INVESTIGATING THE FACTORS THAT AFFECT THE LEVEL OF CRIME IN THE UK

Contents

Introduction

The aim of this project is to analyse the effectiveness of apprehension and punishment in influencing the UK's level of crime by using a supply of labour model. The model allows for an individual's labour supply and consumption of leisure to both consist of different intensities of legal and illegal activities. It intends to relate criminal behaviour to economic behaviour so that any individual with a given taste for crime will alter their incentives to changes in the costs and benefits associated with the type of activity. This model is based on a study[1] by Matti Virén which uses Finnish aggregate time series data from the period 1951 – 1995 and compares the results to pooled international cross country data. The study also takes into account the role of demographic and socio-economic factors but the results show that they are of little importance compared to apprehension and punishment. I shall therefore include these factors in my study, as I am interested in seeing how significant they are when taking UK data into account.

The next section discusses the economic theory in further detail, such as outlining crucial assumptions, forming and manipulating equations and setting up a detailed hypothesis.

[1] See References page for further details

Analysis Of The Theory

An individual can allocate his or her time between leisure , work (legal) *e* or criminal (illegal) activity *h*. The rates of return from legal and illegal activity are given by *w* and *r*, and taxes[2] are ignored in this model. The individual's utility depends positively on leisure and consumption U = U(L, C) and it is also assumed that both are normal goods.

There exists a valuation parameter α that denotes the individual's preference for crime compared to conventional leisure so that total leisure time *L* is made up of Conventional Leisure + α(time spent in criminal activities). If $\alpha > 1$, the individual prefers crime to conventional leisure whereas if $\alpha = 1$, time spent in both activities are equivalent to one another. In these cases, an increase in time spent in crime would lead to a rise in the individual's total leisure and therefore raise his or her utility. However if $\alpha < 0$, the utility function will depend negatively on crime as total leisure will be purely equivalent to conventional so the individual would regard crime as being part of work rather than being part of leisure. Therefore any criminal activity that takes place given these tastes would be difficult to explain if it is not associated with a rate of return.

The total level of punishment for an apprehended individual is likely to depend both on the amount of crime that takes place and the level of return that accrues to the person. For this analysis, it would be appropriate to ignore the effect of the level of return as this would help to simplify the model. Total punishment may therefore be given by *hs* where h is the amount of crime as explained earlier and s indicates the severity of the punishment. For now we will take *hs* to represent a monetary fine but for the collection of data, prison sentences shall be used.

There exists a probability *p* of an individual participating in illegal activity being caught and if so has to pay the fine *hs*. *1 – p* denotes the probability of the good state occurring, where the individual pursuing in illegal activity is not caught. Both of these states provide uncertainty in the model so that an individual who is attempting to maximise their utility will take this into consideration. It is assumed that *p* is constant so that the level of crime is a function of the probability of detection so that h = h(p). This however may not be true as this function could easily be reversed to give p = p(h , P) where P is a pre determined reference value for the probability of

[2] Although post tax incomes may be included in the actual data

detection so that the overall probability also takes into account the amount of crime. This method would be more complicated which is why the function $h = h(p)$ will be used in this model.

All individuals receive a transfer level of income A which is irrespective of their earnings and therefore their behaviour.

An individual will attempt to maximise his or her expected utility by taking into account the above factors that will influence their decision in participating in all types of activities. This gives the expected utility equation:

$$E(U) = (1 - p)u\,(L, C) + pu\,(L, C - hs) \quad \mathbf{(1)}$$

Where:

$$L = 1 - e + h\alpha \quad \mathbf{(2)}$$

$$C = A + rh + we \quad \mathbf{(3)}$$

Equation 2 describes the situation previously mentioned where $1 - e$ represents conventional leisure and $h\alpha$ is the level of crime that is made up of leisure when the taste for crime parameter is taken into account. Equation 3 shows the individual's level of consumption before his or her level of punishment is taken into consideration, which requires the assumption that all income is spent on consumption. In the bad state, the individual will be punished and the consumption will be equal to $C - hs$ once the fine has been paid. Equation 1 is the result of combining the leisure and consumption levels into the sub utility functions of the possible states where the individual selects their levels legal and illegal activity that will maximise their expected utility. The sub utility functions are strictly taken to be quasi concave so that they are increasing in both leisure and consumption.

The 1st order conditions for the maximisation of expected utility are as follows:

$$\frac{\delta EU}{\delta h} = \alpha(1 - p)\hat{u}_1 + r(1 - p)\hat{u}_2 + \alpha p\bar{u}_1 + p(r - s)\bar{u}_2 = 0 \quad \mathbf{(4)}$$

$$\frac{\delta EU}{\delta e} = -(1 - p)\hat{u}_1 + w(1 - p)\hat{u}_2 - \alpha\bar{u}_1 + pw\bar{u}_2 = 0 \quad \mathbf{(5)}$$

where $\hat{u}_1$ and $\hat{u}_2$ are the differentials of the leisure components of the utility functions such that $\hat{u}_1 = \hat{u}_2 = \frac{\delta u\,(L, C)}{\delta L}$. Similarly $\bar{u}_1$ and $\bar{u}_2$ are the differentials of the consumption components so that $\bar{u}_1 = \bar{u}_2 = \frac{\delta u\,(L, C)}{\delta C}$.

