AN ECONOMIC ANALYSIS OF RECORDED PROPERTY CRIMES IN ENGLAND AND WALES.

By

D.J. PYLE.

A THESIS SUBMITTED FOR THE DEGREE OF DOCTOR OF PHILOSOPHY AT THE UNIVERSITY OF LEICESTER.

NOVEMBER, 1983.

Thesis

17.4.1984

CONTENTS

		page
Chapter 1:	Introduction: Economic Analysis and Crime	1
1.	Objectives and Methods of the thesis	1
2.	Crime and Law Enforcement in England and Wales	11
3.	Economists and Crime: An Historical Perspective	21
4.	Outline of the thesis	26
Chapter 2:	Economic Models of Criminal Behaviour: A Review.	30
1.	Becker's Model	32
2.	Ehrlich's Model	38
3.	Block and Heineke's Model	54
4.	Some concluding comments on "economic" Models of Crime	60
Appendix to Chapter 2:	The Time Allocation Model with Variable Leisure	73
Chapter 3:	Econometric Studies of Crime: A Survey	78
1.	Methodological Preliminaries	79
	(i) Simultaneous Determination of Crime and Sanctions	79
	(ii) Measurement Error in the Crime Variable	85
2.	A Review of Empirical Studies	89
	(i) North American Studies	90
	(ii) British Studies	123
3.	Conclusion	133

		page
Chapter 4:	A Model of Property Crimes in England and Wales.	137
1.	An Aggregate Study	137
2.	Model Specification	144
	(i) Supply of Offences Functions	146
	(ii) Police production functions	155
	(iii) Police manpower equation	161
	(iv) The recording equations	166
3.	The Complete Model	172
	(i) Specification and Partial Solution	172
	(ii) Identification of the Model	173
	(iii) Data Sources	174
Appendix to Chapter 4		177
Chapter 5:	Results of Model Estimation	183
1.	Estimation Procedure	184
2.	All Property Offences	188
	(i) Main Estimates	188
	(ii) Some Alternative Hypotheses	196
3.	Separate Offence Groups	212
	(i) The main estimates	212
	(ii) Substitution amongst crimes	217
4.	Some Brief Conclusions	219
Appendix to Chapter 5		262

		page
Chapter 6:	Interpretation of Results and Conclusions	269
1.	Introduction	269
2.	The Explanation of The Recorded Crime Rate	273
3.	The Determination of the Detection Rate	294
(i)	Effect of More Police Manpower	295
(ii)	The effect of Workload upon the detection rate	300
4.	Employment in the Police Service	305
5.	Alternative Measures of the Probability of Detection	309
6.	Reduced Form of the Model	311
7.	Incapacitation	318
8.	Conclusions	321
Appendix to Chapter 6		328
Statistical Appendix		
Bibliography		

CHAPTER 1 INTRODUCTION: ECONOMIC ANALYSIS AND CRIME

1. Objectives and Methods of the Thesis

In England and Wales between 1955 and 1981 the number of recorded property crimes, i.e. burglaries, robberies and thefts, increased at an average annual rate of over 7%. At the same time the volume of resources devoted to law enforcement was increased substantially. For example, public spending on law enforcement grew at 14.5% per annum in nominal terms and at 4.5% per annum in real terms between 1955 and 1981.[1] However, as yet, there seems to be no tangible pay off to that commitment. One of the objectives of this thesis is to enquire into the effectiveness of increases in police resources in reducing crime.

However, our concern is wider than this. Any meaningful analysis in this area requires that the whole process generating the level of recorded property crime statistics be subjected to detailed scrutiny. Logically, therefore, we need to consider individuals' decisions to commit crimes and the process by which those crimes once committed become reported to the police and are recorded by them. Law enforcement activity is just one input into that process, which can affect individuals' decisions to engage in crime and/or the decision to record/ report an event as a crime.

---

[1] The growth in nominal expenditure on law enforcement has been calculated from statistics of public expenditure on police, prisons and law courts published in the National Income and Expenditure blue book. The growth in real spending has been calculated by deflating nominal expenditure by a general government expenditure deflator. These calculations are obviously not exact. Law courts, for example, deal with some non-criminal cases. Also no allowance has been made for probation services. However, the figures give a rough guide to the orders of magnitude involved.

The process generating the aggregate level of recorded crimes is obviously complex, requiring an understanding not just of individual criminal behaviour, but also of the interaction between criminals, victims and the law enforcement authorities. That complexity is reflected in the model that we will eventually estimate.

What light, however, can economics throw upon the generation of recorded property crime statistics? The answer to that question is the ultimate goal of this thesis. The search for an answer takes us down two major lines of enquiry. The first involves an enquiry into and assessment of "economic" theories of criminal participation. The second requires an analysis of the police "production function". In both areas the emphasis will be upon applied economics. We shall not attempt to offer any fundamentally new theoretical or methodological approaches, although we do derive some new and interesting theoretical results from existing models.

Economic theories of criminal participation are all based upon the simple notion that (potential) criminals are rational economic agents who attempt to maximise expected utility. The most popular model is one that analyses how individuals allocate their time between competing activities, i.e. illegitimate activity, legitimate activity and leisure. Of course, participation in crime introduces an element of risk (the probability of capture and punishment) into the decision-making exercise. Economic models of criminal activity are fundamentally different from existing criminological models, which tend to focus on the psychological/character deficiencies of criminals. The economic approach is fully discussed in Chapter 2.

Economists have tended to treat police forces as if they were multi-product firms, who use inputs of factors of production in order to produce "outputs". The precise definition of these outputs is a subject of some controversy (see Pyle, 1983, Chapter 6). The primary interest here, however, is how do police forces combine resources so as to produce "deterrence" This subject is treated at various points throughout the thesis, but especially in Chapters 3, 4 and 6.

The primary objective then is to see if economic analysis can be used to explain variations in recorded property crime rates across police force areas in England and Wales. Our interest is, therefore, mainly in terms of testing refinements of existing models rather than with constructing new theoretical approaches.

It would, of course, be mischievous to claim that no-one had previously attempted to apply these "economic" models to criminal justice data (in Chapter 3 we offer an extensive survey of such work). However, the vast majority of previous attempts to apply economic analysis to the study of crime and law enforcement have used data for North America. So far there have only been two major studies using data for England and Wales. These are the investigations by Carr-Hill and Stern (1979) and

Wolpin (1978).[2] In view of the existence of these earlier analyses we should provide some justification for a third economic analysis of crime in England and Wales.[3]

The studies by Carr-Hill and Stern and Wolpin are quite different in approach. Carr-Hill and Stern constructed a small, simultaneous equation model whose endogenous variables were (i) the aggregate crime rate, (ii) the detection rate for all crimes and (iii) the number of policemen per capita. The model was estimated using cross-section data for police force areas. By contrast Wolpin (1978a) estimated a single equation model. He used national annual time-series data for the period 1894-1967 to estimate separate crime "supply" equations for larceny, burglary, robbery, auto-theft, malicious wounding, felonious wounding , all offences against the person and all indictable

---

2 There have also been two rather less important empirical studies, by Hilton (1979) and Baldry (1976). Hilton's study is an interesting attempt to overcome the recording problem (see later). However,it is so riddled with mathematical errors that the results must be suspect. Baldry's work is almost entirely theoretical. He does,however,undertake a rather sketchy time-series study. Unfortunately,only one variable (the time trend) is generally significant. Sadly, he is led to conclude, "(t)he regression results reported ... do not give much support to the theoretical analysis which occupied most of the earlier chapters." (p.304).

A more recent study by Willis (1983) was published too late to be included in the literature survey. The object of this work was to explain spatial variations in the rates of violent crime,sexual offences and theft in England and Wales in 1979. Willis estimated a simultaneous equation model which included various deterrence and socio-economic measures. He concluded that "(s)patial variations in crime rates can be predicted by spatial differences in risk of capture,punishment,police protection,unemployment, but environmental factors (unspecified) still remain significant" (p.261, our emphasis).

3 The studies of Carr-Hill and Stern and Wolpin are reviewed at length in Chapter 3. Here we merely focus on the principal defects of these studies and how they are overcome in this thesis.

offences.[4] Each equation was estimated by ordinary least squares (O.L.S.) and no attempt was made to estimate the crime equations as part of a simultaneous equation model.[5] If the relationship between the crime-rate and the law enforcement variables is simultaneous then O.L.S. estimation will generally yield biased and inconsistent estimates (Stewart and Wallis, 1981, Chapter X).

Possible simultaneities between these variables have generated some debate in the economics of crime literature. As this issue is discussed at length in Chapter 3, we will only sketch the essentials of the argument at this stage. The economic theory of criminal participation (see Chapter 2) predicts that the crime rate is likely to be inversely related to the detection rate. However, it is also argued by some that <u>at the macro level</u> the detection rate is inversely related to the crime rate. The argument is that a higher crime rate exerts pressure upon a fixed amount of police resources, thus leading to a lower detection rate. The negative effect of the crime rate upon the detection rate is unlikely to arise, of course, if one had access to information relating to individuals. There, increased criminal activity by a single individual is unlikely to exert pressure upon police resources thus reducing his chances of

---

[4] Wolpin also used national time-series data, this time for 1929-68, to examine the deterrent effect of capital punishment. However, we do not examine that study in detail (see Pyle, 1983, Chapter 4).

[5] Wolpin did estimate a simultaneous equation model for all offences only. The endogenous variables were then the crime rate, the unconditional conviction rate and the number of policemen per capita. The simultaneous equation estimates show that the relationship between the crime rate and the unconditional conviction rate is simultaneous. This must cast some doubt upon Wolpin's single equation estimates, although a direct comparison is not possible.

capture.[6] With micro-level data the detection rate could be treated as an exogenous variable in the crime supply equation. However, there has been no really serious attempt to estimate the economic model using data for individuals[7], and certainly Wolpin's effort never came near to doing so.

Empirical investigations have been forced to use macro-level data, i.e.crime and law enforcement data for cities, counties, states etc. Even so, it has been argued that the crime-rate might not exert a negative effect upon the detection rate if the pattern of crime is stable over time and/or across areas (see, for example, Ehrlich, 1979). Furthermore, in those circumstances, law enforcement resources will be fully adjusted to the pattern of crime, so that a higher crime-rate will not put pressure on law enforcement resources and would not lead to a lower detection rate.

Obviously there is some disagreement about the simultaneity between the crime rate and the detection rate. In view of this it would seem preferable to adopt the more general (i.e. simultaneous) framework. Should the relationship prove not to be simultaneous then little harm is done. However, to assume that no simultaneity exists when indeed it does would be much more dangerous. Accordingly, we have adopted a simultaneous equation approach and the results given in Chapter 5 seem to confirm that choice.

---

[6] Of course, an individual's probability of detection may be influenced by the amount of time he devotes to crime for other reasons. For example, "specialists" might develop their evasion skills. This is briefly considered in Chapter 2.

[7] See Witte (1980) for a first attempt.

Since most studies have found a negative effect of the crime rate upon the detection rate, Wolpin's decision to estimate the supply of offences functions by O.L.S. seems incomprehensible. This must rank as a serious criticism of both his approach and results. Other, perhaps less damaging, criticisms can be made. For example, he used time-series data for the period 1894 to 1967. During that time there were substantial changes in society generally, in definitions of crime, in the organisation of the police service and very probably in attitudes to reporting and in recording practices (on the last see Hough and Mayhew, 1983, pp.2 and 14). There must be some suspicion that structural changes over the period have been so substantial that Wolpin's results are invalidated. Certainly, Carr-Hill and Stern found evidence of a structural break between periods as close together as 1961 and 1966. Of course, a convincing refutation of Wolpin's results would require a formal test for structural change and without access to his data that simply is not possible. It would be an interesting test to perform and it is a pity that Wolpin did not undertake it.

There seem to be good reasons for doubting Wolpin's model selection (and hence estimation technique) and his choice of a data set with which to estimate the model. We have tried to avoid these mistakes by adopting a more general model specification and by using cross-section rather than time-series data.[8]

Carr-Hill and Stern also tried to avoid these problems by estimating a simultaneous model for a cross-section of police

---

[8] Use of cross-section data does not avoid all of the problems. For example, differences in reporting and recording practices may still exist between areas.

force areas. However, their analysis is not immune from criticism. For example, they made no attempt to disaggregate the crime variable, merely grouping all indictable (i.e. serious) offences into an aggregate measure. Also, the specification of the crime equation of the model gives rise to some concern. For example, neither earnings in legitimate activity nor length of imprisonment was included, nor was there any attempt to consider explicitly the "displacement effect", i.e. how differences in illegal returns between areas can lead to crime being displaced from one area to another.

Carr-Hill and Stern's failure to disaggregate the crime variable may be quite serious.[9] Other empirical work has shown that there are often quite significant differences in the sizes of the coefficients in the crime equations (see Chapter 3). Certainly the inclusion of both crimes of violence and property crimes in a single aggregate must be treated with caution. It might be argued that violent crime is susceptible to an "economic" explanation (see, for example, Ehrlich,1975), but it would seem to be a much less straightforward application of the model. We have avoided this thorny issue by excluding crimes of violence altogether.

The specification of each equation of Carr-Hill and Stern's model is examined in detail in later chapters. However, one aspect of the equation specification has quite important consequences and should be dealt with here. At the heart of the model are two equations. The first explains the crime rate and

---

[9] They briefly analysed breaking and entering offences. Interestingly the results for this single class of offences are substantially different from those for aggregate offences, particularly the coefficients of the deterrence variables (compare their Table 6.8 with Table 6.A.1).

the second explains the detection rate. The crime rate is argued to depend upon a number of law enforcement and socio-economic/demographic variables. These variables include measures of the age/sex and social class composition of the population. The detection rate is also explained by a number of law enforcement and socio-economic/demographic variables. Identification of each equation is achieved by excluding from it some of the model's pre-determined variables. For example, the crime equation is identified by excluding from it some of the socio-economic/demographic variables, e.g. population size, the proportion of the population defined as middle class etc.

