crime was revived by Lochner (2004). He formalised Ehrlich's theory in a dynamic theoretical model which predicts human-capital through education and training raising the opportunity cost of crime. Through standard probit modelling, using self-report data for the U.S. from the National Longitudinal Survey of Youth, he finds a strong negative relationship between education levels and property crime. Though the purpose of our studies is very similar, our methodology is very different primarily as Lochner wasn't constrained to the use of aggregate data. Machin et al. (2010) is the only prominent empirical paper to tackle the relationship between UK education and crime – they find a statistically significant negative relationship, using micro-data. This type of analysis isn't, however, appropriate for our research question as it can't be applied to the recession period due to unavailability of micro-data, nor can it control for all relevant socio-economic, deterrence and demographic factors.

Our methodology is influenced primarily by Buananno and Leonida (2004); this is a predominantly theoretical paper, which formulates a dynamic model of crime, work and education which our paper adapts and empirically tests. It is only in their follow-up study, Buananno and Leonida (2009), where they rigorously test the model using a panel dataset for the 20 Italian regions from 1980-1995. They find a robust, negative causal effect of education on crime. Comparing with Lochner (2004), the results suggest that the education-crime relationship persists even across different types of education system. There are several potentially important factors omitted from their analysis which we rectify. Most importantly, we control for the quality and not just quantity of education, as this is arguably even more important in determining earnings potential. Also we assess the effects of on-the-job training prevalence and not just education on crime rates. Furthermore, we focus our analysis on the human-capital formation of 16-24 year olds; this is the age-group that is statistically most prone to crime and for which current earnings are least representative of potential future earnings; levels of education are far more important. Finally, we emphasise the importance of our results in the context of policy.

3. Theoretical Framework and Testable Hypotheses

3.1 Assumptions

The economy is comprised of individuals deciding on time allocation between: education, crime and work.

Whilst at work, individuals can enrol in on-the-job training or engage in productive work - training is unpaid, but raises human-capital levels. Individuals can also choose not to work, instead enrolling in education. Individuals aim to maximise disposable income.

Individuals have initial human-capital level h_0 dependent solely on innate ability. Subsequent human-capital represents innate learning ability and ability gained through education and training. So human-capital at time t is: $h_t = h(s_{t-1}, t_{t-1}, \varepsilon)$, and $h_0 = h(\varepsilon)$ where: s_t is time spent in education, t_t is time spent in on-the-job training and ε is time-invariant innate ability.

Individuals can also allocate time to crime, c_t. If someone commits crime, they get a pecuniary benefit with probability $(1 - \pi_t)$, where $\pi_t = \pi(c_t)$ represents the probability of apprehension and increases in c_t. If caught, criminals go to jail for the whole period and receive a punishment $P_t = P(c_t)$ which is increasing in c_t. This reflects the simultaneity issues in terms of crime and law-enforcement, not identified by Buonanno and Leonida' theoretical model (2009). Pecuniary benefit, $B_t = B\left(c_{t,} y_t^*\right)$ depends on hours of crime committed and the level of economic activity y_t^*; pecuniary benefit is increasing in both variables.

We normalise total time in each period to 1, such that $L_t = 1 - s_t - c_t$ where: L_t is total time spent at work. Work is split into productive hours l_t and training, such that $L_t = l_t + t_t$. Only productive hours are compensated at exogenous wage rate w_t, which represents the demand-determined portion of earnings. As earnings are also dependent on productivity, each period individuals earn $w_t l_t h_t$. Individuals discount the future with a discount factor of β^t.

3.3 Maximisation Problem

Assume there are only two time periods, and education and training only occur in the 1st. This isn't unreasonable, as the two periods could be early career stages (aged 16-24) and late stages (25+). Individuals in the earlier stages of their career devote a far higher proportion of time on average to education and training than those in the later stages. In other words:

$T = 2 \Rightarrow t \in \{0,1\}$, $s_1 = 0$, $t_1 = 0$.

$$\max_{s,t,c} \sum_{t=0}^{1} \beta^t y_t \text{ subject to } (l_t + t_t) + s_t + c_t = 1,\ L_t, s_t, c_t \geq 0 \tag{1}$$

Total Disposable Income is therefore:

$$y_t = \begin{cases} w_t h_t l_t + B(c_t) \text{ with probability } (1-\pi_t) \\ -P(c_t) \qquad \text{with probability } \pi_t \end{cases} \tag{2}$$

For simplicity consumption in prison isn't modelled as is likely to be minimal.

$$\Rightarrow \max_{s,t,c_0,c_1} \begin{cases} (1-\pi)[w_0 h_0 (1 - s_0 - t_0 - c_0) + B] - \pi P_0 \\ +\beta\left[(1-\pi)[w_1 h_1 (1-c_1) + B] - \pi P_1\right] \end{cases} \tag{3}$$