Equations 4 and 5 show that the individual will select their level of crime and legal labour supply given the exogenous variables (A, w, r, p, α, s). This is provided that the second order conditions hold so that the individual is maximising his or her utility. I intend to use the assumption that the legal labour supply is fixed at $e = \bar{e}$, perhaps due to the labour force operating under contracts for a given number of hours per day or a binding labour supply constraint. This will enable me to concentrate fully on the endogenous variable h whilst $\bar{e}$ is explanatory, helping to further simplify the model.
The following function summarises the main hypothesis that I wish to investigate for the remainder of the project so that h is dependent on all the variables inside the brackets:

$$h = h(\underset{-}{A}, \underset{-}{w}, \underset{+}{r}, \underset{-}{p}, \underset{+}{\alpha}, \underset{-}{s}, \underset{-}{\bar{e}}) \quad \textbf{(6)}$$

The signs below each variable correspond to the predicted signs of their comparative statics for h. The variable w affects the income of the individual when participating in legal activity so higher values should reduce the incentives for the individual to commit a crime as they would earn more from legal activity. A rise in lump sum income A tends to lower criminal activity as it reduces incentives for the individual to supply labour in both legal and illegal activity to earn money (similar argument to standard labour supply model)[3]. However r denotes the return from illegal activity and will increase the individual's incentive to commit a crime if this parameter rises. Variables p and s reflect the cost of committing a crime, which is why a higher value of p will raise the probability of the person having to pay the fine hs, whilst an increase in s will raise the value of the fine. A higher value of α means that crime is regarded more as leisure than work meaning that an individual can gain more utility by increasing participation in criminal activities, making h and α positively associated. $\bar{e}$ is negatively associated with h because if the individual decides to work more, he will have less free time to participate in criminal activities and will be earning higher incomes in legal activity. One could therefore argue that crime and unemployment would be positively associated with one another as higher

[3] It may be argued that crime will rise as the individual has more free time from working less. However we continue to assume that people will engage in criminal activities purely for earnings purposes.

unemployment rates tend to increase frustration and increase the need to steal. Sociologists often argue this point.

The above justifications for the comparative statics are intuitive however the appendix in the journal mentioned earlier mathematically derives the predictions from 1st order conditions 4 and 5.

The assumption that all individuals are identical might be unrealistic if we consider how occupational choices vary across the whole population. However most of the variables mentioned in the model earlier would help take into account the heterogeneity of the individuals (shown in the integration formula below). One parameter that would play a vital role in distinguishing individuals would be the wage rate w as this reflects the person's productivity in legal work and is a likely candidate for explaining varying occupational choices. The taste for crime parameter α would also act as a reliable method of accounting for the heterogeneity individuals within a population but can only be measured by relating it to demographic and socio economic factors. The use of these factors will be discussed later.

At this stage a new variable *H* shall be introduced, which represents the aggregate level of crime committed by the entire population and can be found by applying the following integration formula:

$$H = \int_a^b h(A, w, r, p, \alpha, s, \bar{e})\, f(w)\, dw \qquad \textbf{(7)}$$

where [a,b] represents the population distribution and h is the level of crime determined for a particular person as discussed earlier. The f(w) term is used as a frequency distribution for the wage rate of each individual, that helps us take into account the differences in productivity[4]. It should be noted that for this project equation 7 is only relevant as a definition of the variable H as aggregate crime datasets will be used to represent this dependent variable[5].

The regression I wish to use is derived from the comparative statics shown in (6), where the coefficients on the variables should have the sign pattern that I predicted in my hypothesis and ε is an error term[6]:

[4] Or the taste for crime parameter if f(α) is used instead.
[5] The journal however uses a series of operations to obtain equation 8 from 7.
[6] Note that this is the initial structure for the regression but is likely to change as the project progresses.

$H = \beta_0 + \beta_1 A + \beta_2 w + \beta_3 r + \beta_4 p + \beta_5 \alpha + \beta_6 s + \beta_7 \bar{e} + \varepsilon$ (**8**)

Discussion of Variables and Data

For this section I shall be summarising the data I collected for the variables I talked about in the previous section. The time period I used was 1950 – 2000 for UK data as a whole, which gives a total of 51 observations for the regression and should therefore be quite reliable. I have constructed some time series graphs using Microsoft Excel so that I am able to compare the trends of H with some of the exogenous variables mentioned earlier. Correlation coefficients will also be used, however is should be noted that these coefficients are for initial comments only as regression coefficients are likely to be more realistic.