The arguments for including some of these variables in the "production function" and excluding them from the crime equation seem weak and unconvincing. Fisher and Nagin (1978) argue that, given our current knowledge of the determinants of crime, it is extremely doubtful that we can argue categorically that some socio-economic/demographic variables do not affect the crime rate, whilst simultaneously arguing that these same variables do influence the detection rate. This suggests that identification of the crime equation has been achieved by what appears to be a quite arbitrary decision.

We have tried to avoid this problem by searching for other workload and resource variables to include in the police production function, e.g. traffic accidents, civilian employees in the police service etc. The role of these variables is quite unambiguous. They are expected to directly influence the detection rate, but not the crime rate. These additional variables make the identification of the crime equation much more clear-cut.

Carr-Hill and Stern left untested a number of interesting and important hypotheses about the determination of crime rates. For example, they made no attempt to test whether legitimate earnings opportunities had any effect upon the amount of crime. The economic model of criminal behaviour employed in this thesis (see Chapter 2) argues that both earnings in legitimate activity and the unemployment rate are likely to influence the amount of crime.[10] Neither of these influences was included in Carr-Hill and Stern's crime equation. We have attempted to rectify this shortcoming. As we shall see, unemployment, at least, is a major factor in explaining property crime rates (see Chapter 6).

Two rather less central hypotheses relating to the determination of crime rates, which were also ignored by Carr-Hill and Stern, are (i) whether crime is displaced between areas by differences in relative returns to illegal activity and (ii) whether the <u>length</u> of imprisonment exerts a significant deterrent effect. Some North American studies (see Chapter 3) point to the existence of spillover effects. Carr-Hill and Stern were quite dismissive about the existence of such effects, arguing that they were unlikely to occur because of the small monetary nature of most thefts. Instead, we have incorporated a variable to reflect variations in relative rewards between areas. Interestingly this variable is often statistically significant, especially in the burglary and robbery equations (see Chapter 6).

Length of imprisonment has also been found by some inves-

---

[10] However, the direction of the effect is not altogether unambiguous, because of wealth effects. This point has not always been appreciated. Evidence on the effect of earnings and unemployment is mixed. See Chapter 3 and Freeman (1982) for a full discussion.

tigators to be a significant determinant of crime rates (see Chapter 3). At a time when there is so much discussion of the need to reduce prison sentences it is interesting to examine the effect of this variable. The results (see Chapter 6) bring into question the conventional wisdom on lengths of imprisonment.

We have reservations also about the specification of the other equations of Carr-Hill and Stern's model, but these are dealt with fairly extensively in later chapters. We feel that they have committed a number of errors of both commission and omission in the specification of their model. We also feel that these errors are sufficiently important to warrant another attempt to explain variations in rates of recorded property crimes across police force areas in England and Wales.

2. Crime and Law Enforcement in England and Wales

Detailed information about "offences recorded as known to the police"[11] is published annually in Criminal Statistics. In 1975 the total number of such offences was 2.106 million. That figure had increased substantially from 0.744 million recorded offences in 1960, i.e. an average growth rate of 7.2% per annum. The number of recorded offences has continued to grow fairly rapidly since 1975, so that by 1981 it had reached 2.794 million offences.

Of course, this represents only those offences which are

---

11 This was the title used in the 1975 and 1976 edditions of Criminal Statistics. Such offences have since been relabelled as "notifiable offences recorded by the police". No substantial change in definition is involved, except that after 1977 offences of criminal damage valued at £20 or under were included.

recorded by the police and not the "true" number of offences. Evidence from victim surveys (see, for example, Hough and Mayhew, 1983) indicates that the actual number of offences may be considerably larger.[12]

The vast majority of recorded offences are committed against property, as can be seen in Table 1.1. There we give an analysis of recorded offences in 1975 by major type of crime. Only some 4-5% of recorded offences were crimes committed against persons. Analysis of recorded offences for other years shows a remarkably similar pattern. The choice of 1975 was made because it is one of the sample years used in the analysis of Chapters 5 and 6.

TABLE 1.1 Offences recorded as known to the police, England and Wales, 1975.

	Number	As % of total
1. Violence against the person	71,002	3.4
2. Sexual offences	23,731	1.1
3. Burglary	521,867	24.8
4. Robbery	11,311	0.5
5. Theft and handling stolen goods	1,267,674	60.2
6. Fraud and forgery	123,055	5.8
7. Criminal damage	78,546	3.7
8. Other offences	8,445	0.4
Total	2,105,631	100.0

Source: Criminal Statistics 1975, HMSO Cmnd 6566.

12 Conversely actual offences may have grown more slowly. For example, evidence from the General Household Survey suggests that between 1972-3 and 1978-9 the number of reported burglaries increased by 4% p.a., whereas actual burglaries rose by only 1% p.a.

The vast majority of recorded crimes are offences of either burglary or theft and handling of stolen goods. Whilst evidence from victimisation surveys shows that under-reporting of crime varies across types of crime (see Hough and Mayhew, 1983, Table 2, p.11) it would require some incredible magnitudes of under-reporting of other crimes if burglaries and thefts were not to represent a major proportion of actual crimes.

In the empirical analysis of this thesis we have concentrated upon the crimes of burglary, theft and handling of stolen goods and a third, relatively minor category of offences, robbery. Robbery lies on the fringes between crimes against the person and crimes against property. However, it is such a small group of offences that its inclusion in the aggregate is unlikely to alter dramatically the results. We have, however, decided to exclude offences of fraud and forgery from the later analysis. Offences of fraud or forgery may go undetected for a considerable length of time. Once detected they are almost certain to be reported and in those cases the detection rate will appear close to 100%. In view of the complexities involved in interpreting the statistics relating to this class of offences it was decided to exclude them from the study.

We have also excluded violent and sexual crimes from the analysis. The reasons behind the commission of such crimes are undoubtedly complex. The objective of this research is to examine "economic" theories of offending. It seems unlikely that the economic approach can be easily applied to such crimes. Further, an acceptable model of the determination of rates of violent and sexual crime would impose data requirements that could not be met at the aggregate level.[13]

In Table 1.2 we present some rather more detailed information on numbers of offences of burglary, robbery and theft in England and Wales in 1975. A substantial minority of these recorded offences (about 0.5 million) were either thefts of or from motor vehicles. These offences have grown in number over the last few years as vehicle ownership has increased. Likewise, the number of thefts from meters has tended to fall as fewer houses now have pre-payment meters for either gas or electricity.

---

[13] Such as data on the numbers of broken homes, single parent families, cases of child abuse etc. for each police force area.

TABLE 1.2 Recorded Property Crimes in England and Wales in 1975

		As % of total
Burglary		
Burglary in a dwelling	237,353	
Aggravated burglary in a dwelling	419	
Burglary in a building other than a dwelling	277,551	
Aggravated burglary in a building other than a dwelling	106	
Going equipped for stealing	6,438	
sub-total	521,867	29.0
Robbery	11,311	0.6
Theft and Handling Stolen Goods		
Theft from the person of another	20,851	
Theft in a dwelling other than from an automatic machine or meter	49,665	
Theft by an employee	31,280	
Theft or unauthorised taking from mail	1,584	
Theft of pedal cycle	78,602	
Theft from vehicle	239,432	
Shoplifting	175,552	
Theft from automatic machine or meter	27,164	
Theft or unauthorised taking of motor vehicle	264,896	
Other theft etc.	333,070	
Handling stolen goods	45,578	
sub-total	1,267,674	70.4
All recorded property crimes	1,800,852	100.0

Source: Criminal Statistics 1975, HMSO Cmnd 6566.

The majority of crimes listed in Table 1.2 involve the loss of relatively small amounts of property, as can be seen from Table 1.3.

TABLE 1.3 Offences of burglary, robbery and theft recorded as known to the police: value of property stolen. 1975.

Number of offences

Offence and classification number	Value Stolen							Total
	Nil	Under £5	£5 and under £25	£25 and under £100	£100 and under £500	£500 and under £1,000	£1,000 and over	
BURGLARY								
28 Burglary in a dwelling	47,591	24,865	54,706	54,106	42,527	8,141	5,417	237,353
29 Aggravated burglary in a dwelling	232	33	47	50	38	12	7	419
30 Burglary in a building other than a dwelling	70,882	41,962	60,998	55,758	36,983	6,391	4,570	277,551
31 Aggravated burglary in a building other than a dwelling	57	7	10	9	10	5	8	106
Sub-total	118,769	66,867	115,761	109,923	79,558	14,549	10,002	515,429
ROBBERY								
34 Robbery	2,071	2,672	2,515	1,873	1,176	337	662	11,311
THEFT AND HANDLING STOLEN STOLEN GOODS								
39 Theft from the person of another	1,103	4,364	9,218	4,622	1,307	141	96	20,851
40 Theft in a dwelling other than from automatic machine or meter	885	11,013	17,359	13,707	5,789	557	355	49,665
41 Theft by an employee	567	7,828	9,313	6,804	4,798	966	1,004	31,280
42 Theft or unauthorised taking from mail	149	961	306	98	47	4	19	1,584
44 Theft of pedal cycle	443	2,709	47,341	27,747	359	3	—	78,602
45 Theft from vehicle	9,868	48,619	77,456	79,362	21,450	1,698	979	239,432
46 Shoplifting	4,501	118,833	38,375	10,920	2,582	205	136	175,552
47 Theft from automatic machine or meter	2,145	8,215	12,317	4,191	283	11	2	27,164
49 Other theft or unauthorised taking	8,617	89,790	121,340	75,345	31,106	4,256	2,616	333,070
Sub-total	28,278	292,332	333,025	222,796	67,721	7,841	5,207	957,200
Total	149,118	361,871	451,301	334,597	148,455	22,727	15,871	1,483,940

Source: Criminal Statistics 1975.

The distributions of amounts stolen are highly skewed with large numbers of offences involving small sums, but with a few offences of very large sums. Nearly 59% of burglaries, 64% of robberies and 68% of thefts involved property worth less than £25. Only about 5% of burglaries, 9% of robberies and 1½% of thefts involved sums in excess of £500.

The average value of property stolen in all offences reported in Table 1.3 is approximately £73 (this assumes an upper limit for the final class of £2,000).[14] These sums seem small in absolute terms, but when compared with, say, average gross weekly earnings for adult male workers in that year (approximately £61) they look a little larger. In fact in 1975 over 36% of adult male workers earned less than £50 and 10% earned less than £38 per week gross.[15]

The picture is one of a rapidly rising level of recorded offences, most of which are crimes against property. Further, the majority of these offences are burglaries and thefts of relatively small absolute amounts of property.

Only a minority of recorded property crimes are solved by the police and as Table 1.4 indicates the detection rate has steadily declined over the last ten years.

---

14 It seems likely that the average value of property stolen in all crimes (reported or not) will be less than this. Victimisation surveys indicate that some crimes are not reported because of the small amount of property stolen (see below).

15 Of course the average amount stolen is not necessarily a precise indicator of the loss to a victim or the gain to a criminal. For example, the victim may suffer anger and distress at the loss of his property. The criminal may have to sell the stolen goods at less than their market value.

TABLE 1.4 Clear up rates for selected offences, 1971-81 (%s)

	Burglary	Robbery	Theft and Handling	All Offences
1971	37	42	43	45
1972	37	43	43	46
1973	37	46	43	47
1974	34	40	42	44
1975	34	40	41	44
1976	34	33	41	43
1977	31	28	40	41
1978	32	30	40	42
1979	31	31	40	41
1980*	31	29	39	40
1981*	30	25	38	38

Source: Criminal Statistics 1981, Cmnd 8668.

Note: Clear up statistics for 1980 and 1981 are not strictly comparable with those for earlier years, because of a change in recording practices from 1 January 1980.

The almost continuous fall in clear up rates has occurred at the same time that employment in the police service has been steadily increasing. See Table 1.5.

TABLE 1.5 Employment in the police service

	At 31 December each year Actual Strength	Authorised Establishment
1971	96,859	109,095
1972	99,671	110,255
1973	100,611	112,168
1974	102,102	114,637
1975	107,138	116,007
1976	109,476	116,880
1977	108,201	116,980
1978	109,075	117,668
1979	113,309	118,322
1980	117,423	118,930
1981	119,575	120,008

Source: Annual Abstract of Statistics, 1983.

There are a number of alternative hypotheses that might explain the simultaneous rise in recorded crimes and fall in detection rates at a time when police employment has been increasing. One hypothesis is that increases in police manpower lead to the reporting/recording of more minor incidents which are difficult to solve. An alternative explanation is that the rise in crime is due to other factors (e.g. rising unemployment). The rise in crime then puts pressure on existing police resources, which lowers the detection rate. Increases in police employment, in response to the rising crime rate, will tend to offset this. However, if the increases are insufficient we will observe rising police employment, rising levels of recorded crime and falling detection rates.

Which, if either, of these two hypotheses is correct cannot be decided on the basis of simple correlation techniques. The causal relationships involved are fairly complex and care is required in trying to unravel the statistics. However, the analysis of the following chapters will greatly improve our understanding of the situation even though we will not be using time-series data. Despite using cross-section data we should still be able to reach valid conclusions about the way crime and law enforcement variables are determined. On the whole the results favour the second hypothesis discussed above.

One important problem facing all attempts to explain crime-rates is the recording problem. Surprisingly, it has received relatively little attention in the literature. It is firmly believed that not all crimes are either reported or recorded. However, the extent of under-recording is only imperfectly known. Further, if under-recording varies across areas or over time then the use of recorded crime-rates may give a misleading impression of the real pattern of crime. Unless, of course, the recording/reporting decision can be accurately modelled. (See Chapter 3 for an elaboration on this.)