The FOC are[2]:

$$\frac{\partial y}{\partial c_0} : \frac{d\pi_0}{dc_0}\left[w_0 h_0 (1 - s_0 - t_0 - c_0) + B_0 + P_0\right] + (1-\pi_0) w_0 h_0 + \frac{dP_0}{dc_0}\pi_0 = (1-\pi_0)\frac{\partial B_0}{\partial c_0} \tag{4}$$

$$\frac{\partial y}{\partial c_1} : \frac{d\pi_0}{dc_0}\left[w_1 h_1 (1 - c_1) + B_1 + P_1\right] + (1-\pi_1) w_1 h_1 + \frac{dP_1}{dc_1}\pi_1 = (1-\pi_1)\frac{\partial B_1}{\partial c_1} \tag{5}$$

$$\frac{\partial y}{\partial s_0} : (1-\pi_0) w_0 h_0 = \beta\left[(1-\pi_1) w_1 \frac{\partial h_1}{\partial s_0}(1-c_1)\right] \tag{6}$$

$$\frac{\partial y}{\partial t_0} : (1-\pi_0) w_0 h_0 = \beta\left[(1-\pi_1) w_1 \frac{\partial h_1}{\partial t_0}(1-c_1)\right] \tag{7}$$

[2] The relative sizes of $\frac{\partial h_1}{\partial s_0}$ and $\frac{\partial h_1}{\partial t_0}$ determine what is more important in crime-determination, education or training.

The left-hand-side of each equation represents marginal cost and right-hand-side marginal benefit. Equations (4) and (5) show three marginal costs of an extra hour of crime: Firstly, the probability of being caught increases. Secondly, there is a direct opportunity cost of an hour of potentially productive paid work. Finally, the severity of punishment increases if caught. The marginal benefit is the expected increase in pecuniary reward. The mechanism through which education and training affects crime is by raising legal returns (the opportunity cost of crime). Equations (6) and (7) show the marginal cost of an extra hour of education or training is only the direct opportunity cost of an hour of potentially productive paid work. The marginal benefit is the discounted expected increase in earnings due to higher ability in the next period.

3.3 Testable Hypotheses

The key hypothesis is that education and training reduce crime in the 2^{nd} period. Furthermore, more crime in period 1, meaning less education and training, lowers the opportunity cost of committing crime in period 2 as human-capital isn't as high, leading to more crime in period 2 (crime-inertia). Also higher punishment, P_t and more efficient law-enforcement π_t reduce expected returns from crime. Finally, a contemporaneous rise in wage will reduce crime by encouraging more work.

4. Empirical Methodology

4.1 Functional Form

We test the theoretical model using two panel specifications. We firstly use fixed-effects as it tackles how, due to time-invariant individual heterogeneity, unobservables affecting human-capital may also affect crime rates, causing inconsistent estimates. By including region-specific fixed-effects we control for factors which are constant over time within regions. Year dummies are included also, controlling for factors that vary on a yearly basis unilaterally between regions e.g. technological progress which affects security systems as well as effectiveness of schooling techniques. Pooled OLS can't control for all of these factors and would likely cause inconsistent estimates. Our benchmark fixed-effects regression adopts the log-linear crime function specification, as coefficients can then be easily compared, and can help minimise problems from measurement error in crime rates (Ehrlich, 1976):

$$\ln(y_{ijt}) = \beta_0 + \beta_1 \ln(x'_{ijt}) + \beta_2 \ln(z'_{ijt}) + \varphi_t + \gamma + v_{ijt}$$

where y_{ijt} is the number of crimes per 1,000 population in police force area i for crime category j at time t; x'_{ijt} is the vector of key human-capital variables; z'_{ijt} is the vector of law-enforcement and socio-economic control variables; $\varphi_t$is a vector of year dummies; γ is a vector of regional fixed-effects and v_{ijt} is the error term.

Our theoretical model predicted crime-inertia; however, the previous one-way fixed-effects model encounters 'Nickell bias' when estimating dynamic panel data, particularly in the small T case (Baum, 2013). Therefore our second model uses the dynamic difference-GMM estimator proposed by Arellano-Bond (1991). This estimator is applicable when independent variables aren't strictly exogenous as they are correlated with past and perhaps present values of the error term (Baum, 2013), which is the case for the lagged dependent variable, as it is correlated with the fixed-effects; due to simultaneity it is also the case with the law-enforcement variables. So we treat law-enforcement and lagged crime as pre-determined and replace with GMM-style instrumental variables. The difference-GMM specification is as follows, with time-invariant fixed-effects dropping out:

$$\Delta\ln(y_{ijt}) = \beta_0 + \beta_1 \Delta\ln(y_{ijt-1}) + \beta_2 \Delta\ln(x'_{ijt}) + \beta_3 \Delta\ln(z'_{ijt}) + \varphi_t + v_{ijt}$$

4.2 Variables

The dependent variables are theft, burglary and robbery rates per 1000 the 3 most prevalent blue-collar crimes that also vary in perceived severity.