It is important at this stage to discuss how I defined my variables, as it was not possible to obtain the data that would be a close match and therefore estimates had to be used. Variables such as H, w and ē were relatively easy to define as they are factual data that have been recorded over long periods of time. H was used as the total number of known 'indictable' offences[7], which include offences that have not been 'cleared up'[8]. The average wage rate for all types of industries per year may be used to represent r and ē may be estimated by using the average working time per person in hours in the UK. The probability parameter p cannot be used as a theoretically determined value as it is not possible to determine the actual probability of someone being caught, therefore the following formula needs to be used as an estimate:

$$p = \frac{\text{Number of cleared up offences}}{\text{Number of known offences (H)}} \quad \textbf{(9a)}$$

This is the formula that is used in the journal and is simply a ratio of those captured to the total number of known offences. One limitation of this method is that the variable H corresponds to the endogenous one in the regression so it may be the case that p will depend on the value H. This problem was mentioned earlier but trying to make this variable fully exogenous would complicate the model further which is why formula 9 would be a suitable estimate.

[7] Indictable excludes offences on a less serious scale such as motoring.
[8] Offences cleared up include those that have been arrested, summoned, cautioned and those that are known to be guilty but cannot be prosecuted due to a particular reason.

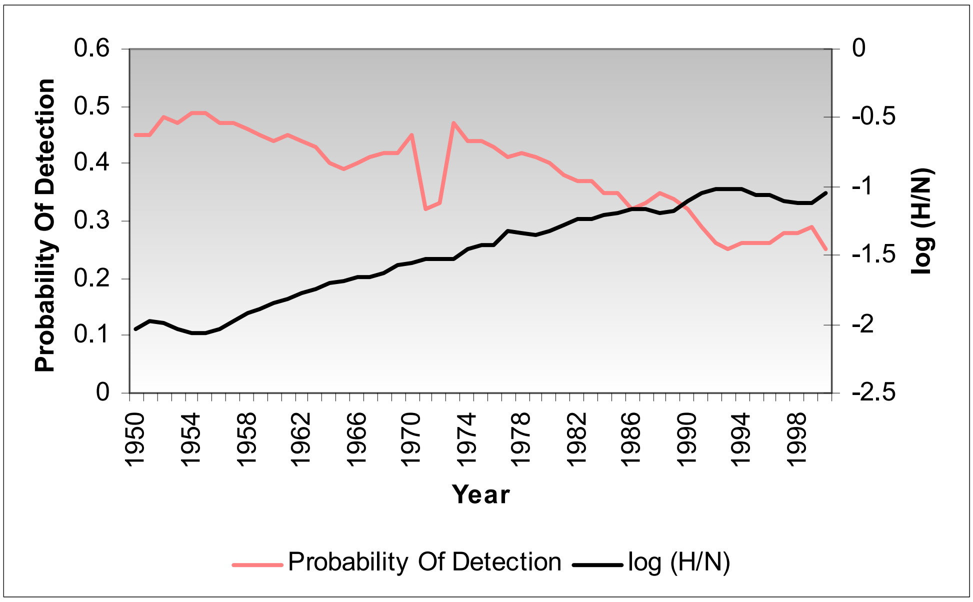
The parameter s reflects the cost of committing a crime if one is captured and an appropriate measure would be the severity index of punishment, as used in the journal. When I researched my data I found that fines are more associated with the less serious crimes and therefore data on prison sentences would be more suitable. There are many methods of estimating this index, but one method I have chosen to use is a ratio of the number of criminals convicted spending a prison sentence over 6 months to the number of offences cleared up (**9b**). The higher this ratio is, the higher the proportion of severe sentences out of all offences cleared up and therefore the higher the value of s.

Another parameter that would be difficult to measure is the rate of return from committing a crime as there are no official statistics and the rate of return cannot be pre determined before and individual commits the crime. One method recommended by the author in the journal is to use national income or consumption as a proxy as a rise in one of those can provide more opportunities for crime and hence increase it's return. The problem with this method is that an increase in national income could show up as a rise in the rate of return in both legal and illegal activity so the sign of this coefficient would be quite ambiguous.

There are measurement problems with transfer income A as it is very laborious to record the incomes for all individuals independent of their incomes from labour. This is why the author abstains from using this variable however I think it might be appropriate to use social security payments to unemployed individuals as a proxy. It may therefore be argued that a rise in incomes from social security should lower an individual's incentive to commit a crime. This is because it is likely to be a very important component of A but one limitation is that it only applies to a small percentage of the UK population as it considers only those who are unemployed.

For α, it is almost impossible to find data that relates to an individual's preferences for crime, which is why demographic and socio economic factors will have to be used as they would play an important role in determining an individuals preferences. Factors that I consider relevant to the UK are net migration, unemployment rates and the distribution of wealth as these are likely to influence incentives to participate in illegal activity. It is possible that net migration would lead to a rise in the level of crime, perhaps due to an increase in potential conflicts between different nationalities. The unemployment rate for males might be a more appropriate measure as female employment was considered less compulsory as a source of income for households in the mid 20th century.