It is only recently that information on the extent of under-recording of crime in England and Wales has become available. The British Crime Survey (discussed in Hough and Mayhew, 1983) is the first national victimisation survey in the UK. Some 11,000 households were interviewed to find out whether members had been victims of crimes in the past year, whether they had reported these crimes, and if not, why they had not reported the incidents. Table 1.6 shows the extent to which incidents recorded in the Survey were reported to the police.

TABLE 1.6 Reporting of offences by class of offence (%s)

Vandalism	22
Theft from a motor vehicle	30
Burglary	66
Theft of a motor vehicle	95
Bicycle theft	64
Theft in a dwelling	18
Theft from a person	31
Robbery	47
Wounding	39
Sexual offences	28

Source: Hough and Mayhew (1983, p.11)

The extent of under-recording varies considerably from one crime to another. The reasons for this are many and varied. However, the Survey revealed that the two prime reasons for not reporting an offence to the police were (i) that the offence was felt to be too trivial and (ii) that the victims felt that the police would not have been able to do anything. A fuller list of reasons and their relative importance is given in Table 1.7.

TABLE 1.7 Reasons for not reporting crimes (%s)

	Personal Offences	Household Offences
Offence too trivial	38	49
Police could do nothing	16	34
Inappropriate for police	13	5
Fear/dislike of police	6	1
Inconvenient	5	2
Police would not be interested	3	9
Fear of reprisals	2	<1
Reported to other authorities	3	2
Other reasons	21	10

Note: Columns sum to more than 100% because multiple reasons for not reporting were allowed.

Source: Hough and Mayhew (1983, p.11)

Interestingly reasons sometimes advanced by criminologists, such as fear/dislike of the police, seem to be of little significance. The two main reasons can be easily incorporated into the recording equation of the model (see Chapter 4).

3. Economists and Crime: An Historical Perspective

Whilst it is only recently that the economics of crime has become a popular branch of applied microeconomics, economists have for a long time had an interest in questions of crime and law enforcement.

For example, Adam Smith argued in the Theory of Moral

Sentiments (Smith, 1759) that social harmony or order could only be obtained by the exertion of certain forms of control over some aspects of human nature. Despite Smith's association with a free enterprise economy, he was not insensitive to the idea that individuals' pursuit of their own ends might lead them to act in ways that had harmful consequences for others. In such situations he felt that it was unrealistic to rely upon each individual's disposition to seek the approval of his/her fellows. General rules of justice and morality had to be constructed.

In The Wealth of Nations (Smith, 1776) Smith went further. He argued that one of the three functions of supreme importance which every State had to perform was, " ... the duty of protecting, as far as possible, every member of society from the injustice or oppression of every other member of it..." (Book IV,Chapter ix,p.51).

In his Lectures on Justice, Police, Revenue and Arms (Smith, 1763), he even briefly considered the relationship between crimes and economic circumstances. He argued, "(n)othing tends so much to corrupt mankind as dependence, while independency still increases the honesty of the people. The establishment of commerce and manufactures, which brings about this independency, is the best police for preventing crimes. The common people have better wages in this way than in any other, and in consequence of this a general probity of manners takes place through the whole country. Nobody will be so mad as to expose himself upon the highway, when he can make better bread in an honest and industrious manner", (pp.155-6).

Smith was not the first author to advance the argument that crime might be related to economic circumstances. Bonger (1916) attributed the first "scientific" exposition of the link to Thomas More. In Utopia, More strongly attacked the economic conditions prevailing in England. He also attacked the severity of the penalties for many crimes. Raphael Hythloday (More's narrator) argued, "(n)either is there any punishment so horrible, that it can keep them from stealing, which have no other craft whereby to get their living ... (G)reat and horrible punishments be appointed for thieves, whereas much rather provision should have been made, that there were some means, whereby they might get their living, so that no man should be driven to this extreme necessity, first to steal, and then to die." (More, 1551, p.29).

Beccaria-Bonesana expressed a similar sentiment when he wrote "... if theft is ordinarily the crime of poverty and despair, if this offence is committed only by that class of unfortunate men to whom the right of property ... has left no possession but mere existence, the imposition of a fine will contribute only to multiply thefts, by increasing the number of the indigent ..." (Beccaria-Bonesana, 1870, p.167).

Engels (1892) subscribed to the same view. He argued, in The Condition of the Working Class in England, "(a) class which bears all the disadvantages of the social order without enjoying its advantages, one to which the social system appears in purely hostile aspects - who can demand that such a class respect this social order? ... The contempt for the existing social order is most conspicuous in its extreme form - that of offences against the law" (pp.129-30).

The authors mentioned above based their arguments largely on introspection. However, as Bonger (1916) showed, during the nineteenth century there were numerous attempts to explore the link between crime and economic circumstances by statistical means. Bonger (1916, Chapter 2) surveys and comments upon several attempts to examine this link. Many of these studies were carried out by French statisticians such as Guerry, Quetelet, Ducpetiaux and Moreau-Christophe. However, similar studies for other countries were undertaken by Mayr, Von Oettingen and others. Most of these studies found that changes in the economic circumstances of the working class and great disparities in wealth between classes were associated with changes in the level of crime. However, later in the nineteenth century and the early part of this century, the idea that crimes were motivated by economic necessity was neglected, if not treated with scorn.

To some extent this neglect was caused by the rise of alternative schools of thought on the causes of criminality. Authors such as Lombroso and Ferri disputed the connection between economic conditions and crime. At the same time they claimed that the principal causes of crime were to be found in the physical and psychological make up of individuals, including " ... anomalies of the skull, brain, viscera, sensibility, reflex activity ... intelligence and feeling, especially of the moral sense and the peculiarities of the criminal dialect and literature ... race, age, sex ... civil status, profession, residence, social class and education ..." (Ferri, 1893, pp. 150-1). Economic factors, as such, were argued to be relatively minor influences upon crime. Work of this kind took criminology off into entirely new areas.

Lombroso, for example, was convinced that criminals were not variations from a norm, but a different sub-species of man, having distinct physical and mental characteristics, such as " ... assymetry of the face; excessive dimensions of the jaw and cheekbones ... ears of unusual size ... excessive length of arms ..." (quoted by M.E. Wolfgang in H. Mannheim (ed) Pioneers in Criminology, p.186). We do not dwell upon the virtues or otherwise of such an approach, though most economists would no doubt agree that it was unfortunate that criminologists did not follow a line of thinking suggested sometime before by Bentham. Bentham argued that criminal behaviour was entirely rational. Individuals pursued pleasure and avoided pain. If some individuals chose to perform criminal acts in the pursuance of pleasure, this must be because there was insufficient deterrence (or pain) attaching to those acts. (Bentham, 1896.)

It was not until the 1960s that economists once again began to discuss the causes of crime. Interest was sparked off by a number of articles by Belton Fleisher (1963, 1966a, 1966b). In these studies Fleisher examined, by correlation techniques, the relationship between unemployment, income and delinquency. He found strong correlations between income and unemployment levels and the rate of delinquency, using data for the cities of Chicago, Boston and Cincinnati. However, Fleisher's work lacked a rigorous theoretical treatment of the decision to engage in crime. Becker (1968) provided the first such analysis based upon the economist's utility maximising framework. This article has been influential in encouraging economists to study both criminal choice and policies to control crime. Since its appearance many further contributions have been made concerning either theoretical models of criminal behaviour or empirical studies of the determinants of crimes. Subsequently economists have extended their concern to examinations of law enforcement agencies and the formulation of optimal criminal justice policies. However, it is the economic explanation of criminal activity which forms the focus of this thesis.

4. Outline of the thesis

The ultimate objective of this thesis is an assessment of the extent to which economic analysis can be used to explain statistics of recorded property crime in England and Wales. In order to do this we will need to construct a small scale econometric model of the processes which generate those statistics. That model incorporates hypotheses about (i) why individuals commit crimes, (ii) how those crimes become reported to and recorded by the police, (iii) how the police "produce" deterrence and (iv) how society responds to crime by allocating resources to law enforcement.

In Chapter 2 we begin by examining the economic approach to criminal participation. This approach argues that (potential) criminals are not unlike other individuals. They are not necessarily mentally retarded or physiologically distinct. It is argued that all individuals decide whether or not to engage in criminal activity on the basis of the expected costs and benefits associated with crime compared with those arising from alternative uses of time and resources. Accordingly, individuals' decisions about participating in illegal activity are fairly straightforward applications of the theory of choice in risky situations.

At the heart of the economic approach is a model of the allocation of time between competing activities. Previous manipulations of this model have assumed that the amount of time devoted to leisure is fixed. This turns out to be a particularly restrictive assumption, the consequences of which have not previously been realised. One consequence, if one also assumes decreasing absolute risk aversion (which seems to be widely accepted in the risk literature), is that criminal activity is normal, i.e. it has a positive wealth effect. This in turn is sufficient to generate a whole string of unambiguous predictions about the effect of changes in law enforcement and earnings variables upon the amount of time devoted to illegal activity.

We feel uneasy abcut this property of the time allocation model and so in the Appendix to Chapter 2 we relax the assumption of fixed leisure. The result is that the model no longer generates unambiguous predictions about the effects of changes in law enforcement and earnings variables. This result has not previously been derived. It shows that earlier attempts to locate the source of the model's unambiguous predictions in particular assumptions about the measurement of psychic costs and benefits of illegal activity (see Block and Heineke, 1975) were possibly misplaced.

In Chapter 3 we review previous attempts to model the determination of the crime rate and the detection rate empirically. We begin by considering a number of methodological problems confronting attempts to estimate crime/law enforcement models at the macro level, i.e. the problems of (i) potential simultaneity between crime rates and detection

detection rates and (ii) under-recording of crime. Whilst both of these problems present some difficulties, they are not insurmountable. The remainder of Chapter 3 is an exhaustive critical assessment of earlier empirical studies.

In Chapter 4 we begin the task of constructing a formal model to explain recorded property crime-rates, detection rates and police employment in England and Wales. The model consists of four equations and one identity. The specification of each of the model's equations is dealt with in some detail. The equations model the determination of (i) the "true" crime-rate, (ii) the detection rate, (iii) police employment and (iv) the proportion of offences recorded/reported. The recording equation along with the identity is used to eliminate the unobserved variables, i.e. the "true" crime-rate and the "true" detection rate. Finally in Chapter 4 we consider the data sources that have been used to estimate the model.

The bulk of Chapter 5 is devoted to the presentation of the results of model estimation. However, there is also a brief discussion of choice of estimation technique and a number of tests of the model structure. The model has been estimated for three different samples, four different types of crimes, two (alternative) measures of the detection rate and two (alternative) measures of the severity of punishment. This generates a substantial body of results, which are further increased by performing a number of tests of alternative hypotheses.

In Chapter 6 we draw, from this large collection of results, some general conclusions about the determination of property crime-rates, detection rates and police employment.

On the whole the economic approach offers a reasonably good explanation of criminal justice data. Increases in the certainty and severity of punishment both tend to reduce rates of recorded property crimes. On the other hand increased payoffs to illegal activity and reduced legitimate earnings opportunities both tend to increase recorded property crime rates. The model also indicates that increases in police resources have a small, but positive effect, upon the detection rate and that increases in police workload have an adverse effect upon it.

A further conclusion of the research is that the clear up rate and the conviction rate are not alternative indicators of the detection rate. They perform quite differently in the crime equation and are explained sometimes by quite different variables. The difference between them is fully explored in Chapter 6. Our conclusion is that the clear up rate may be a relatively poor indicator of the probability of detection.

Most of Chapter 6 is concerned with interpreting the structural equations of the model. However, meaningful predictions about the overall effect of a change in one of the model's exogenous variables can only be found by deriving the multipliers from the reduced form of the model. This is done in Chapter 6 too. However, as our primary interest is in understanding behaviour rather than with making forecasts, the examination of the reduced form is only brief. Finally in Chapter 6 we touch upon the question of whether imprisonment reduces crime through incapacitation of offenders or through a general deterrent effect. However, the results here must be regarded as extremely tentative.

Chapter 2 : Economic Models of Criminal Behaviour: A Review

The idea that crimes may be at least partly explained by economic forces has long been the subject of speculation (see, for example, Bonger (1916)). However, the first attempt to build a rigorous economic theory of participation in crime did not come until quite recently. Its appearance can be dated quite precisely as 1968 with the publication of Becker's "Crime and Punishment: An Economic Approach" in the Journal of Political Economy (Becker (1968)). There Becker argued that criminals behaved basically like all other individuals in that they attempted to maximise utility subject to a budget constraint. The important distinguishing characteristic of criminal activity, which Becker treated as an aspect of labour supply, was the inherent uncertainty of its rewards owing to the possibility of detection and subsequent punishment.

According to Becker's thesis an individual committed a crime if the expected utility to be derived from committing it was greater than the utility to be gained from engaging in the alternative legitimate activity. Involvement in crime was, therefore, determined by the relative benefits and costs associated with various activities.

Becker drew from this analysis a number of important and controversial conclusions for the design of criminal justice policy, but we do not discuss these points here (see Pyle (1983, chapter 5)) for an extended treatment). We concentrate instead upon the economic theory of criminal participation itself. Our concern is with examining the decision to commit crime(s) and how that decision is affected by certain criminal justice variables and other socio-economic factors. We are not directly concerned with planning an optimal policy towards crime.

We begin by briefly exploring Becker's analysis of criminal choice. However, since Becker's original contribution there have been a number of significant theoretical developments. Becker's model is just one of a class of models concerned with the allocation of time (or effort) between legitimate and illegal pursuits. These models have, in various ways, tried to acknowledge the existence of any non-monetary benefits and costs of criminal activity. Whilst this has most often been achieved by converting psychic costs and benefits into a wealth equivalent (see, for example, Becker (1968) and Ehrlich (1973)), others have tried to generalise the model to situations where monetary (or wealth) equivalents cannot be so assigned (see Block and Heineke (1975)). Ehrlich (1973) extended Becker's model, whilst staying within the time allocation framework, to allow for non-specialisation in either criminal or legitimate activity. He also applied the model to an examination of the crime of murder and the deterrent effect of capital punishment (Ehrlich (1975a)). Given the importance of these contributions we will spend some time examining the properties of both Ehrlich's and Block and Heineke's models. As we shall see, both of these models have some restrictive assumptions which produce some rather odd properties. Therefore, in the appendix to this chapter, we offer a generalised model of the allocation of time between illegal and legitimate activities.