Regarding the key human-capital variables, we have variables for the proportion of those aged 16-24 with highest educational attainment being at least higher-education. Given the significant wage premium in the UK for higher-education, this coefficient should be negative. We also include a variable for the dropout rate of students from 16 to 17. If in equilibrium marginal criminals are school-leavers, lacking sufficient education to earn a high wage, this variable should be positive. We measure the quality of education using GCSE average point scores – an improvement on Buananno and Leonida (2009) who don't factor in education quality. We choose GCSE scores as this exam is more likely to be homogenous nationwide than say university exams, meaning we can control for exam difficulty – between police force areas (PFAs), higher average GCSE scores should therefore reflect better educated students. According to signalling theory, comparatively high GCSE scores are important in indicating to universities and employers the quality of applicants and hence are important in determining earnings potential, which as explained should be negatively related to crime. We are only able to measure the quantity of training due to lack of data on quality. This is measured by the proportion of males aged 16-24 who've received training in the past 13 weeks.

Regarding our controls variables, we control for earnings of part-time males and youth unemployment rates. These measures target those most likely to commit crime - those with significant temporal flexibility and on low wages. In line with Ehrlich (1973) we proxy for illegal income opportunities using economic activity (real gross-value-added per capita). To model crime preference we also control for the age-structure of the population, given that Lochner (2004) mentions that biological studies suggest, ceteris paribus, the young are psychologically more crime-prone.

The issue of simultaneity causing a spurious positive relationship between crime and law-enforcement is well-documented; it is arguable authorities will react to higher crime rates by raising law-enforcement efforts (Worral and Kovandzic, 2010). In the absence of a credible instrument and constrained by data, even in our basic log-linear model we opt for a 'partial solution' to simultaneity, using lagged law-enforcement variables[3] (Li & Reuveny, 2003). The intuition is that current values of a variable can't influence past values of another variable. We use lagged: detection rates, crime-specific conviction rates, police officers per capita and crime-specific average monthly sentence-lengths. For law-enforcement variables, coefficients should be negative, as they should increase expected crime costs.

5. Data Description

We construct a panel dataset for England and Wales, disaggregated primarily at PFA level from the financial year 2004/5 to 2011/12. The dataset had to be constructed to allow sufficient flexibility of modelling and to assess the time period intended, which covered a single economic cycle. Due to lack of data availability only 28 areas were analysed[4]. Sample bias shouldn't be an issue as there is no systematic pattern for which regions have data correctly aggregated. Indeed an improvement on previous works is that all our variables are aggregated at the smallest level (PFA), given data availability, minimising problems of inconsistent estimators due to measurement error.

[3] The difference GMM estimator in specification (iii) also tackles the problem.
[4] The vast majority.

5.1 Dependent Variables

Dependent variables are the rates per 1,000 of theft, burglary and robbery. This data is from the Home Office's *Crime in England and Wales* publications from 2004/5 to 2011/12. See appendix 1.2 for a more detailed description.

5.2 Independent Variables

There are 3 main categories of independent variable:

1) Socio-economic: Youth unemployment rates, population sizes, average weekly earnings and age profiles are sourced from the *nomis* website. The measure of economic activity, gross value-added, is sourced from the ONS's *Regional Gross Disposable Household Income (GDHI) 2011* report.
2) Human-capital: Highest educational attainment and training prevalence were obtained from *nomis*, whilst drop-out rates and GCSE average point scores were sourced from the *Local Authority Interactive Tool*.
3) Law-enforcement: Ministry of Justice freedom of information requests were used to obtain crime-specific sentence lengths and crime-specific conviction rates. Detection rate data was unavailable on a crime-specific basis so a general detection rate variable was obtained from *Crime in England and Wales.* Officers per capita data was sourced from Parliament's *Police Service Strength* combined with *nomis* population estimates.

Appendix 1.1 summarises the independent variables and predicted signs using rational choice.

5.3 Descriptive Statistics

Table 1 describes the key variables of interest. As can be seen, the prevalence of the three crime types is inversely related to consensus about severity. Theft rates vary most, with lowest rates at roughly 20/1000 in Cumbria in 2011, and the highest in Nottinghamshire at 107/1000 in 2004. Interestingly

Nottinghamshire is also the county with the lowest GCSE average point score across the sample at 324.4 in 2005, suggesting a possible negative relationship between acquisitive crime and education.

Table 1. Descriptive Statistics per 1,000 Population of Key Variables.