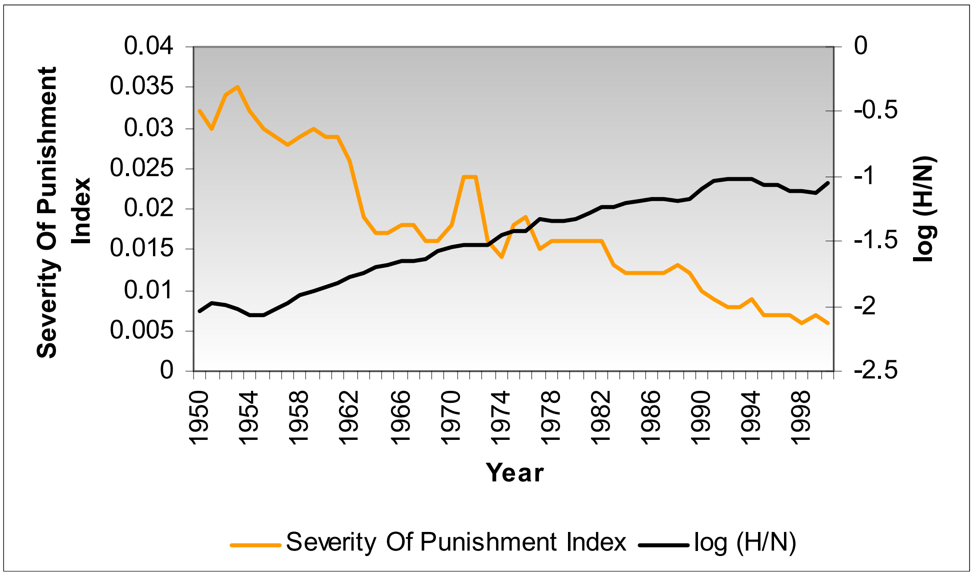
The 1st graph I wish to illustrate are both series for the total number of offences and the probability of detection. I have divided H by the population N as I feel that per capita crime would be a more appropriate measure as it would take into account the changes in criminal activity relative to the whole population. I have also logged[9] this variable to make it more linear.



The graph shows that in this period, the level of crime per capita has risen quite significantly but begins to level off after 1990. This has been associated with a fall in the probability of detection and both datasets have a correlation coefficient of –0.87 correct to 2 decimal places, calculated in Microsoft Excel. This relationship initially agrees with my hypothesis[10], that they should be inversely related.

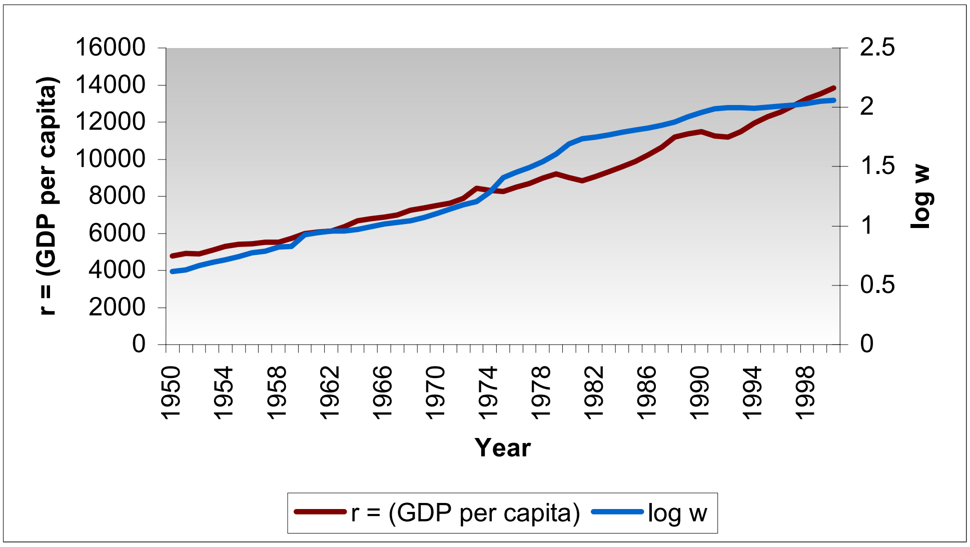
The next graph shows how crime per capita and the severity of punishment index have changed over time:

[9] Base 10 logs have been used for the entire project.
[10] Refer to the sign pattern in (6) for the full hypothesis.



The severity of punishment index has fallen during this time period with small fluctuations and also has a correlation coefficient of –0.94 with crime per capita. This value and the graph therefore initially show that there is a negative relationship as predicted by my hypothesis and that it is a strong relationship.

The next graph compares how the rates of return from both legal and illegal activity have changed over time. The legal rate of return is given by the logarithm of unit labour costs and that for the illegal (criminal) sector is given by the GDP per capita proxy.