A second class of models has been developed by authors such as Allingham and Sandmo (1972), Kolm (1973) and Singh (1973). These view the offence decision as a portfolio allocation problem. Here the individual is assumed to choose what portion of his wealth to put at risk by engaging in crime (see Heineke (1978b) for a review of the properties of these models). However, these models are only suitable in situations where all of the benefits and costs (including punishment) associated with illegal activity can be assigned monetary values and more importantly where the labour input into crime is small. Each of the articles mentioned above has focussed exclusively on the crime of income tax evasion. The fact that the benefits of successful income tax evasion are purely monetary may seem to make it a suitable crime for this kind of treatment. However, it is doubtful whether all of the consequences of unsuccessful tax evasion are purely monetary e.g. the loss of respectability if convicted. Also, if income tax evasion is a time consuming activity then portfolio models will be inappropriate. The empirical analysis of chapters (4-6) concentrates upon the crimes of burglary, robbery and theft. The execution and planning of these crimes is, in varying degrees, a time-consuming activity. In view of the uncertainty attaching to the applicability of portfolio models to such crimes we do not discuss them directly. We concentrate instead upon the time allocation models of Becker, Ehrlich and Block and Heineke.[1]

1. Becker's Model

Becker developed an "economic" theory of criminal behaviour as a direct response to various sociological, criminological and psychological theories based upon skull types, biological inheritance, differential association, anomie and family upbringing.[2] He wished to build a rather more general theory of criminal participation which could incorporate such non-economic theories as special cases.

He argued that an individual's decision whether or not to act criminally could be analysed by exactly those tools used by economists in

---

1. It would be wrong to over-emphasise the differences between these two classes of models. Ehrlich's model has many of the properties of a portfolio model of the allocation of time (rather than of wealth). Consequently the predictions of his model are remarkably similar to those of Allingham and Sandmo.

2. A fairly comprehensive survey of such theories of crime is contained in Mannheim (1960).

analysing other decisions i.e. by utility theory. His basic contention was that all individuals were rational utility maximisers. They decided whether or not to commit a particular crime by comparing the utility they would expect to gain from acting illegally with that which they could gain by using their time and resources in the pursuit of legitimate endeavours.

To Becker, then, an individual became a criminal not so much because his motivation differed from that of other individuals, but because his perception of the costs and benefits associated with criminal acts was different.

Becker's model is a relatively straightforward adaptation of the subjected expected utility hypothesis to the problem of criminal participation. A possible weakness of this approach is its insistence that individuals should not derive pleasure from the undertaking of risk itself. In this case they should not actually enjoy committing crime for its own sake. Each individual is assumed to obey the von Neumann-Morgenstern axioms for behaviour in risky situations. (S)he is assumed to compare the expected utility to be gained from the risky alternative (engaging in crime) with that to be obtained from the riskless activity (legitimate employment).[3]

Suppose that an individual has a present wealth of W_o. He is contemplating committing a crime the potential gain, if successful, being G and the expected loss, if caught, is L. (G and L are monetary equivalents of any gains or losses.) The probability of being caught and punished is p.

---

3. Becker implicitly assumed the returns from legitimate work to be riskless. This is clearly an oversimplification, because periods of unemployment or sickness will make the returns from legitimate activity risky too. However, social security benefits will tend to reduce the consequences of such risks. We discuss the consequences of unemployment "risk" for entry into crime and the amount of time devoted to crime below.

If he committed the crime the individual's expected utility (EU) would be; given by,

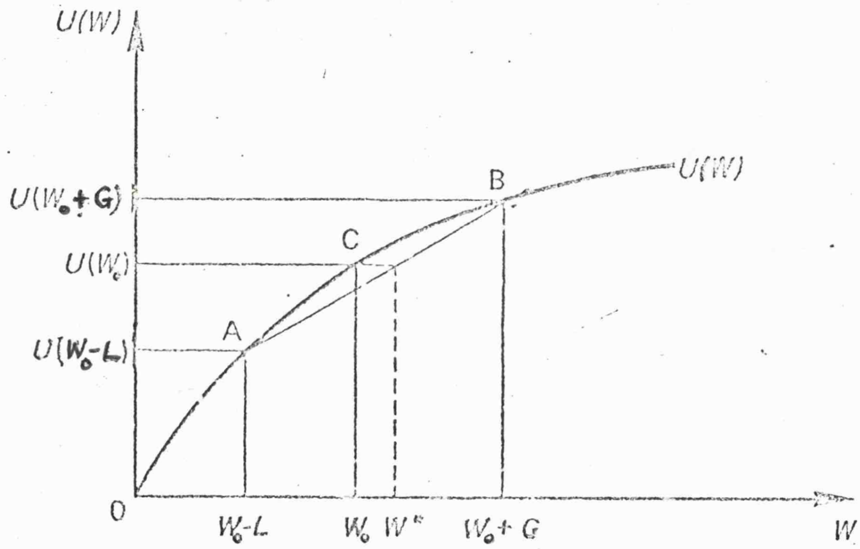
$$EU = pU(W_o - L) + (1 - p)\, U(W_o + G) \qquad (1)$$

where U( ) is the individual's von Neumann-Morgenstern utility index.

If EU $> U(W_o)$, the utility of the certain alternative, then he will commit the crime. Whether EU will be greater than $U(W_o)$ will depend upon (i) the individual's attitude to risk and (ii) the sizes of L, G and p. Even if he is risk averse (i.e. has a diminishing marginal utility of wealth) he will commit the crime if p and L are sufficiently small and G is sufficiently large. To see this consider Figure 2.1.

In Figure 2.1 we have drawn a utility of wealth function for someone who is risk averse. The utility of the certain alternative is given by $U(W_o)$ i.e. by point C. The expected utility of the risky alternative will be somewhere along the chord AB. Precisely where will depend upon the probability of being caught. If p = 1 then EU = $U(W_o - L)$ i.e. point A. If p = 0 then EU = $U(W_o + G)$ i.e. point B. For values of p between 0 and 1 EU will be given by points along AB. If p is sufficiently small, so that expected wealth $= p\,(W_o - L) + (1 - p)\,(W_o + G)$ is greater than W* then the crime will be committed even though the individual risk averse. However, a risk avoider would clearly reject fair risks, i.e. situations where the expected wealth from criminal activity was equal to W_o, and would even reject some favourable risks (where expected wealth is greater than W_o but less than W*) Crime must, therefore, pay before someone who is risk averse will enter the activity.

It is fairly easy to show that a risk neutral individual would accept some fair risks, whilst someone with a preference for risk would even accept


U(W)
U(W)
B
U(W₀+G)
C
U(W₀)
A
U(W₀-L)
0
W₀-L
W₀
W*
W₀+G
W

some unfavourable risks.[4] Whether individuals engage in crime will obviously depend upon (i) expected gains and losses, (ii) individuals' perceptions of the probability of being caught and punished and (iii) attitudes to risk.

Changes in the probability of capture and punishment, the severity of punishment and gains from crime can be investigated quite simply by differentiating equation (1) with respect to p, L and G. i.e.

$$\frac{\partial EU}{\partial p} = U(W_o - L) - U(W_o + G) < 0$$

$$\frac{\partial EU}{\partial L} = - p\, U'(W_o - L) < 0 \qquad (2)$$

$$\frac{\partial EU}{\partial G} = (1 - p)\, U'(W_o + G) > 0$$

where $U'(\ )$ is the marginal utility of wealth, which is assumed to be positive.

Clearly changes in either the certainty or severity of punishment (p and L respectively) will reduce expected utility from engaging in crime and so will reduce the number of crimes committed (irrespective of attitudes to risk). On the other hand an increase in expected gains from crime (G) will increase expected utility and hence offending.

Becker, therefore, postulated a supply of offences function for the ith individual which was of the form,

$$C_i = C_i (L_i, p_i, u_i)$$

where C_i is the number of offences committed per period of time by the ith

---

4. Clearly whether crime "pays" will depend upon individuals attitudes to risk. For example, risk preferrers who repeatedly accept unfair risks will eventually find their wealth reduced.

individual, L_i and p_i are individual i's subjectively held views of the severity and certainty of punishment and u_i represents factors such as "... the income available to him in legal and other illegal activities, the frequency of nuisance arrests, and his willingness to commit an illegal act". (Becker (1968, p. 177)). He then suggested a "market" supply of offences function having the same general properties i.e.

$$C = C(L, p, u)$$

where L, p and u are the average values of L_i, p_i and u_i respectively.

Becker's predictions about the deterrent effects of punishment were unambiguous.[5] His model clearly lends support to a deterrence theory of crime. However, Becker's model has relatively little to say about the precise magnitudes of the deterrent effects, even as to which is the larger. Whether certainty of punishment (p) or its severity (L) is a more effective deterrent was felt, by Becker, to hinge upon individual's attitudes to risk.[6]

Becker's approach was subsequently refined and extended by Ehrlich (1973). He incorporated into the concept of opportunities not only punishments but also rewards from illegal and legitimate pursuits. In other words he tried to link the theory of criminal choice to the theory of the optimal allocation of resources to competing activities in conditions of risk.

---

5. Later contributors did not always share this view. See below.

6. This view was subsequently refuted by both Brown and Reynolds (1973) and Heineke (1975). See Pyle (1983, Chapter 5) for a discussion of this point.

2. Ehrlich's Model

Ehrlich formulated the criminal choice problem in terms of state-preference theory. It is only legitimate to apply state-preference theory to situations where all of the possible outcomes can be given monetary values. Accordingly, Ehrlich needed to attach monetary equivalents to the various psychic costs and benefits arising from criminal and legitimate activity.[7]

State-preference theory not only requires that all the possible outcomes have definite monetary values, but also that during any time period only one of a number of well defined states of the world will occur. Ehrlich generally assumed only <u>two</u> possible states of the world. These were (i) the individual is caught and punished and (ii) he is not caught and, therefore, not punished. Other states of the world are, of course, possible, e.g. individuals are caught, but not punished or innocent individuals are wrongfully arrested and punished. However, for the exposition of this section we shall follow Ehrlich and assume only two possible states of the world i.e. (i) and (ii) above.[8]

---

7. He, therefore, defined an individual's wealth as "... assets, earnings within the period and the 'real wealth' equivalents of non-pecuniary returns from legitimate and illegitimate activity". (Ehrlich (1973, p. 525)).

8. It would be wrong to give the impression that Ehrlich was not aware of other possible outcomes. For example in an appendix to his paper he introduced the possibility of unemployment in legitimate activity. Whilst this makes the analysis considerably more complex (<u>two</u> new states of the world being added), it does not alter the model's basic predictions. Except that unemployment "risk" means that individuals are more likely to enter criminal activity in the first place and that an increase in unemployment is likely to lead those already engaged in crime to spend more time in that activity. This latter result depends in part upon their attitude to risk. See Section 4 of this chapter.

We will define X_u as the money value of the individual's wealth, both precuniary and non-pecuniary, if he is caught and punished. Likewise we will define X_s as the money value of his wealth if he is successful in not being caught and punished. Monetary wealth will therefore differ in the two states by the monetary equivalent of the punishment.

Individuals have to decide how to allocate their available time between legitimate and illegal activities. Ehrlich assumed that individuals allocated a fixed amount of time (t_c hours) to consumption activities (i.e. leisure).[9] Leisure activities are implicitly assumed by Ehrlich to be legitimate pursuits i.e. they do not include activities such as drug taking, illicit sexual behaviour and so on. It is relatively easy to generalise the model to allow for these kinds of activities, however.

Given a fixed allocation to leisure the remaining t hours are allocated between either illegal or legitimate income generating activity.[10] If we label t_i as the amount of time devoted to crime, then $t - t_i$ $(= t_l)$

---

9. This assumption turns out to be crucial in determining some of the comparative static properties of Ehrlich's model. Fixing leisure time makes crime and legitimate work substitutes. It also leads to the perhaps strange prediction concerning the "normality" of criminal behaviour (see below and the appendix to this chapter where we relax that assumption).

   In an appendix to his paper Ehrlich did relax this assumption, but then imposed an equally restrictive assumption that the utility function was strictly separable i.e.

   $\frac{\partial^2 U}{\partial X_i \partial t_c} = 0 \quad i = u, s.$ This implies that the marginal utility of leisure is independent of one's wealth.

10. Note that criminal activity seems to be restricted to income generating acts such as burglary, robbery, fraud, theft, etc. Criminal activities such as rape, assault, drug-taking which do not generate income are implicitly excluded, except where they generate psychic benefits which have a monetary equivalent.

hours is available for legitimate employment. Ehrlich further assumed that returns to both forms of activity depend solely upon the amount of time spent in that activity.[11] Also, the size of the punishment is argued to depend only upon the amount of time spent in crime. Therefore, we can write an individual's wealth in the two states of the world as,

$$X_u = W_o + W_i\ (t_i, \alpha) + W_1\ (t - t_i, \beta) - F_i\ (t_i, \gamma) \tag{3}$$

and $$X_s = W_o + W_i\ (t_i, \alpha) + W_1\ (t - t_i, \beta)$$

where W_o is the value of his wealth which is independent of his endeavours, W_i is wealth generated from illegal activity, W_1 is wealth arising from legitimate work, F_i is the monetary equivalent of the punishment and α, β and γ are shift parameters.