Variable	Mean	Standard Deviation	Minimum	Maximum
Theft	44.12	12.49	20.07	106.90
Burglary	10.33	3.42	4.00	24.00
Robbery	0.95	1.12	0.00	6.00
Dropout	10.30	3.17	3.30	20.00
Higher-education	12.31	3.13	6.40	25.40
Training	20.08	2.33	13.50	25.80
GCSE Score	405.74	42.04	324.40	538.10

Figure 1 compares the total of theft/burglary/robbery rates per 1000 with GCSE average point-score. There is a suggestive negative relationship:

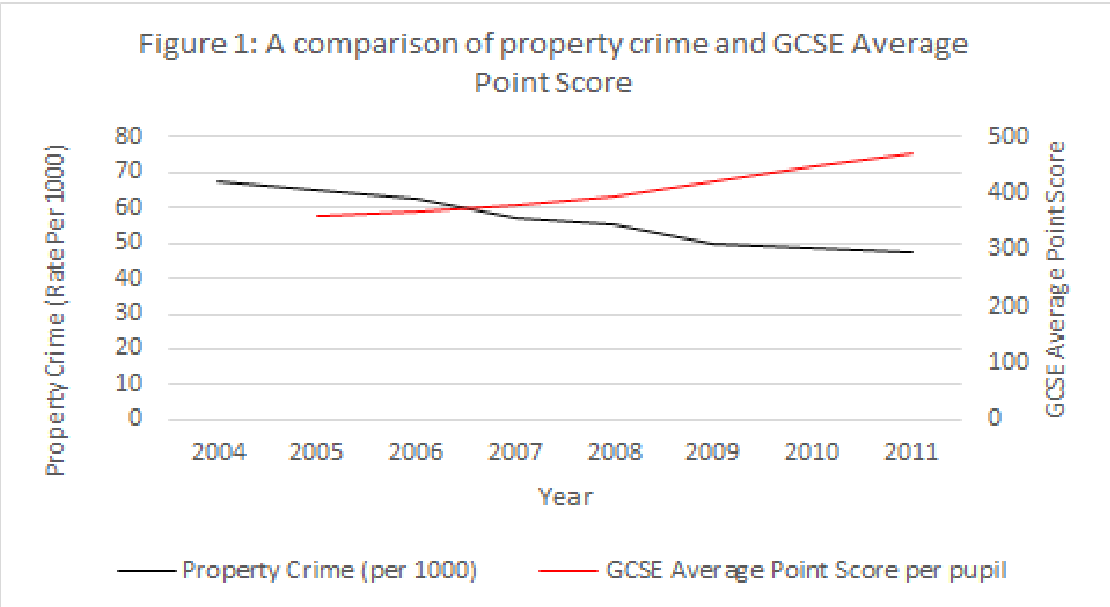
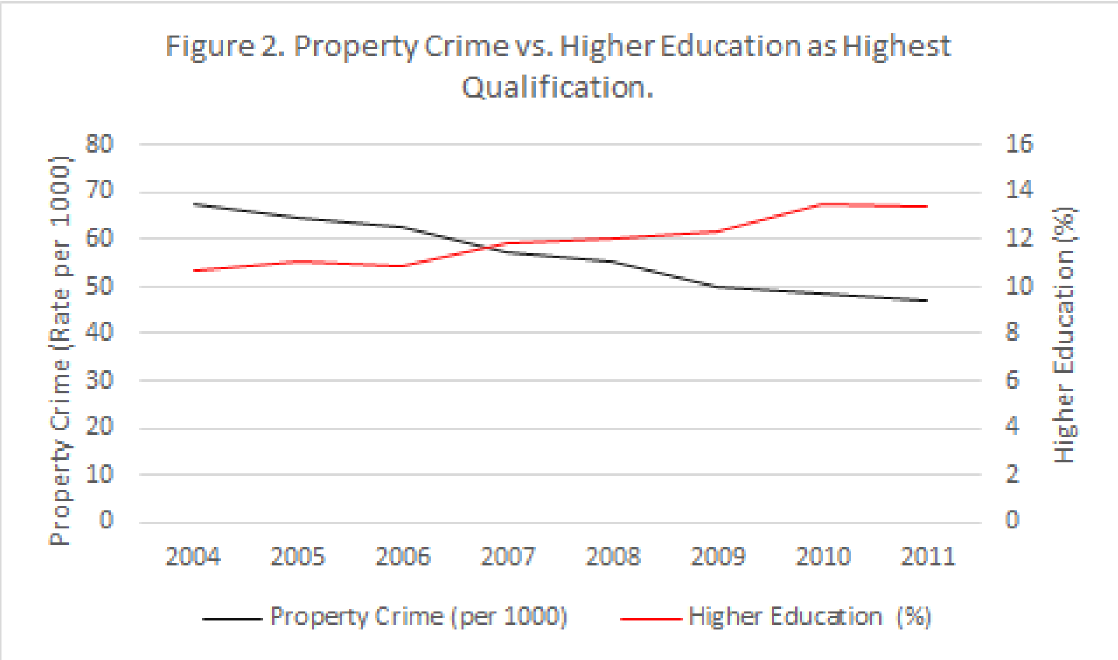