The variable r has risen steadily in the period shown which once again initially agrees with my hypothesis that there should be a positive relationship between the rate of return and the number of offences. However there has been an overall rise in the wage rate of the legal sector, indicating an observed positive relationship with the level of crime, contradicting my hypothesis. This is something I talked about earlier, where I mentioned that there may be a possible conflict in using national income as a proxy for r, as wage growth might be rising as a result of economic growth in this situation. Multicollinearity might arise because it can be seen from the graph that these 2 explanatory variables could be highly intercorrelated. It may be wise therefore to drop the wage rate variable from the regression.

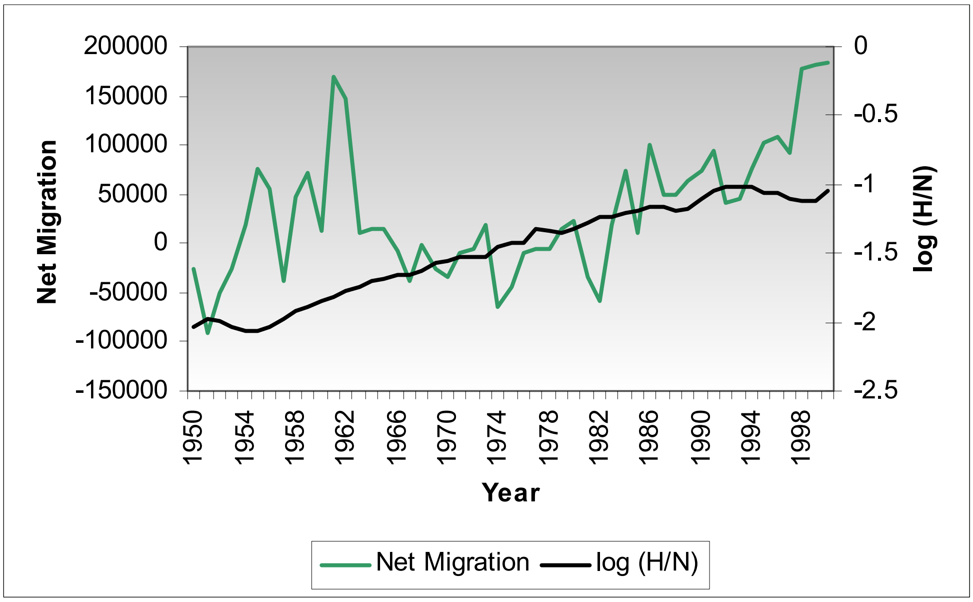
The table below shows a summary of demographic statistics. Values for logarithms have been rounded to the nearest decimal place whilst other values have been rounded to the nearest whole number.

	Population	Net Migration	Log (Unemploment)	log (male Unemployment)	log (Benefits/National income)
Correlation Coefficient with log (H/N)	0.97	0.38	0.91	0.92	0.98
minimum value	50280	-90200	-2.34	-2.16	-2.47
maximum value	59756	183000	-1.27	-1.04	-0.81
Mean	55360	32655	-1.79	-1.55	-1.61
standard deviation	2725	66385	0.36	0.35	0.61

The most important measure that needs to be discussed is the correlation coefficient with the dependent variable log (H/N). All of the variables (except net migration) have values that are close to 1, indicating at this stage that they are closely correlated with the dependent variable. The sign of the coefficient on log (benefits/national income) shows that there has been a positive correlation between this and the dependent variable. This would be hard to explain because higher benefits should provide individuals with higher transfer income and therefore reduce their incentives to commit crimes. Both types of unemployment have a positive correlation with crime, perhaps due to increased frustration as mentioned earlier. All 4 measures show that both unemployment statistics follow almost the same pattern mainly because I found that female unemployment makes up a very small proportion of total unemployment. It would therefore be appropriate to use total unemployment to take into account both genders in the model. The positive correlation coefficient for population is likely to arise because a rise in population would increase the strain on the demand for finite resources, thus forcing more individuals to resort to crime.

The data suggests that there is weaker correlation between net migration and the dependent variable, possibly making this a less suitable variable to use in the model.

The graph on the next page displays the ambiguity of the relationship between crime and net migration.



The graph shows that overall there is a weak fluctuating positive relationship between crime and net migration but from the period 1962 – 1968, there is a negative correlation. Net migration might be considered a weak variable perhaps because it takes into consideration the effects of emigration from the UK which is not as likely to influence crime as much as stand alone immigration data. The problem I encountered was not being to able to find immigration data for the period that I am using so I shall still consider this variable for my model.

For the variable ē I was unable to find data for average weekly hours worked for the period I required and shall therefore be dropped. I shall be relying on the unemployment variable to capture the effects of changes in the participation in legal activity but will be limited as it can only include number of persons rather than number of hours. It was also difficult to find statistics regarding the distribution of wealth before 1970, which is why this measure will also not be used in representing the taste for crime parameter.