Ehrlich adopted a theoretical framework in which each individual considers how to allocate his time and resources between crime and legitimate employment for each period in turn.[12] Each individual is assumed to make his choice so as to maximise his expected utility in that period, which is given by,

$$EU = p\ U(X_u) + (1 - p)\ U(X_s) \tag{4}$$

where p is the probability of being caught and punished and U( ) is a

---

11. This implicitly rules out situations where crimes are committed whilst engaging in legitimate activity i.e. "on the job" crimes such as computer fraud, white collar crime etc. The model could, however, be fairly easily adapted to partially incorporate such activities by, for example, making returns to illegitimate activity a function of time devoted to legitimate work as well as time spent in illegitimate activity.

12. It is, of course, conceivable that choices this period about how to allocate one's time are not independent of previous choices. Suppose having decided to engage in crime in a previous period one is caught and punished. The acquisition of a criminal record may then have an influence upon the amount and kind of legitimate activity, if any, that is on offer this period. For the purposes of this chapter we ignore that complication.

von Neumann-Morgenstern utility index. In what follows we shall assume that p is independent of t_i. The argument that p may instead depend upon t_i has a superficial plausibility. However, it is not altogether clear whether more time spent in crime is likely to increase or reduce the chances of one being caught.[13]

In this model each individual has only one choice variable available to him i.e. either t_i or t_l. Once one of these is selected the other is automatically determined and so, therefore, will be his wealth in states u and s. Given that p is fixed exogenously he can maximise (4) by an appropriate choice of t_i alone. Differentiating (4) with respect to t_i and setting the result equal to zero gives the following first order condition for utility maximisation,

---

13. Ehrlich investigated the possibility that p was (positively) related to t_i at the margin. His results were basically unaffected by this assumption, however.

$$\frac{dEU}{dt_i} = p\,U'(X_u)(W_i' - W_1' - F_i') + (1-p)\,U'(X_s)(W_i' - W_1') = 0 \qquad (5)^{14}$$

where U ( ) is the marginal utility of wealth (assumed positive) and

$$W_i' = \frac{dW}{dt_i},\ W_1' = \frac{dW}{dt_1} \text{ and } F_i' = \frac{dF_i}{dt_i}.$$

As $U'(\ ) > 0$ and $1 > p > 0$ and interior optimum clearly requires

that $W_i' > W_1'$

and $W_i' - F_i' < W_1'$;

---

14. In setting (5) equal to zero we are implicitly assuming that $t > t_i > 0$ i.e. a local, interior maximum holds. If either $t_i = 0$ or $t_i = 1$ then (5) would be an inequality. The second order condition for a maximum is,

$$\frac{d^2EU}{dt_i^2} = D = p\,U''(X_u)(W_i' - W_1' - F_i')^2 + p\,U'(X_u)\left[\frac{dW_i'}{dt_i} + \frac{dW_1'}{dt_1} - \frac{dF_i'}{dt_i}\right] +$$

$$(1-p)\,U''(X_s)(W_i' - W_1')^2 + (1-p)\,U'(X_s)\left[\frac{dW_i'}{dt_i} + \frac{dW_1'}{dt_1}\right] < 0$$

where $U''(\ )$ is the second derivative of the utility function. This condition would be satisfied in any one of a number of different situations, e.g.

(i) $U''(X_u),\ U''(X_s) < 0$ and $\frac{dW_i'}{dt_i},\ \frac{dW_1'}{dt_1} < 0,\ \frac{dF_i'}{dt_i} > 0.$

(ii) $U''(X_u) = U''(X_s) = 0$ and $\frac{dW_i'}{dt_i},\ \frac{dW_1'}{dt_1} < 0,\ \frac{dF_i'}{dt_i} > 0$ and

(iii) $U''(X_u),\ U''(X_s) > 0$ but the expressions in the square brackets sufficiently negative.

D will be useful when examining the comparative static properties of Ehrlich's model.

Finally we shall assume that all of the functions used in this Chapter are continuous and possess continuous derivatives of sufficient order to enable us to reach the conclusions we do.

Rearrangement of (5) gives

$$\frac{- p\, U'(X_u)}{(1 - p)\, U'(X_s)} = \frac{W_i' - W_1'}{W_i' - W_1' - F_i'} \tag{6}$$

The left hand side of (6) is an expression for the slope of an indifference curve in X_u, X_s space. This can perhaps be more easily seen as follows. As

$$EU = p\, U(X_u) + (1 - p)\, U(X_s)$$

then along any indifference curve in X_u, X_s space

$$dEU = p\, U'(X_u)\, dX_u + (1 - p)\, U'(X_s)\, dX_s = 0$$

or

$$\left.\frac{dX_s}{dX_u}\right|_{EU} = \frac{- p\, U'(X_u)}{(1 - p)\, U'(X_s)} \tag{7}$$

Similarly we can see that the right hand side of (6) is an expression for the slope of a transformation function in X_u, X_s space.

$$\frac{dX_s/dt_i}{dX_u/dt_i} = \left.\frac{dX_s}{dX_u}\right|_t = \frac{W_i' - W_1'}{W_i' - W_1' - F_i'} \tag{8}$$

Clearly both the indifference curves and the transformation curve in X_u, X_s space are negatively sloped. However, before we can actually draw them we need to know more about their properties i.e. are they convex or concave to the origin?

Differentiating (7) again we obtain

$$\frac{d^2X_s}{dX_u^2} = \left[- p(1-p)U'(X_s)U''(X_u) + p(1-p)U'(X_u)U''(X_s) \frac{dX_s}{dX_u}\right] \Big/ \left[(1-p)U'(X_s)\right]^2$$

If both $U''(X_s)$ and $U''(X_u)$ are negative (i.e. individuals are risk averse) then $\frac{d^2X_s}{dX_u^2}$ will be unambiguously positive and the indifference curves will be convex to the origin. Preference for risk ($U''(X_s) > 0$ and $U''(X_u) > 0$) would imply indifference curves concave to the origin. Finally risk neutrality ($U''(X_s) = U''(X_u) = 0$) implies linear indifference curves. Recall footnote 14 and the sufficient conditions for a maximum.

The concavity of the transformation curve can be found by differentiating (8) with respect to X_u. This gives

$$\frac{d^2X_s}{dX_u^2} = \frac{(W_i' - W_1' - F_i')\left[\frac{dW_i'}{dt_i} + \frac{dW_1'}{dt_1}\right]\frac{dt_i}{dX_u} - (W_i' - W_1')\left[\frac{dW_i'}{dt_i} + \frac{dW_1'}{dt_1} - \frac{dF_i'}{dt_i}\right]\frac{dt_i}{dX_u}}{(W_i' - W_1' - F_i')^2}$$

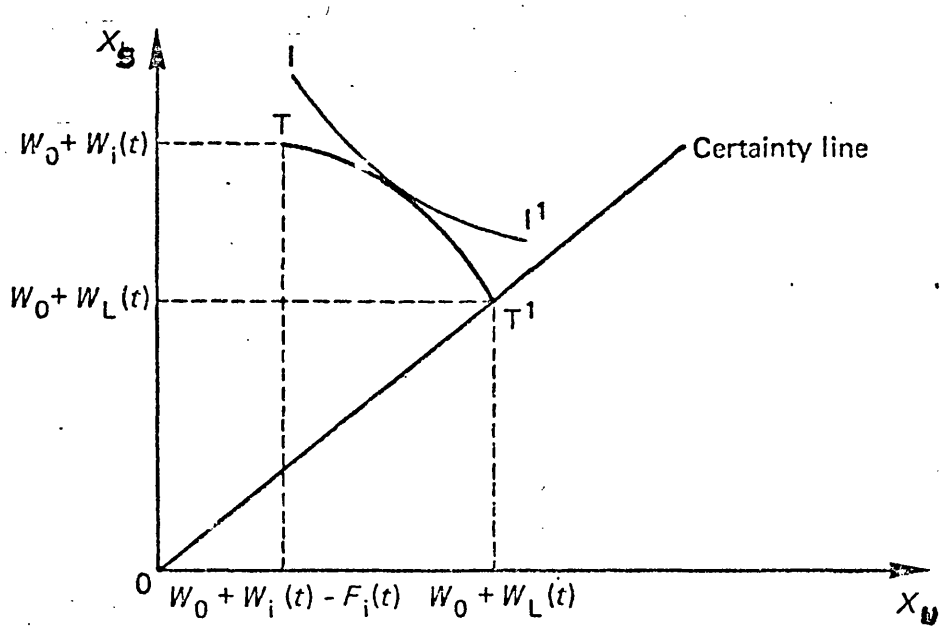
The transformation curve will be unambiguously concave if the expressions in the square brackets are both negative i.e. if $\frac{dW_i'}{dt_i} < 0$, $\frac{dW_1'}{dt_1} < 0$ and $\frac{dF_i'}{dt_i} > 0$.[15] It will be linear only if the expressions in the square brackets are exactly zero. Again recall the second order condition for a maximum given in footnote 14.

---

15. This amounts to assuming diminishing returns to both legitimate and illegal activity. Increasing returns to both kinds of activity would imply a convex transformation curve. An interior optimum seems to be less likely in that situation. A convex transformation curve was ruled out by Ehrlich.

If we are prepared to assume that individuals are risk averse and that the transformation curve is concave to the origin then we can draw a diagram to illustrate the case of someone who diversifies his effort between crime and legitimate activity. This is done in Figure 2.2. However, we should note that convexity of the indifference curves and concavity of the transformation function do not guarantee an interior optimum. We could, for example, have a corner solution at either T or T'.

Figure 2.2 Risk aversion and the optimal allocation of time to illegitimate activity



Note: If an individual only engages in legitimate activity then irrespective of whichever state of the world obtains his wealth will be $W_o + W_1(t)$. This is represented by point T'. As he spends more time in crime then wealth in State s increases, but that in State u will decline. If this were not to be the case then there would be no incentive to engage in criminal activity. As a consequence $W_o + W_i(t) > W_o + W_1(t)$. Likewise $W_o + W_i(t) - F_i(t) < W_o + W_1(t)$. For without that assumption no one would ever engage in legitimate activity. It is reasonable to argue, therefore, that TT' is downward sloping (see (8)).

An interior optimum could be achieved if the indifference curves were linear and even if they were concave, provided that in the latter case their curvature is less marked than it is for the transformation curve. (See footnote 14 on the second order condition for a maximum.)

It is interesting to ask what condition must hold, at the margin, before an individual would be willing to become involved in crime? This can be found by evaluating

$$\left.\frac{dEU}{dt_i}\right|_{t_i = 0} = p\, U'(X_u)(W_i' - W_1' - F_i') + (1 - p)U'(X_s)(W_i' - W_1') > 0$$

which can be rewritten as

$$\frac{W_i' - W_1'}{W_i' - W_1' - F_i'} > \frac{-\,p\, U'(X_u)}{(1 - p)U'(X_s)} \tag{9}$$

In other words, at T' the transformation curve must have a steeper slope than an indifference curve passing through that point. As at T' $X_u = X_s$ then (9) can be simplified to provide the following "entry" condition,

$$W_i' - p\, F_i' > W_1'$$

"Entry" into illegal activity requires that the marginal expected return in crime be greater than the marginal return in legitimate employment. In this sense crime must pay before an individual will <u>enter</u> the "profession". Whether crime pays <u>at the optimum</u> depends upon the attitudes to risk.[16]

In order to establish qualitative predictions about the supply of offences function we need to consider how the amount of time individuals devote to crime responds to changes in the various factors affecting their decision. In particular we are interested in how t_i will respond to changes in the certainty and severity of punishment, the differential return from illegal activity and so on. In order to demonstrate the comparative static properties of the model we shall assume an interior optimum i.e. equation (5) holds.

It is now a relatively straightforward exercise in comparative static analysis to examine the effect of changes in the deterrence and other variables by differentiating equation (5) with respect to each variable.

---

16. The proof of this proposition is relatively straightforward, but rather tedious. Therefore, we sketch only the essentials of the proof.

For an interior solution equation (6) must hold. An interior solution also implies that $X_s > X_u$. For a risk avoider $U''(\ ) < 0$, so that $U'(X_s) < U'(X_u)$. For a risk neutral invididual $U'(X_s) = U'(X_u)$ and for a risk preferrer $U'(X_s) > U'(X_u)$. Insertion of these conditions into equation (6) and some simplification shows that, <u>at the optimum</u>,

(i) for a risk avoider $E(W_i') = W_i' - p\,F_i' > W_1'$

(ii) for a risk neutral individual $E(W_i') = W_1'$

and (iii) for a risk preferrer $E(W_i') < W_1'$

These conditions, when allied with the "entry" condition that

$$E(W_i') > W_1'$$

and the assumption of diminishing returns to both legitimate and illegitimate activity, are sufficient to ensure that a risk avoider will spend <u>less</u> time in crime than someone who is risk neutral and he in turn will spend less time in crime than a risk preferrer.

First, consider the effect of a change in the probability of detection (p). In this case

$$\frac{\partial t_i}{\partial p} = \frac{-U'(X_u)(W_i' - W_1' - F_i') + U'(X_s)(W_i' - W_1')}{D} < 0 \qquad (10)^{17}$$

where D is the second order condition for a maximum and is, by definition, negative (see footnote 14). The model predicts that the probability of detection exerts an unambiguous deterrent effect.