Figure 2 also suggests a negative relationship between the proportion of 16-24 year olds with at least higher-education and the same measure of crime. The regression analysis in Section 6 aims to infer causality:



6. Results

6.1 Log-linear Specification

Our multivariate analysis begins with the baseline log-linear crime equation for each of the 3 crime types. After conducting a Hausman test, the test-statistic showed the fixed-effects estimator was appropriate. Furthermore, our test for autocorrelation showed we should reject the null of no autocorrelation. The autocorrelation was corrected using clustered standard errors (Wooldridge, 2011).[5] The regression results are displayed in Table 2[6], with column (i) showing results for just education quantity, and column (ii) results including both quality and quantity.

[5] Results for both tests are found in appendix 2.

Table 2. Log-linear Results (Coefficients).

	Dependent Variable					
Independent Variable	Theft		Burglary		Robbery	
	(i)	(ii)	(i)	(ii)	(i)	(ii)
Real GVA	1.00***	0.81***	0.93	0.72	1.03	0.82
Youth Unemployment	0.11***	0.10***	-0.02	-0.05	0.37**	0.34**
Earnings	-0.06	-0.03	-0.08	-0.04	0.07	0.12
Detection (t-1)	-0.20**	-0.18**	-0.28**	-0.24*	-0.41*	-0.37*
Conviction (t-1)	-0.18	-0.23	-0.24***	-0.22***	0.01	0.03
Police (t-1)	0.00	0.00	-0.02	-0.04	0.00	-0.01
Sentence Length (t-1)	0.03	0.04	-0.04	-0.04	-0.03	-0.04
GCSE Score	N/A	-0.86**	N/A	-1.24**	N/A	-1.22**
Dropout	0.05**	0.05**	0.02	0.02	0.01	0.01
Higher	-0.04	-0.03	-0.07**	-0.06***	-0.11***	-0.10***
Training	0.04	0.00	0.03	-0.03	-0.08	0.01
Youth	0.51	0.12	1.09	0.686	-1.78	-2.17
Young Adult	1.62	1.41	0.15	-0.16	0.70	0.41
Mature Adult	0.82	0.71	-0.56	-0.54	-2.42	-2.53
Elderly	-0.42	-0.44	-0.99	-0.54	-1.29	-1.30
2005	(Omitted)	(Omitted)	(Omitted)	(Omitted)	(Omitted)	(Omitted)
2006	-0.08	-0.01	0.04	0.12	0.07	0.15
2007	-0.15***	-0.06	-0.03	0.08	0.02	0.12
2008	-0.20**	-0.08	0.00	0.16	-0.07	0.10
2009	-0.22**	-0.05	0.03	0.26	-0.19	0.04
2010	-0.20**	0.02	0.04	0.34	-0.06	0.23
2011	-0.18	0.07	-0.02	0.33	-0.177	0.17
Constant	-12.74	-4.65	-4.28	6.84	3.96	15.29

*p<0.01, **p<0.05, ***p<0.10 once accounting for one-sided or two-sided test.

All variables are in logs.

No. observations = 134 (all specifications).

6.1.1. Analysis of human-capital variables:

Specification (i):

The only statistically significant human-capital variable for theft is dropout rates. A 1% rise in school dropout rates is associated with a 0.05% rise in theft, which is also economically significant. To contextualise, the coefficient suggests that if Wiltshire, which had a dropout rate of 3.7% in 2004/5, had the same dropout rate as Essex (13.4%) that same year (a 262% increase), ceteris paribus, this would have led to a 13.1%[7] increase in Wiltshire's theft rate. This result shows that if uneven dropout rates are reflective of uneven quality of education, some areas may experience comparatively greater negative crime externalities due to the unequal nature of the UK's education system. The result also suggests that, in equilibrium, marginal thieves may be school dropouts. This is unsurprising given we are considering a contemporaneous relationship between dropout rates and thievery; theft is considered an entry-level crime and recent 16 year-old dropouts may turn immediately toward theft. This is because pecuniary rewards for theft, although relatively low compared to other crimes, may seem large relative to the age-group's limited legal opportunities.

Higher-education is the only significant human-capital variable for burglary and robbery – the coefficients are -0.07 and -0.11 respectively. The rationale for significance is that variation in this variable is from those aged 18-24, who should have better legal income opportunities than 16 year-old dropouts, as they have more schooling years. If this age-group choose to then engage in crime the pecuniary reward justifying criminality should be larger – on average illegitimate earnings from robbery and burglary are higher than theft. The higher-education premium substantially increases this age-group's earnings potential and hence the opportunity cost of crime, which in-turn reduces crime. Data from the *UCR* (2003) supports this theory – from 1998-2001 robbery and burglary arrest rates consistently peak at age 18, whilst larceny-theft consistently peaks at 16. Buananno and Leonida (2009) also find that in Italy increased high school completion rates, not university completion rates

7 262x0.05=13.1

significantly reduce theft, which again corroborates with the theory. Our variable measuring the effects of on-the-job training is insignificant, which contrasts Lochner (2010) whose evidence suggests that 'job training for young adults appears to reduce self-reported arrests' - we believe this finding is due to limitations in our training variable's construct (explained in Section 6.3).