Discussion Of Results

For this section, I intend to use my datasets to run regressions for my model by using the programme PC Give. I shall then interpret the meanings of their coefficients, discussing how they compare to my initial hypothesis. I will also describe the results of the diagnostic tests and use them to evaluate the accuracy and limitations of my results. I shall only be concerned with results information that I am familiar with and that I feel are relevant to the model. The values for rate of return, net migration and population have been scaled down to smaller numbers to avoid small decimal coefficients from arising. Full details of how the variables have been defined along with PC Give regression output results can be found in the appendix section.

The updated hypothesis below includes predictions for the demographic factors I introduced earlier and the variables from the original hypothesis that I am still using.

$$\text{Log}(H/N) = [\underset{+}{r},\ \underset{-}{p},\ \underset{-}{s},\ \underset{+}{M},\ \underset{+}{\log U},\ \underset{+}{Pop},\ \underset{-}{A}] \quad (\mathbf{10})$$

It should be noted that variables w and ē have been dropped due to the reasons discussed earlier.

The initial regression is run by directly regressing all explanatory variables, without the use of lags:

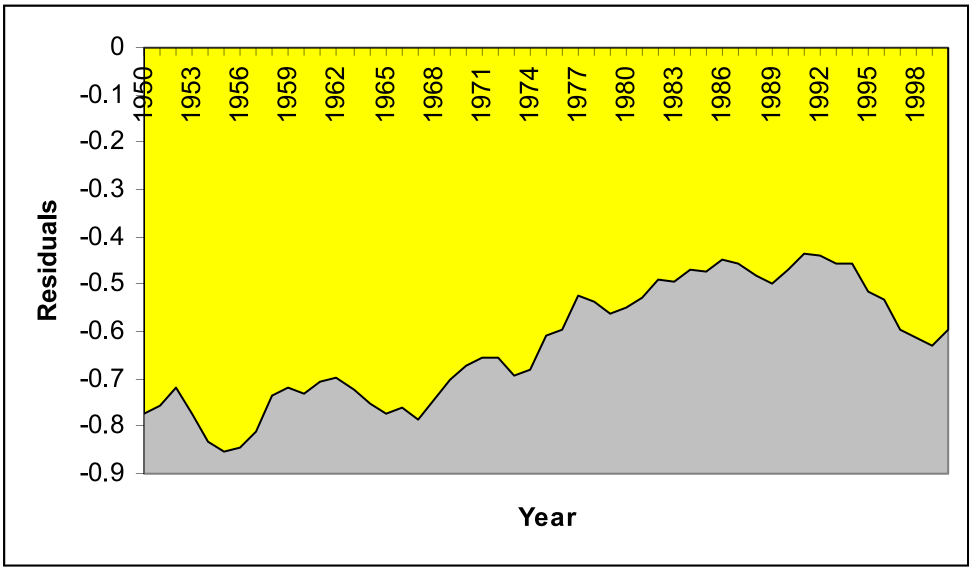
$$\log(H/N) = \underset{(0.401)}{-3.435} - \underset{(0.137)}{0.3128}p - \underset{(1.91)}{5.209}s - \underset{(0.153)}{0.1757}r + \underset{(0.0646)}{0.176}\log U \qquad \mathbf{EQ(1)}$$

$$+ \underset{(0.0804)}{0.2203}A + \underset{(7.67)}{54.06}Pop - \underset{(0.000949)}{0.001304}M + \varepsilon$$

The estimated coefficients[11] are given by the values multiplying the variables, numbers in brackets refer to the standard errors of the coefficients and ε is the error term. The coefficient signs show that variables p, s, logU and Pop seem to agree with my hypothesis made earlier, so that probability and severity of punishment will have a negative effect on the level of crime whilst the other 2 will have a positive effect. The behaviour of explanatory variables A, r and M however seem to contradict the

[11] The value on the logU term refers to the elasticity of log(H/N) with respect to logU, whilst the coefficients of the remaining variables refer to the semi elasticity. These are not of particular importance to this study as the direction of the change is mainly of concern rather than the scale.

hypothesis. Perhaps the national income variable should have been associated with the rate of return in the legal sector w as this includes recorded economic activity (legal) and the coefficient in EQ(1) has a negative sign. The results show that the R^2 value is very close to 1, meaning that the dependent variable values are being almost fully explained by the regression. The F test also has a high value of 869 and is marked by **, so that a hypothesis test for all coefficients being equal to zero may be rejected, making the explanatory variables significant. It should be stressed however that both of these values are very exaggerated and therefore there might be a problem with the regression. A heteroskedasticity test has been marked by * which indicates that there may be some weak evidence only to suggest that this may be present in this regression structure. This means that one of the assumptions of using Ordinary Least Squares (OLS) to estimate the coefficients is being invalidated, which means that the variances of error terms are not constant in this regression. The presence of heteroskedasticity in this regression is ambiguous however as the Reset test accepts the hypothesis that this OLS assumption is not being violated. Below is a graph which shows how the residuals (difference between actual and calculated log(H/N) from regression) changes over time so that it may be easier to deduce graphically if there is a heteroskedasticity problem.