The effect of an increase in the severity of punishment can be found by differentiating (5) with respect to the shift parameter γ and solving for $\frac{\partial t_i}{\partial \gamma}$. This gives

$$\frac{\partial t_i}{\partial \gamma} = p\,\frac{U'(X_u)\,F'_{i\gamma} + U''(X_u)(W_i' - W_1' - F_i')\,F_{i\gamma}}{D} \qquad (11)$$

By definition $F_{i\gamma} > 0$. The first order condition requires that $W_i' - W_1' - F_i' < 0$. If also $F'_{i\gamma} > 0$ and $U''(X_u) < 0$ then $\frac{\partial t_i}{\partial \gamma}$ is unambiguously negative. Should these conditions not hold then the effect of an increase in the severity of punishment may be perverse. However,

---

17. By assumption $U'(X_u)$, $U'(X_s) > 0$. The first order condition requires that $W_1' - W_1' - F_i' < 0$ and $W_i' - W_1' > 0$.

there remains a strong supposition that $\frac{\partial t_i}{\partial \gamma} < 0.$ [18]

Before we are able to investigate the effect of an increase in returns to illegal activity $(\frac{\partial t_i}{\partial \alpha})$ or returns to legitimate endeavours $(\frac{\partial t_i}{\partial \beta})$ we need to examine the impact of a change in exogenously determined wealth i.e. W_o. If we differentiate equation (5) with respect to W_o and solve for $\frac{\partial t_i}{\partial W_o}$ we obtain the following,

$$\frac{\partial t_i}{\partial W_o} = - \frac{\left((1 - p)U''(X_s)(W_i' - W_1') + p\,U''(X_u)(W_i' - W_1' - F_i')\right)}{D} \qquad (12)$$

The sign of this expression depends upon whether or not individuals display

---

18. An increase in the average punishment which left the marginal punishment unchanged would imply that $F_{i\gamma}' = 0$. If then an individual had a preference for risk (i.e. $U''(X_u) > 0$) an increase in γ would lead him to spend more time in criminal activity.

decreasing absolute risk aversion.[19] If they do, then $\frac{\partial t_i}{\partial W_o}$ is unambiguously positive and increases in exogenously determined wealth will lead individuals to spend more time in illegal activity, i.e. crime is "normal".

Normally, one would expect an increase in wealth to lead to a fall in the supply of work effort unless leisure is an inferior good. However, Ehrlich's assumption that leisure is fixed is crucial at this point. That assumption, when allied to the assumption of decreasing absolute risk aversion, is sufficient to cause $\frac{\partial t_i}{\partial W_o} > 0$.

The fact that Ehrlich's model predicts that criminal activity is normal does not seem to have always been appreciated in the literature.

---

19. To see this we define the Arrow-Pratt measures of absolute risk aversion as

$$R_u = -\frac{U''(X_u)}{U'(X_u)} \quad \text{and} \quad R_s = -\frac{U''(X_s)}{U'(X_s)}.$$

If we now substitute these expressions into (12) the top line becomes

$$R_s(1-p)\,U'(X_s)(W_i' - W_1') + R_u\,p\,U'(X_u)(W_i' - W_1' - F_i')$$

which can be further simplified to

$$R_s.S + R_u.T$$

From equation (5) we can see that $S = -T$, so that we can write the top line of (12) as $T(R_u - R_s)$. As $X_s > X_u$ and decreasing absolute risk aversion is defined as $\partial R/\partial X < 0$, then $R_u > R_s$. As $T = p\,U'(X_u)$ $(W_i' - W_1' - F_i') < 0$ the top line is negative and

$\partial t_i/\partial W_o > 0$

Ehrlich himself does not comment upon it, largely one suspects because he failed to establish that it existed. Heineke (1978b, p. 21) establishes it but fails to comment on its peculiarity. Carr-Hill and Stern (1979, pp. 53-5) using a somewhat different theoretical model, similar to that in section 1 of this chapter, establish the result that the wealthy are more likely to commit crimes. However, they claim that "their" result is at variance with the time allocation models.[20] At the same time they claim that the "normality" prediction arises because the economic model ignores ".... important issues concerned with the formation of attitudes and preferences ...." (p. 56).

In fact the proof of the normality of criminal activity has been "fudged". As the allocation of time to leisure is fixed then increases in wealth cannot lead to more time being devoted to leisure. All that can happen is that time may be reallocated between crime and legitimate endeavour.[21] If we further assume that individuals display decreasing absolute risk aversion then as crime is risky and legitimate endeavour is riskless it follows that individuals must respond to an increase in wealth by spending more time in criminal activity and less in legitimate work.

---

20. "The models of the allocation of time between legal and illegal activities generally arrive at the conclusion that the poor are more likely to offend" (Carr-Hill and Stern (1979, p. 53)).

21. If there was a fixed working week in legitimate activity then t_1 would, of course, be entirely unaffected by changes in anything!

This result seems unsatisfactory and it is interesting to ask whether it is dependent upon the assumption that leisure is fixed. In the appendix to this chapter we develop a generalisation of Ehrlich's model which dispenses with that assumption.[22] There we establish that the assumption of fixed leisure is crucial to producing unambiguous predictions about the effects upon t_i of changes in wealth, legal and illegal returns and so on. In general it is not possible to establish unambiguous predictions. This should not, of course, be particularly surprising. As we know from choice theory price and "wage" changes produce both income and substitution effects. In general income effects cannot be signed, a priori, and so unambiguous predictions cannot be established.

Returning to Ehrlich's model we consider the effect of a change in returns to illegal activity i.e. $\frac{\partial t_i}{\partial \alpha}$. Differentiating equation (5) with respect to α we obtain,

$$\frac{\partial t_i}{\partial \alpha} = - \frac{W_{i\alpha}' \, ({}^{\partial EU}/\partial W_o)}{D} + W_{i\alpha} \frac{\partial t_i}{\partial W_o} \qquad (13)$$

---

22. Heineke (1978b) has also attempted to generalise Ehrlich's model in the same way. Unfortunately his conclusions must be treated with some scepticism, because he ignored the time constraint in establishing the first order conditions for a maximum. This led him to conclude that an interior optimum required the wage rate in legal activity to be zero! Far from leading him to re-examine his attempts at differentiation he concluded that this was one of ".... the consequences of the specialised monetary equivalents" (p. 15)! In an appendix to his paper Ehrlich did allow leisure time to vary, but imposed the restrictive assumption of strict separability of the utility function i.e. $\frac{\partial^2 U}{\partial X_i \partial t_c} = 0$ $\quad i = u,s$. This implies that the marginal utility of leisure is independent of wealth. This unreasonable and restrictive assumption enables him to produce another set of unambiguous predictions about the effects upon t_i of changes in the certainty and severity of punishment.

By definition both $W_{i\alpha}'$ and $W_{i\alpha}$ are positive. If we accept that $\frac{\partial t_i}{\partial W_o} > 0$ ((12) above) then $\frac{\partial t_i}{\partial \alpha} > 0$ and an increase in illegal "pay offs" will cause individuals to spend more time in illegal activity.

Finally an increase in returns to legitimate activity can be found by differentiating (5) with respect to β and solving for $\frac{\partial t_i}{\partial \beta}$ i.e.

$$\frac{\partial t_i}{\partial \beta} = \frac{W_{1\beta}' \left(\partial EU/\partial W_o\right)}{D} - W_{1\beta} \left(\partial t_i/\partial W_o\right) \qquad (14)$$

which will be negative if $\frac{\partial t_i}{\partial W_o} > 0$.

In establishing the comparative static properties of Ehrlich's model we have, of course, assumed an interior optimum in which individuals allocate part of their time to illegal activity. This generates a series of unambiguous predictions about the effects of the various parameter changes upon the amount of time devoted to crime - conditions (10) to (14) above.

However, individuals who specialise either in legitimate activity or illegal activity may be unaffected by marginal changes in these parameters and so $\frac{\partial t_i}{\partial p}$, $\frac{\partial t_i}{\partial \gamma}$ etc may in that case be zero. However, the model would predict that if these parameters were increased sufficiently then even "specialists" would eventually be led to alter their behaviour.

The response of individuals is seen, therefore, to depend upon the extent of their involvement in crime. "Professional" criminals may not, therefore, respond to small changes in the probability of conviction or the severity of punishment. Such behaviour is, of course, not necessarily irrational, but may be an entirely rational response to the opportunities facing them.

The models of Becker and Ehrlich treat the psychic costs and benefits associated with crime and legitimate activity in a similar manner i.e. by assigning to them monetary equivalents. In that case the decision to engage in crime can be summarised entirely in terms of its effect upon monetary wealth (especially as leisure is fixed). Some investigators have questioned whether such an approach is capable of capturing all of the influences upon the decision to engage in crime. In particular Block and Heineke (1975) argue that this approach generates a series of unjustified, unambiguous predictions ((10) to (14) above) which do not hold when the criminal choice problem is widened to include its non-monetary aspects. We now briefly discuss their model and its predictions about the effects upon t_i of changes in the deterrence and other variables.

3. Block and Heineke's Model

Block and Heineke argued that a general treatment of criminal choice must consider explicitly the psychic costs of engaging in crime and legi - mate activity rather than collapse their influences into a monetary equivalent. They did this by including the amounts of time spent in crime and legitimate work as arguments of the utility function. The individual's utility function then becomes,

$$U = U(t_i, t_1, W)$$

where W is the individual's level of wealth.

It is further assumed that $\frac{\partial U}{\partial t_i}$ and $\frac{\partial U}{\partial t_1} < 0$ i.e. that "work" of both kinds is unpleasant or onerous.

In what follows we shall adapt Block and Heineke's model to be consistent with the earlier treatments of Becker and Ehrlich. The essential difference between our treatment and that of Block and Heineke (henceforth BH) is that they treated the probability of capture as a random, stochastic variable. Instead we shall treat it as a fixed, but unknown parameter. This has the advantage that it focuses our attention more closely upon the crucial role played by psychic costs. The differences in the predictions made by this model and that of Ehrlich can then be firmly identified as being due to the treatment of psychic costs and not to different assumptions concerning the probability of detection. BH, like Ehrlich, assumed leisure to be fixed. They also restricted their analysis to crimes of theft, for which the typical punishment is a fine. This is advantageous, because it narrows attention to the role of psychic costs in the decision to engage in crime. An analysis involving prison sentences is offered by Block and Lind (1975).

Each individual is assumed to maximise expected utility by selecting the appropriate level of t_i, the amount of time devoted to theft. As leisure is fixed this is the individual's only choice variable. Expected utility is then given by,

$$EU = (1 - p)U(t_i, t_1, X_s) + p\,U(t_i, t_1, X_u) \qquad (15)$$

Where X_s and X_u are the individual's levels of monetary wealth in the two possible states of the world, i.e. success in crime (s), and failure in crime (u) and p is the probability of capture and punishment. We shall define X_s and X_u as follows,

$$X_s = W_o + W_i\,(t_i, \alpha) + W_1\,(t - t_i, \beta)$$

$$X_u = W_o + W_i (t_i, \alpha) + W_1 (t - t_i, \beta) - F_i (t_i, \gamma)$$

i.e. exactly as Ehrlich did (see p (40) above).[23]

"Entry" into crime requires that

$$\left.\frac{dEU}{dt_i}\right|_{t_i = 0} > 0$$

As $X_s = X_u$ at $t_i = 0$, then this condition can be written fairly simply as,

$$W_i' - p F_i' > W_1' + \frac{U_{t1} - U_{ti}}{U'(\quad)} \tag{16}$$

where U_{tj} is the partial derivative of U with respect to t_j, $j = 1, i$ and $U'(\quad)$ is the marginal utility of wealth.

By definition $U'(\quad) > 0$, but as both U_{t1} and U_{ti} are negative the sign of $U_{t1} - U_{ti}$ will depend upon which is the larger in absolute terms. Individuals with a greater aversion to crime than to legitimate activity (i.e. $U_{t1} - U_{ti} > 0$) would only engage in crime if the "net" return (i.e. $W_i' - p F_i' - W_1'$) outweighed the psychic disadvantage of engaging in it. Indeed some individuals may display such a large aversion to participation in crime that even very large net returns to criminal activity would be insufficient to induce them to depart from the straight and narrow.

For those who are prepared to engage in crime an interior optimum

23. In fact BH assumed returns to crime and legitimate activity to be independent of the amounts of time spent in those activities. This is less general than Ehrlich's treatment and we adapt BH's model to make it more general on this point.

$(t > t_i > 0)$ would be found where $\frac{dEU}{dt_i} = 0$ i.e. where

$$(1 - p)U_{ti}(t_i, t_1, X_s) - (1 - p)U_{t1}(t_i, t_1, X_s) + (1 - p)U'(t_i, t_1, X_s)$$

$$(W_i' - W_1') + p\, U_{ti}(t_i, t_1, X_u) - p\, U_{t1}(t_i, t_1, X_u) + p\, U'(t_i, t_1, X_u)$$

$$(W_i' - W_1' - F_i') = 0 \qquad (17)$$

The comparative static properties of the model can be found by differentiating (17) with respect to W_o; p, γ, α and β in turn and solving for their effects upon t_i.

First, take the effect of a change in exogenously determined wealth (W_o).

$$\frac{\partial t_i}{\partial W_o} = \Big[- (1 - p)U_{tiX_s}(X_s) + (1 - p)U_{t1X_s}(X_s) - (1 - p)U''(X_s)(W_i' - W_1')$$

$$- p\, U_{tiX_u}(X_u) + p\, U_{t1X_u}(X_u) - p\, U''(X_u)(W_i' - W_1' - F_i')\Big]/D \qquad (18)^{24}$$

where D is the second order condition for a maximum and is, therefore, negative. The arguments of the utility functions have been shortened to wealth alone so as to save space.

If we are prepared to assume that $U_{t_jX_k} = 0 \quad j = i, 1$ and $k = u, s$

---

24. $U_{t_jX_k}$ $\qquad j = i, 1\ ;\ k = u, s$

is the second cross partial derivative of the utility function. It indicates how the marginal utility of time spent in various tasks changes as wealth increases. Presumably $U_{t_jX_k} < 0$ i.e. the disutility of "work" of both kinds increases as wealth increases.

then equation (18) reduces to equation (12) and $\frac{\partial t_i}{\partial W_o}$ is unambiguously positive _if_ individuals display decreasing absolute risk aversion. If, however, the utility function is not strictly separable, i.e. $U_{t_j X_k} \neq 0$, then the sign of (18) is ambiguous.[25] To be able to sign it one must be prepared to make fairly strong a priori assumptions not just about the signs of the $U_{t_j X_k}$, but also their relative sizes.