Specification (ii):

When we also consider education quality, we find GCSE average score is the most statistically significant of our human-capital variables. The elasticities with respect to theft, burglary and robbery are -0.86, -1.24 and -1.22. To contextualise this, if Nottinghamshire in 2006/7 could have improved its GCSE average score, which proxies for education quality, to that of Hertfordshire in the same year (an 11.4% improvement), ceteris paribus, we'd expect its burglary rate to fall 14.1%[8]. Using Nottinghamshire's burglary rate and population figures for 2006/7 this translates into an expected 1840 fewer burglaries. Given the average cost of items stolen and damage incurred in burglaries nationwide in 2006/7 was £2069 (*Crime in England and Wales*, 2011) this equates to an expected saving in excess of £3,800,000[9]. Furthermore, the coefficients from the previous specification for the dropout, training and higher-education variables barely change, showing robustness.

6.1.2. Analysis of control variables:

In both specifications, lagged detection rates significantly reduce all 3 crime-types. This is unsurprising as detection rates measure policing quality. The number of officers per capita has a near 0 effect in all specifications suggesting the quantity of policing is unimportant. Conviction rates are only significant for burglary in both specifications – a possible explanation is that burglary tends to involve more calculated decisions than theft or robbery, so burglars' instincts may be closer to the rational offender, who carefully calculates expected costs. By contrast, results show sentence lengths seem ineffective

[8] 11.4x-1.24=-14.1
[9] We acknowledge costs might be incurred in improving education performance; however, performance can be improved by reallocating existing resources.

at deterring any crime. We find no statistical significance in any of our measures of the population's age structure, which suggests high rates of youth crime are rather due to socio-economic rather than psychological factors. Youth unemployment significantly increases theft and robbery rates but is an insignificant determinant of burglary rates. Part-time earnings appear to be an insignificant determinant of all crime types. Comparing these last two results, this could suggest that a significant reduction in labour market opportunities was needed (e.g. due to unemployment rather than falling earnings) for people to turn to crime. Our measure of economic activity was large and positive for all crime types, as expected, but statistically significant only for theft.

6.2 Dynamic Specification

By also conducting the difference-GMM we can examine the robustness of our results and test for crime-inertia. The results of our dynamic specification can be found in Appendix 3.1. Both the Sargan and AR(2) tests indicate an appropriate specification[10]. Our key finding is that our crime-specific lagged dependent variable only significantly increases theft. The coefficient on theft is 0.63 which is large and shows persistence in theft. Our explanation for why only theft exhibits inertia is that offenders consider it a less serious crime, with low risk of apprehension and with a less severe degree of punishment; therefore it may be more subject to habitual behaviour. Also as thieves are less likely to be punished with prison sentences and on average spend less time in prison, they are less likely to undergo substantial rehabilitation. Buananno and Leonida (2009) also find a positive coefficient on lagged theft, albeit smaller at 0.30, suggesting theft-persistence is less of an issue in Italy. Our results also imply that for this period in the UK, ceteris paribus, crime inertia wasn't much of an issue for robbery or burglary. Although this contradicts the prediction of our theoretical model, this could be because the theoretical model doesn't allow for the possibility of criminal rehabilitation, which is more likely to occur for burglars and robbers given they have longer average sentences and are more likely to be imprisoned as punishment than thieves; the possibility for rehabilitation challenges the dynamic

[10] Details of the GMM estimator diagnostics tests are found in Appendix 3.2.

through which criminal inertia occurs in the model, as there is less human-capital deterioration whilst in prison.

Our results are weakened by small sample size, increasing the standard errors, and reducing the number of statistically significant variables. But even in this specification, we see statistically significant negative coefficients on: average GCSE scores for theft and burglary, detection rates for theft and robbery. For example, due to the lagged-dependent, the long-run elasticity of theft with respect to average GCSE scores is calculated to be -2.60[11]. This shows the robustness of our previous results.