The graph shows that the residuals steadily rises as time progresses and then falls after 1992, making it possible to conclude that the error variances are not constant during the time period used. So heteroskedasticity does appear do exist in this model but it is difficult to determine whether it is adversely affecting the accuracy of the regression due to the ambiguity of the tests.

The Durbin Watson test for serial correlation is rejected, indicating that the assumption of the error terms being independent of one another is valid for this regression.

The Normality test has passed, meaning that the assumption of error terms having a normal distribution is still valid and that the t ratios can be used for hypothesis testing.

The results show that the t ratios for coefficients r and M have smaller absolute values and are therefore likely to be insignificant. It can therefore be observed that perhaps Net Migration and the return from crime variables might not play a significant role in determining the level of crime in the UK in this model.

EQ(2) shows the results for the case when the variables s and p are lagged by 1 year, which could be a more realistic scenario. This is because formulae 9a and 9b used to determine these punishment and detection rates show that the individual will not know the values of these rates in their current year and may therefore need to base current behaviour on the previous year. I also decided to add a lagged version of the level of crime variable as an explanatory variable, perhaps because the level of participation in previous years might play a key role in determining that for the current year, as pointed out by the author.

The results show that the sign pattern of some of the coefficients have changed, as the probability variable p_1 now has a positive effect on crime which disagrees with my hypothesis, but the Net migration parameter now has a weak positive effect on crime. All the diagnostic tests pass and therefore the lagging of these variables has solved the heteroskedasticity problem. One problem that has been created by this is that all the variables except log(H/N)_1, Pop and the constant term have lower t ratios now have small absolute t ratios, making them less significant. The main problem that remains is the exaggerated R^2 and F test values. This is a very serious problem in this model and is mainly to do with inter correlation between certain variables. One example is how the probability variable has been defined, which uses the total level of crime variable H in the denominator, whereas this measure also appears in the dependent variable expression. This is a cause of inter correlation between the variables log(H/N) and p and could perhaps be solved by not using their numerators, so that the population statistic will also not appear in the dependent variable. The limitation of this is that it redefines the probability statistic by making the number of cleared up offences a proxy without taking into consideration changes in the total number of criminal offences.

Although there are some variables I dropped, the diagnostic tests for both regressions do not suggest that there are any omitted relevant variables. The heteroskedasticity test in EQ(1) however suggests that the regression could be made more accurate if maybe one or more of the missing variables were added. The model that I feel is the best for representing my results is EQ(1) because this is the one that matches the coefficient signs in my hypothesis the closest. One problem of course is the presence of heteroskedasticity but the test showed that there was weak evidence and could be put down to maybe a few missing variables. As mentioned earlier, attempting to solve the problem of exaggerated R^2 and F test values could impose a further divergence from my model, giving more misleading results.

It may be summarised from EQ(1) that only the factors probability, severity of punishment, unemployment and population affect the level of crime in the UK the same way I have predicted in the theory. The t ratios suggest that net migration and the rate of return from illegal activity do not appear to be significant factors that an individual would consider when deciding on their level of criminal activity. The only problems with the reliability of the model were the possible presence of heteroskedasticity and exaggerated R^2 and F test values.

Conclusion and Evaluation

Overall I found that the results from my regression only partially agreed with my theory and hypothesis I talked about earlier and tests showed that that were some faults with this regression. There are certain measures that can be taken to avoid these errors from happening and they are mainly concerned with maintaining the precise structure of the model, rather than using proxies to estimate the variables.

For example the definition of the parameter α was changed considerably and was assumed that taste for crime is represented by demographic and socio-economic factors. Factors I chose were net migration, population and unemployment but then there are many other factors such as the distribution of wealth and population age structure that would help to determine people's level of crime. However some of these datasets would require more time and effort to locate which is why they could not be used in representing this parameter. Of course it may be argued that some of these factors might not play any role in determining α, in which case this parameter has been dropped from my regressions, further invalidating my final results. This problem can only be solved by perhaps setting up a survey for each individual of the UK population, asking them to rate their preferences for crime, making α very accurate. This method is very laborious however and cannot possible for me to undertake, but results would be very interesting if this sort of extensive study was carried out.

The method I used for estimating the probability of detecting a crime was criticised earlier on. The probability variable was determined by calculating the ratio of individuals captured to the total number of offences but this is only an estimate based on past data. Accuracy can be increased substantially if a probability reference value could be calculated instead, which might be measured by the strength of the police force and the ability of individuals to avoid being captured. The level of expenditure on training and equipment could measure the former but the latter might require another survey, asking individuals to estimate their probabilities of being captured. This type of survey would be ridiculous for many obvious reasons but honest answers may provide a true estimate of p.

The severity index of punishment is equally as flawed because the average level of time spent in prison is likely to be determined by the type and number of offences, rather than a level set by the authorities as the theory suggests. One possible way I think this could be solved is if the authorities recorded were to construct their own general punishment index that would apply to all types of crime and would be predetermined. This type of data is more likely to exist but was not available for me to use in this study.