Next, consider the effect of a change in the probability of detection (p).

$$\frac{\partial t_i}{\partial p} = \Big[U_{ti}(X_s) - U_{t1}(X_s) + U'(X_s)(W_i' - W_1') - U_{ti}(X_u) + U_{t1}(X_u) - U'(X_u)(W_i' - W_1' - F_i')\Big] / D \tag{19}$$

If either $U_{ti}(X_k) = U_{t1}(X_k)$ $k = u, s$ or $U_{t_j X_k} = 0$ $j = i, 1$ and $k = u, s$, then $\frac{\partial t_i}{\partial p}$ would reduce to the expression given in equation (10) and so would be unambiguously negative. However, if we allow for the more general possibility that neither $U_{ti} = U_{t1}$ nor $U_{t_j X_k} = 0$ then $\frac{\partial t_i}{\partial p}$ cannot be signed unambiguously.

The effect of an increase in the severity of punishment is found by

---

25. A perhaps less stringent condition that would ensure the unambiguous signing of (18) is that,

$$U_{t_i X_k} = U_{t_1 X_k} \qquad k = s, u$$

But this would only be the case if $U_{t_i} = U_{t_1}$ and the point of the generalisation would then be lost entirely.

differentiating (17) with respect to γ and solving for

$$\frac{\partial t_i}{\partial \gamma} = \frac{pU_{t_iX_u}(X_u)F_{i\gamma} - pU_{t_1X_u}(X_u)F_{i\gamma} + pU'(X_u)F'_{i\gamma} + pU''(X_u)(W'_i - W'_1 - F'_i)F_{i\gamma}}{D} \tag{20}$$

Now, if $U_{t_iX_u} = U_{t_1X_u}$ (i.e. $U_{t_i} = U_{t_1}$) then $\frac{\partial t_i}{\partial \gamma}$ reduces to (11) and can be signed according to the conditions shown on p (48). However if moral forces do come into play, so that $U_{t_i} \neq U_{t_1}$ the signing of (20) is complex, especially if $U_{t_1} > U_{t_i}$. However, if $U_{t_i} > U_{t_1}$ then $\frac{\partial t_i}{\partial \gamma}$ is likely to be negative. At first blush this result may seem a little odd i.e. those with "moral" objections to engaging in crime are less likely to be deterred by increases in the severity of punishment than those without such qualms. However, on reflection it may be explainable. If, despite one's moral objections to criminal activity, one is prepared to engage in crime then such individuals are possibly less likely to be deterred by small increases in the severity of punishment compared with individuals who are simply in it "for the money".

Finally, we can find the effects of increases in illegal "pay offs" (an increase in α) and increases in returns to legitimate activity (an increase in β) upon t_i by evaluating $\frac{\partial t_i}{\partial \alpha}$ and $\frac{\partial t_i}{\partial \beta}$. These are as follows,

$$\frac{\partial t_i}{\partial \alpha} = -\frac{W'_{i\alpha}\left(\frac{\partial EU}{\partial W_o}\right)}{D} + W_{i\alpha}\left(\frac{\partial t_i}{\partial W_o}\right) \tag{21}$$

and
$$\frac{\partial t_i}{\partial \beta} = \frac{W'_{1\beta}\left(\frac{\partial EU}{\partial W_o}\right)}{D} - W_{1\beta}\left(\frac{\partial t_i}{\partial W_o}\right) \tag{22}$$

which are as before, i.e. equations (13) and (14). However, it is not possible to sign equations (21) and (22), because the second term in each contains $\frac{\partial t_i}{\partial W_o}$, the wealth effect, which by (18) is ambiguous in this general case. Only if we are prepared to assume that crime is "normal" would it be possible to sign $\frac{\partial t_i}{\partial \alpha}$ and $\frac{\partial t_i}{\partial \beta}$.

It is clear, therefore, that in a more general model, where ethical considerations are incorporated into the individual's set of preferences, unambiguous predictions concerning, for example, the deterrent effects of certainty and severity of punishment are not available. As a result Block and Heineke concluded that, ".... in the area of law enforcement ... policy recommendations do not follow from theory but rather require empirical determination of relative magnitudes" (p. 323). It would perhaps be surprising if that were not the case, given what we know from elementary consumer demand theory and the theory of labour supply.

4. Some concluding comments on "economic" models of crime

In the previous three sections of this chapter we have reviewed a number of theoretical approaches to modelling the decision to engage in crime. In this final section we consider some criticisms and limitations of the economic approach to criminal behaviour.

The first point to make is that the approach suggested by Ehrlich and developed by Block and Heineke is only really applicable to time consuming, income generating offences. Such crimes might be for example most burglaries, some thefts, possibly some robberies, e.g. bank robberies, and all frauds. The model could not be directly used to explain the determination of petty thefts (at least those which involve relatively little time), crimes of violence or such crimes as drug-taking, criminal damage and sexual offences. In later chapters of this thesis, where we attempt to apply the time allocation model to study crimes in England and Wales, we have therefore restricted the analysis to property crimes i.e. burglary, robbery and theft.

Indeed Carr-Hill and Stern (1979) have argued that as the majority of recorded property crimes in England and Wales involve losses that are "on the average comparatively small" (p 12), then the time allocation model is totally inappropriate. They prefer to develop a theoretical approach based upon the model put forward by Becker. However, the theoretical framework of that model is not markedly different from the time allocation model. Nor, indeed, are its conclusions. Compare, for example, Carr-Hill and Stern's conclusion concerning the "normality" of criminal behaviour with the prediction of the time allocation model.

However, it is not altogether clear that the majority of recorded property crimes in England are thefts involving relatively small amounts. In 1975 the average value of property stolen in reported thefts was £72.70.[26] At the same time average gross weekly earnings were £60.00 per week and the bottom ten per cent of males over 21 years of age earned less than £37.60 per week (gross). For those out of work or living on supplementary benefits their "income" levels would be even lower. Also, such individuals are unlikely to have many financial or physical assets. Their only "wealth" is likely to be locked up in their human capital and that is likely to have

26. Calculated from data given in Table 2.3, p. 18 of Criminal Statistics 1975. Of course the distribution is quite highly skewed. Some 68% of thefts involve sums of less than £25.

relatively small value. It is, therefore, not altogether clear that the value of property stolen represents relatively small amounts, at least to the potential criminal. Admittedly, we would need to adjust the above figure for the value of property stolen to take account of the lower resale value of stolen property, but even so potential gains are probably quite high relative to the earnings potential of low paid workers.

Whether or not such "petty" thefts are time consuming is open to debate. It seems reasonable to argue that potential thieves might spend some considerable time searching before they come across an unlocked car door, an open window or an unattended purse. It is highly unlikely that the first car, window or shopping bag they come across will just happen to be left open. There is, therefore, a prima facie case at least for believing that even thefts of relatively small monetary amounts may involve some expenditure of time and effort. There is a least sufficient doubt for us not to entirely rule out of court models based upon the time allocation framework.

However, the application of the economic approach to a consideration of crimes of violence, drug taking and other such offences is more problematical. It is not quite so clear in those circumstances what the measure of potential gain could or should be. Ehrlich (1975a) has suggested using an inter-personal utility framework for explaining, for example, the murder rate. It might also be possible to consider drug taking and engaging in illicit sexual activity, for example, as alternative ways using one's leisure time. This would require us to distinguish between illegal and legitimate leisure pursuits. The time devoted to these two types of activity could then be incorporated directly into the utility function, so that the gain would be measured in utility terms. Whilst such extensions are possible, we share the doubts expressed by other authors about such applications of the economic approach.[27] Accordingly, in the later empirical analyses, we focus entirely upon the crimes of burglary, robbery and theft i.e. crimes which are likely to be motivated largely by the prospect of monetary gain.

It might be argued that the economic model ignores those costs associated with the shame and loss of status/respectability as a result of appearing in court accused of committing a crime. These costs, it could be argued, are independent of t_i and so would not be incorporated into the "loss" function $F_i(t_i, \gamma)$. If such costs are independent of t_i they are certainly not incorporated into the costs of punishment as described in the time allocation model. However, it would be a relatively simple matter to extend the model to include them. This could be done by incorporating a "fixed cost" of court appearance, independent of t_i. Of course, if it really is a fixed cost then the "marginal shame cost" will be zero and will not be expected to influence decisions at the margin.

A further possible criticism of the economic approach is that its conception of attitudes to offending is too simplistic. The approach of Becker and Ehrlich, in particular, treats the decision to engage in crime as a function of wealth alone. Whilst Block and Heineke have widened the utility function to include the amounts of time devoted to crime and legitimate work, this too may be regarded as too simplistic an approach.

---

27. "... the attempt to derive response functions for violent offences from expected utility maximisation is likely to be futile" (Carr-Hill and Stern, 1979, p. 47).

"... crimes which are substantially motivated by the prospect of monetary gain are more likely to display a pattern predicted by the maximisation model than the crimes motivated by personal hatred, jealousy or lust" (Burrows and Veljanovski, 1981, p. 7).

The reasons for engaging in criminal activity may be more subtle and various than suggested by the economic approach. It is extremely difficult to answer such a criticism convincingly. It basically amounts to saying that the assumptions of the economic model are unrealistic. The only answer to which is that whilst they may be unrealistic the real test of whether the economic model is acceptable is whether its predictions are consistent with the evidence. If the economic model fails that test then one would need to return to the drawing board. On the surface, at least, it seems much more reasonable to apply the economic model to property crimes than to crimes of violence, where the individual motivation may indeed be far more intricate and involved.

A possible limitation of the economic approach, as presently developed, is its treatment of "on the job" crime. In the formulation of the time allocation model legitimate and illegal work are treated as competing activities i.e. one hour spent in legitimate activity means one hour less for illegal activity. In practice some crimes are committed during working time. This may be especially so for certain kinds of theft and types of fraud. However, it is unlikely to be the case that robberies and burglaries are committed during working time. Neither is it likely that crimes of violence are committed at work, though as we do not consider them in the later empirical analyses, that is neither here or there.

Of reported thefts very few are, in fact, thefts by an employee. In 1975, in England and Wales, only some 31,280 reported thefts were in this category. This represented only 2.1% of all reported thefts. Of course, employers may (i) not know of the crimes committed by their employees or (ii) may turn a blind eye to them or (iii) may prefer to dismiss the person concerned rather than report the crime. Of the other categories of theft few are what one regards as "on the job" offences e.g. shoplifting, theft from a vehicle, theft of a pedal cycle etc. It would require very substantial under-reporting of "thefts by an employee" before "on the job" crime became a significant part of the crime statistics. From a practical point of view then "on the job" crime might not be as important as might be thought. Therefore, the rather inadequate way in which the economic approach treats it may not be too severe a limitation, especially if the model is restricted to an analysis of recorded offences.

The single most important category of "on the job" crimes, i.e. frauds, are not in fact considered in the empirical analysis of later chapters. The reasons for their exclusion are discussed more fully in chapter 4.

In the time allocation model developed earlier, we did not explicitly consider the possibility that individuals might find themselves involuntarily unemployed. The relationship, if any, between unemployment and crime is an extremely controversial and topical issue. It is interesting to ask, therefore, how the time allocation framework can incorporate unemployment and what predictions it yields about the effect of a change in unemployment upon involvement in crime. The probability of becoming unemployed in legitimate activity has been treated in the time allocation model as an exogenously determined parameter. To some extent this hypothesis is an over-simplification of the interaction between crime and unemployment.

In the framework suggested by Ehrlich individuals are seen to choose how to allocate their working time between legitimate and illegal activity. They may choose to spend part of their time voluntarily unemployed in legitimate activity substituting instead employment in illegal activity. Unemployment risk is then taken to be the independently determined probability they are unable to work as many hours in legitimate activity as they would wish. In fact in the extremely simplified version of the model unemployment constrains their legitimate working activity to precisely zero hours. Individuals' expected utility functions are then written as,

$$EU = (1 - p)(1 - u)U(X_{se}) + (1 - p)u\, U(X_{su}) + p(1 - u)U(X_{ue}) + p\, u\, U(X_{uu}) \quad (23)$$

where X_{se}, X_{su}, X_{ue} and X_{uu} are defined as follows,

$$X_{se} = W_o + W_i(t_i, \alpha) + W_1(t - t_i, \beta)$$

$$X_{su} = W_o + W_i(t_i, \alpha) + B$$

$$X_{ue} = W_o + W_i(t_i, \alpha) - F_i(t_i, \gamma) + W_1(t - t_i, \beta)$$

$$X_{uu} = W_o + W_i(t_i, \alpha) - F_i(t_i, \gamma) + B$$

B is the level of unemployment benefit received if unemployed in legitimate activity and u is the exogenously determined probability of being unemployed in legitimate activity. All other variables and parameters are as defined previously.

It is fairly easy to show in such a formulation that (i) the greater is the risk of becoming unemployed in legitimate activity the more likely are individuals to enter into illegal activity and (ii) an increase in the risk of unemployment will generally lead individuals to devote a larger proportion of their working time to illegal activity. The entry condition $\left.\frac{dEU}{dt_i}\right|_{t_i = 0} > 0$ can be shown to imply that

$$W_i' - pF_i' > (1 - u)W_1' \quad (24)$$

This should be compared with the entry condition in the model without unemployment, given by (9) above. It is clear from this comparison that as u > 0 then individuals are more likely to enter into crime. Further as u increases then their entry into illegal activity becomes ever more likely.