6.3 Limitations

The most important limitation is inability to assess quality of training. This could be why we rarely find statistically significant negative coefficients on the training variable. The quality of job-related-training must be controlled for as only training that is targeted to individuals' weaknesses will raise their productivity and in turn crimes rates. A further limitation is using average GCSE scores to proxy for the quality of education; it may be presumptuous to assume that if GCSE scores are rising, the quality of education for all age-groups is rising. As we have mentioned, marginal robbers and burglars will likely be more experienced, older individuals, and so even if higher GCSE scores do improve earnings potential, there is no obvious reason for as strong a contemporaneous relationship between GCSE scores and robbery and burglary as that found in our regression. But the assumption would mainly be an issue if government efforts to boost GCSE scores caused less resources available to improve other levels of education, meaning education quality as a whole for the nation wasn't rising; however, government spending from 1999-2010 on all areas of education grew at its fastest rate since the mid-1970s (*IFS,* 2011), suggesting no trade-offs in government funding.

[11] -0.96/0.37 = -2.59

7. Discussion

The main hypothesis of our theoretical model was that education and training should be negatively related to crime. Given the concerns about small sample size and the lack of significance of the lagged dependent for two of the three crime types, it seems specification (ii) is the best model to assess this hypothesis. Specification (ii) looks at education quality and quantity as well as training and, in line with the hypothesis, finds a statistically significant negative relationship between both educational quality and quantity and various crime rates - though no relationship is found for training prevalence. Though the quality of education reduces all crime types, different crimes respond differently to the highest educational qualification attained - dropout rates increase theft whilst higher-education is important for reducing burglary and robbery. These findings make sense given these crimes differ in expected pecuniary rewards and risks, so attract different types of criminal depending on their outside options at the margin. Studies which aim to improve on our work should focus on finding suitable measures for training quality and also try to find better instruments for law-enforcement variables.

These findings may be crucial in predicting the effects of the UK's current educational policy. This is because the government is targeting lower dropout rates with laws that raised the compulsory education and training age from 16 to 17 in 2013, increasing to 18 in 2015. But at the same time government has substantially cut funding for university tuition fees, with fees tripling as of 2012, negatively affecting take-up of higher-education, which our results suggest could increase robbery and burglary rates. The likelihood is that the overall effect of the two policies will be crime increasing. This is because higher education is where the highest earnings premium is obtained. Also the tuition fee hikes are a regressive educational policy, disproportionately reducing the opportunities of the poor, a group which our results show are particularly susceptible to crime. A potential area for future research, therefore would be to assess retrospectively how these two policy changes have affected various crime rates, ideally using individual-level data if it becomes available.

Our results provide a reason why in 2004-11 acquisitive crime steadily fell, even through recession. Although economic activity was erratic, the government's focus on human-capital formation was consistent. It will be more challenging for the government to allocate sufficient resources when the economy is recovering and is debt-ridden, suffering from the excesses of previous government's exuberance – as shown already by the tuition fee rises. However, our recommendation is that even if the fiscal position needs to be improved, an important reason government should avoid increasingly regressive human-capital financing policies, like university tuition fee hikes, is they have unevenly distributed crime-increasing effects. Treating higher-education as a normal good and crime as an inferior good, raising the price of higher-education has reinforcing income and substitution effects on crime, causing pressure on crime to increase. The income effect will be strongest on the poor as higher-education expenditure will be a larger proportion of their income, highlighting the regressive nature of the policy. This will then induce a relatively greater substitution toward crime for this group. The justification for the policy recommendation is grounded in our results, which support the literature in showing that those facing unfavourable socio-economic circumstances and who are relatively less educated are more likely to commit crime.

Word Count: 5000

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Appendix

Appendix 1.1: Summary of Independent Variables

Variable Name[12]	Description	Rational Choice Theory	Data Source
Real GVA	Real gross-value-added per-capita.	Pecuniary reward of crime.	ONS - *Regional Gross Disposable Household Income (2011).*
Youth Unemployment	% of population aged 16-24 on claimant count.	Opportunity cost of crime.	ONS - *nomis website.*
Earnings	Real average gross weekly earnings of part-time males.	Opportunity cost of crime.	ONS - *nomis website.*
Higher	% of population aged 16-24 with: Higher Education or more as their highest educational qualification. This includes both unconventional higher education, under-graduate and post-graduate degrees.	Opportunity cost of crime.	ONS - *nomis website.*
Dropout	% Difference in those in education and training from 16 to 17.	Opportunity cost of crime	Department of Education – *Local Authority Interactive Tool.*
GCSE Score	Average Point Score at GCSE.	Opportunity cost of crime.	Department of Education – *Local Authority Interactive Tool.*
Training	% of Males Aged 16-24 who've received training in past 13 weeks	Opportunity cost of crime.	ONS - *nomis website.*
Detection Rate	% of all crimes 'cleared-up' by the police.[13]	Probability of being caught.	*Crime in England and Wales.*
Conviction Rate	% of criminal cases leading to convictions (crime-specific).	Probability of being caught.	Ministry of Justice freedom of information request.
Police	Police officers per capita.	Probability of being caught.	Parliament – *Police Service Strength (2013)* ONS - *nomis website.*
Sentence Length	Average Sentence Length (months).	Severity of punishment.	Ministry of Justice freedom of information request.
Youth/ Young Adult/ Mature Adult/ Elderly (4 variables)	% of population aged: 16-24, 25-44, 45-64, 65 and over.	Crime Preference.	ONS - *nomis website.*

[12] (All variables are in logarithmic form)

[13] For a crime to be 'cleared-up' the crime must be notified/recorded, a suspect identified and a sanction/non-sanction detection must have occurred.