I mentioned earlier that the use of national income as a proxy for criminal rate of return in very inaccurate due to conflicts between earnings in the legal sector. The true rate of return the illegal sector would be extremely difficult to measure as many criminals themselves do not know this information until they have committed the crime. It is possible that a significant proportion of criminals in the UK would associate their returns with non-monetary rewards, such as murders in which case the cost of human life would be of great concern to us and would further complicate this measure.

The variable logU was used to capture legal sector employment changes, however I feel that accuracy in this area could have been improved if data was available for the UK's average weekly hours involved in employment.

One assumption used that forms the basis of this whole model is that all individuals have utility functions that are positively related to leisure and consumption. Whilst it may be argued that it is reasonable, it is likely that there will be exceptions in the UK population where their utility might not be influenced by such variables or perhaps affected negatively. If the determination of utility is ambiguous, it may be inappropriate to use rational choice theory to predict people's behaviour in response to changes in these key variables we have looked at.

References

Main Study – 'Modelling Crime & Punishment' – Matti Virén *Applied Economics, 2001, 33, 1869 – 1879*

Background Reading – 'Crime & Accountability' – Marshall, Tony F

Datasets

Crime and punishment statistics – 'Home Office Criminal Statistics' (Used Books in library 1950 – 2000)

Unemployment and wage statistics – 'British Historical Statistics' – B.R. Mitchell (From library)

Population, Migration and national income statistics – National Statistics (www.statistics.gov.uk and library books for older data)

Appendix

Definition of variables for regression:

$$r = \frac{\text{real GDP per capita}}{1000}$$

$$p = \frac{\text{Number of cleared up offences}}{\text{Total Number of offences}}$$

$$s = \frac{\text{Number of persons convicted for more than 6 months prison sentence}}{\text{Number of cleared up offences}}$$

$$M = \frac{\text{Net migration into UK}}{100000}$$

$$Pop = \frac{\text{Total population}}{100000000}$$

B/Y = Government expenditure on benefits as proportion of real GDP

U = Unemployment rate

EQ(1) Modelling log(H/N) by OLS-CS (using maindata.csv)
The estimation sample is: 1950 to 2000

	Coefficient	Std.Error	t-value	t-prob	Part.R^2
Constant	-3.43490	0.4009	-8.57	0.000	0.6306
p	-0.312760	0.1369	-2.28	0.027	0.1082
s	-5.20923	1.909	-2.73	0.009	0.1476
r	-0.175731	0.1533	-1.15	0.258	0.0297
logU	0.175960	0.06463	2.72	0.009	0.1470
log(B/Y)	0.220333	0.08042	2.74	0.009	0.1486
Pop	54.0565	7.668	7.05	0.000	0.5361
M	-0.00130437	0.0009487	-1.37	0.176	0.0421

sigma	0.031268	RSS	0.0420406941
R^2	0.992981	F(7,43) =	869 [0.000]**
log-likelihood	108.708	DW	0.832
no. of observations	51	no. of parameters	8
mean(log(H/N))	-1.4786	var(log(H/N))	0.117442

Normality test: Chi^2(2) = 3.6529 [0.1610]
hetero test: F(14,28) = 2.0856 [0.0476]*
Not enough observations for hetero-X test
RESET test: F(1,42) = 2.2262 [0.1432]

EQ(2) Modelling log(H/N) by OLS (using maindata.csv)
The estimation sample is: 1951 to 2000

	Coefficient	Std.Error	t-value	t-prob	Part.R^2
log(H/N)_1	0.673191	0.1514	4.45	0.000	0.3252
Constant	-1.50272	0.6247	-2.41	0.021	0.1237
p_1	0.177148	0.1493	1.19	0.242	0.0332
s_1	-1.98970	1.862	-1.07	0.292	0.0271
logU	0.0304666	0.06651	0.458	0.649	0.0051
Pop	24.3600	10.41	2.34	0.024	0.1179
M	0.000174302	0.0009155	0.190	0.850	0.0009
r	-0.138102	0.1477	-0.935	0.355	0.0209
log(B/Y)	0.109376	0.07962	1.37	0.177	0.0440

sigma	0.0284591	RSS	0.03320675
R^2	0.994145	F(8,41) =	870.1 [0.000]**
log-likelihood	111.979	DW	1.32
no. of observations	50	no. of parameters	9
mean(log(H/N))	-1.46743	var(log(H/N))	0.113424

AR 1-2 test: F(2,39) = 2.7913 [0.0736]
ARCH 1-1 test: F(1,39) = 3.8265 [0.0576]
Normality test: Chi^2(2) = 3.5258 [0.1715]

hetero test: F(16,24) = 1.6727 [0.1237]
Not enough observations for hetero-X test
RESET test: F(1,40) = 0.017743 [0.8947]