Appendix 1.2: Summary of Dependent Variables

Variable Name[14]	Description	Data Source
Theft	Cumulative offences per 1000 population of: vehicle offences, theft from the person, theft of a pedal-cycle, shoplifting, and 'other theft offences'.	*Crime in England and Wales.*
Burglary	Cumulative offences per 1000 population of: robbery of business property and robbery of personal property.	*Crime in England and Wales.*
Robbery	Cumulative offences per 1000 population of: Burglary in a dwelling, aggravated burglary in a dwelling, burglary in a building other than a dwelling, aggravated burglary in a building other than a dwelling.	*Crime in England and Wales.*

[14] (All variables are in logarithmic form)

Appendix 2.1 – Results of Hausman Test – Log-Linear Specification (Theft).

H0: Difference in coefficients not systematic

chi^2 = 64.60

Prob > chi^2 = 0.0000

The Hausman test rejects H0, which suggests that the fixed effects estimator is appropriate. Though only results for theft are reported here, the Hausman tests on burglary and robbery showed the same results.

Appendix 2.2 – Wooldridge Autocorrelation Test – Log-Linear Specification (Theft).

H0: no first-order autocorrelation

F(1,19) = 16.555

Prob > F = 0.0007

The Wooldridge test rejects H0, which suggests that there is first-order autocorrelation in our log-linear crime specification. Though only results for theft are reported here, the Wooldridge tests on burglary and robbery showed the same results. We correct for this in our analysis by using clustered standard errors.

Appendix 3.1 – Difference GMM Estimation Results.

	Property Crime		
Variable	Theft	Burglary	Robbery
Lagged Crime (t-1)	0.63***	-0.11	-0.15
Real GVA	0.22	0.83*	-0.88
Youth Unemployment	0.04	-0.07	0.20
Earnings	0.01	-0.06	-0.59***
Detection (t-1)	0.09	-0.18**	-0.14
Conviction (t-1)	0.11	-0.05	-0.09
Police (t-1)	0.00	-0.06**	-0.04
Sentence Length (t-1)	0.05**	-0.03	0.04
GCSE Score	-0.96***	-1.70***	-1.08**
Dropout	-0.01	-0.02	-0.01
Higher	0.00	-0.06	0.01
Training	0.04	-0.09	0.07
Youth	-1.88**	0.29	-0.96
Young Adult	2.14**	1.19	7.61***
Mature Adult	Dropped due to collinearity.	0.40	Dropped due to collinearity
Elderly	1.49**	1.11	2.78**
2005	Dropped due to collinearity.	Dropped due to collinearity	-0.30
2006	0.03	0.19**	0.00
2007	0.02	0.15	-0.01
2008	0.06	0.25**	-0.01
2009	0.05	0.35**	-0.13
2010	0.17**	0.44***	0.02
2011	0.23*	0.44**	Dropped due to collinearity

p-values in parentheses. Unadjusted for one-sided or two-sided tests.
*p<0.01, **p<0.05, ***p<0.10 once accounting for one-sided or two-sided test.
All variables are in logs.
Bold variables are ones for which one-sided tests were carried out.
no. observations = 98

Appendix 3.2 – Difference GMM Specification Test Results and Interpretation.

Property Crime			
Variable	Theft	Burglary	Robbery
AR (2) Test	0.963	0.627	0.257
Sargan Test	28.94	37.20**	35.59***

*p<0.01, **p<0.05, ***p<0.10 once accounting for one-sided or two-sided test.
Sargan tests were not robust, but not weakened by many instruments.

Baum (2013) explains why the AR(2) test for autocorrelation in the residuals is important. The differenced equation's residuals when created are serially correlated, but the assumption of serial independence in the original residuals should mean differenced residuals shouldn't show AR(2) behaviour. Given we have only used lags of t-2 for GMM instruments, finding no autocorrelation in the 2nd order is even more important. Even at the 10% our test-statistic rejects the null of autocorrelation in residuals.

Roodman (2006) describes the importance of the Sargan test. GMM estimation relies on instrument exogeneity. But exactly identified systems don't allow identification of valid instruments. It is essential to have an over-identified system, so that you can test for the joint validity of moment restrictions. The Sargan test evaluates if the system is over-identified. Given the null is that instruments are valid we find our test statistics can't reject h0 at the 5% level[15], showing instrument validity. Also the test isn't weakened by too many instruments.

[15] Though in the case of robbery we reject H0 at the 10% significance level.