The comparative static properties of the model can be developed along lines similar to those used to explain the simple time allocation model. However, we shall examine only the effect of an increase in unemployment risk (u) upon the amount of time spent in illegal activity (t_i). By differentiating the first order condition for utility maximisation we obtain,

$$\frac{dt_i}{du} = \frac{(1-p)\left[U'(X_{se})(W_i' - W_1') - U'(X_{su})W_i'\right]}{(D)} + \frac{p\left[U'(X_{ue})(W_i' - W_1' - F_i') - U'(X_{uu})(W_i' - F_i')\right]}{(D)} \quad (25)$$

Where D is the second order condition for a maximum and so is negative, by definition.

If individuals are risk averse (i.e. $U''(\ ) < 0$) then $\frac{dt_i}{du}$ is unambiguously greater than zero and an increase in the risk of unemployment will cause individuals to devote more time to illegal activity. This can be seen quite simply as follows. If earnings in legitimate employment exceed unemployment benefits then $X_{se} > X_{su}$ and $X_{ue} > X_{uu}$. If the individual is risk averse then $U'(X_{se}) < U'(X_{su})$ and $U'(X_{ue}) < U'(X_{uu})$. In addition $W_i' - W_1' < W_i'$ and $W_i' - F_i' - W_1' < W_i' - F_i'$, so that both of the terms in the square brackets in the expression for $\frac{dt_i}{du}$ are unambiguously negative. As $1 > p > 0$ and $D < 0$ this is sufficient to ensure that $\frac{dt_i}{du} > 0$.

When individuals have an increasing marginal utility of the wealth (i.e. they exhibit a preference for risk) it is not possible to obtain an unambiguous prediction for $\frac{dt_i}{du}$. This is because in that case $U'(X_{se}) > U'(X_{su})$ and $U'(X_{ue}) > U'(X_{uu})$. It is still possible that $\frac{dt_i}{du} > 0$. We cannot, however, state that as an unambiguous conclusion of the model.

We can see, therefore, that the time allocation model yields a number of reasonable predictions about the effect of unemployment upon participation in illegal activity. Yet, there are a few criticisms which can be levelled at the way unemployment is incorporated into the model. For example, the risk of unemployment may not be entirely independent of one's actions. In particular individuals who spend some time engaged in illegal activity are likely to run a greater risk of being unemployed in legitimate activity. This might occur for one of several reasons. They are, for example, likely to have a patchy employment record with long periods of relatively little legitimate work experience. This is likely to prove unattractive to a potential employer. Such an employment record would occur even if one were highly successful as a part-time criminal. It is even more likely when less successful criminals are considered. They may very well have a criminal record, possibly even with spells of imprisonment. The probability of being unemployed for such individuals seems to be rather greater than for "successful" criminals, let alone law abiding individuals with continuous employment records. It might seem reasonable to argue, therefore, that u is not an exogenously determined constant, but is itself endogenously determined by, for example, either t_i or p or both. Indeed, u may depend <u>not</u> upon p or t_i in the current period, but their values in previous periods. The risk of unemployment this period may depend upon, amongst other things, one's previous criminal record and one's previous employment record. These, in turn, are likely to be dependent upon the amount of time devoted to illegal activity in previous periods and whether one was caught and punished in those periods.

This indicates a further limitation of the economic approach. It is a one-period choice framework. Every period the slate is wiped clean and each individual decides afresh how to allocate his time and resources between illegal and legitimate activities. Choices made several periods previously do not influence the opportunities open to the individual now. Casual empiricism would suggest that such an hypothesis bore very little relationship to fact.

A more rigorous economic theory of criminal behaviour might then be based upon a model of inter-temporal utility maximisation, where individuals are assumed to maximise the present value of a stream of future expected utility. Of course, expected utility in each time period would still be a weighted average of the utilities deriving from the various, alternative outcomes. However, the probabilities of the occurrence of these outcomes in any time period would themselves be influenced by choices made in previous periods and the outcome of those choices. If in any particular time period an individual chose to spend some time engaged in criminal activity, but was caught and punished, then his legitimate employment opportunities may be harmed in all future periods. Further, as a known criminal, his chances of successfully avoiding punishment as a result of future criminal activity might also be affected. An extreme version of this would be if the punishment took the form of a prison sentence. During the period of imprisonment legitimate earnings would drop to zero and even illegal earnings may be substantially diminished. A period of imprisonment may then affect future earnings upon release and lead to police harassment.

Obviously such a model would be extremely complicated even to write out. It would be even harder to establish its properties. I am not aware of any attempt in the literature to develop such a model, though, of course, the basic idea of such inter-temporal effects has been alluded to (see, for example, Avio (1975)). The testing of such a model would also present very considerable data problems, requiring presumably extremely detailed cohort data on employment and criminal records of particular individuals.

The economic model makes another simplifying assumption that has also been brought into question. That assumption is that a fine equivalent of a punishment always exists. Related to this is the assumption that the effects of committing a crime can also be represented solely in terms of their effect upon monetary wealth. We have encountered this criticism before (see previous section of this chapter).

Block and Lind (1975) have suggested that the general form of the individual's utility function should be U(W, C, S) where W is his wealth, C is a set of attributes relating to the crime and S is a set of attributes relating to the punishment. Imagine an individual whose wealth is given by W'. He commits a crime whose attributes are C'. The penalty is S'. For a wealth equivalent of the crime and punishment to exist there must be a level of wealth W* such that

$$U(W', C', S') = U(W^*, 0, 0)$$

The monetary equivalent would then be given by $W^* - W'$. Block and Lind claim that in general there is no reason to believe that W* exists. Its existence clearly depends upon the severity of the punishment, the nature of the crime and the individual's level of wealth. If the individual's wealth is already at a subsistence level then even for a relatively mild punishment no wealth equivalent could exist. Even where the individual has quite substantial wealth no monetary equivalent of the punishment may exist if the penalty is extremely severe.

The implications of this point for modelling criminal choice have already been examined in part, at least, when we considered the model of Block and Heineke. However, the criticism is perhaps rather less serious in practice than might appear. After all what Block and Heineke and Block and Lind are saying is that the <u>attributes</u> of the sentence and the <u>attributes</u> of the crime will affect the decision to engage in crime. The individual's decision is made not simply on the grounds of monetary equivalences. Whilst this is a valid criticism of previous theoretical modelling of criminal choice, it is possibly less significant when considering the empirical literature. There, investigators have attempted to incorporate at least some of the attributes of the sentence in the supply of offences function e.g. the type of sentence (whether a fine or imprisonment), length of imprisonment etc.

Finally, it should be noted that the economic approach actually generates remarkably few falsifiable predictions about criminal behaviour. The models developed in the previous sections are in general unable to yield entirely unambiguous predictions about the effects of changes in law enforcement variables and returns in different forms of activity upon the amount of time devoted to crime. This point seems to have rarely been made in the literature on the subject. It is a slightly disturbing conclusion, because it implies that it would be difficult to find evidence that would either reject or confirm the economic hypothesis. More or less whatever the signs of the estimated coefficients one could find a reason for accepting the economic hypothesis. Some investigators, presumably responding to this situation, have been led to construct models with much more restrictive assumptions concerning, for example, the functional form of the utility function (see, for example, Baldry (1974)). Whilst this may generate unambiguous predictions that are in principle, falsifiable, it does not necessarily produce an ultimate test of the economic hypothesis. One would merely be testing the specific form of the general model. As alternative specifications are available, one would need to investigate the whole set of alternatives. If some failed and some passed the test it would then be a matter of judgement as to which set of specific assumptions one felt to be the best approximation to the real world.

The value of the economic approach probably lies not so much in providing testable predictions, therefore, as in suggesting the kinds of factors that will influence individual's participation in criminal activity and in organising the collection of data for the estimation of crime supply functions. In the following chapter we attempt to review some of the major contributions to the empirical analysis of crime.

Appendix to Chapter 2 : The Time Allocation Model with Variable Leisure

In Chapter 2 we examined a number of theoretical models of criminal behaviour. All of these models treated involvement in crime as a decision about the allocation of time between competing activities. It is a characteristic of treatments using this approach that the amount of time devoted to leisure has been assumed to be fixed. There have been few attempts to examine the case where leisure is free to vary. Where this has been attempted, it has been done only by making other, possibly restrictive assumptions e.g. a separable utility function (Ehrlich, 1973) or a linear utility function and a Cobb-Douglas consumption technology (Baldry, 1974). The one attempt to provide a general treatment is marred by technical flaws (Heineke, 1978b). It seems a useful exercise, therefore, to set out the model incorporating the assumption of variable leisure and to derive its comparative static properties. This is the purpose of this Appendix. In fact, we examine the case where leisure is free to vary, but where individuals must work a fixed number of hours in legitimate activity. This case is sufficiently general to reveal the absence of unambiguous theoretical predictions.

We assume that individuals are required to work $\bar{t}_1$ hours in legitimate activity. They can, of course, choose not to enter the (legitimate) labour force. Whether they do so will depend upon whether total expected utility is greater with legitimate work than without it. For simplicity we examine the case where individuals decide to enter the workforce. In that case expected utility would be given by

$$EU = (1 - p)\, U\,(X_s,\ t_c) + p\, U\,(X_u,\ t_c) \qquad \text{(A1)}$$

where

$$X_s = W_o + W_1(\bar{t}_1) + W_i(t - t_c, \alpha)$$

and $$X_u = W_o + W_1(\bar{t}_1) + W_i(t - t_c, \alpha) - F_i(t - t_c, \gamma)$$

Individuals are assumed to choose the value of t_c (or t_i) so as to maximise expected utility. If we assume an interior optimum, then the maximum will be given by

$$\frac{dEU}{dt_c} = -(1-p)U^s(X_s, t_c)W_i' + (1-p)U^{t_c}(X_s, t_c) - pU^u(X_u, t_c)(W_i' - F_i')$$
$$+ pU^{t_c}(X_u, t_c) = 0 \qquad \text{(A2)}$$

where $U^s(\;)$ and $U^u(\;)$ are marginal utilities of wealth and $U^{t_c}(\;)$ is the marginal utility of leisure.

We shall assume that the second order condition for a maximum is satisfied. It would clearly be satisfied if individuals had (i) a diminishing marginal utility of wealth in both states of the world, (ii) a diminishing marginal utility of leisure and (iii) there were diminishing returns to both forms of activity. It would also be satisfied for other less stringent sets of conditions too numerous to list.

We can now investigate the comparative static properties of the model. In particular we wish to find the effect upon time devoted to illegal activity (t_i) of changes in (i) exogenous wealth (W_o), (ii) the probability of capture (p), (iii) illegal returns (α) and (iv) the severity of punishment (γ). As

$$\frac{\partial t_i}{\partial \theta} = -\frac{\partial t_c}{\partial \theta} \qquad \theta = W_o, p, \alpha \text{ and } \gamma$$

we can proceed by finding the effects of changes in these four parameters upon the amount of leisure.

(a) A increase in exogenous wealth

$$\frac{\partial t_c}{\partial W_o} = \frac{(1-p)U^{ss}(\,)W_i' - (1-p)U^{t_c s}(\,) + pU^{uu}(\,)(W_i' - F_i') - pU^{t_c u}(\,)}{(D)} \tag{A3}$$

where D is the second order condition for a maximum, which by definition is negative.

The derivatives $U^{t_c s}$ and $U^{t_c u}$ indicate how the marginal utility of leisure changes as wealth increases. It seems reasonable to argue that they are both positive, in which case the second and fourth terms of the numerator will be negative. The first and third terms in the numerator will also be negative if both U^{ss} and U^{uu} are negative (i.e. diminishing marginal utility of wealth) and W_i' and $W_i' - F_i'$ are positive. Some of these requirements are unlikely to be satisfied, especially the requirement that the marginal punishment should be less than the marginal return in illegal activity i.e. $W_i' - F_i' > 0$. Indeed, the first order condition, (A2) above, probably requires that $W_i' - F_i' < 0$. In that case or if individuals have an an increasing marginal utility of wealth it is not possible to sign $\frac{\partial t_c}{\partial W_o}$ unambiguously, although it is still possible that crime is an inferior activity.

(b) An increase in the probability of detection

$$\frac{\partial t_c}{\partial p} = \frac{-U^{s}(\,)W_i' + U^{t_c}(X_s, t_c) + U^{u}(\,)(W_i' - F_i') - U^{t_c}(X_u, t_c)}{D} \tag{A4}$$

Again this derivative cannot be signed unambiguously unless we are prepared to assume that $U^{t_c}(X_s, t_c) = U^{t_c}(X_u, t_c)$ and that $W_i' - F_i' < 0$. The former requirement is that the marginal utility of leisure is independent of whichever state of the word applies and, therefore, of wealth. If, however, $U^{t_c}(X_s, t_c) \simeq U^{t_c}(X_u, t_c)$ it may still be possible to sign $\frac{\partial t_c}{\partial p}$, even in the case where $W_i' - F_i' > 0$. This would require, however, that individuals had an increasing marginal utility of wealth. In that case $\frac{\partial t_c}{\partial p}$ would be approximately given by

$$\frac{W_i'\left[U^u(\ ) - U^s(\ )\right]}{D} - \frac{F_i' U^u(\ )}{D}$$

As $X_s > X_u$ and if $U'' > 0$ then $U^s(\ ) > U^u(\ )$ and the first term would be positive. As $F_i' > 0$ then the second term would also be positive and the overall effect of an increase in the probability of detection would be to increase the amount of time devoted to leisure and hence to reduce the amount of time devoted to criminal activity. However, if $U^{t_c}(X_s, t_c) > U^{t_c}(X_u, t_c)$ by a substantial margin, then the prediction about the sign of the derivative (A4) cannot be unambiguous.

(c) <u>An increase in returns to illegal activity</u>

$$\frac{\partial t_c}{\partial \alpha} = \left[(1-p)U^s(\ )W_{i\alpha}' + (1-p)U^{ss}(\ )W_i' W_{i\alpha} - (1-p)U^{st_c}(\ )W_{i\alpha} + pU^u(\ )W_{i\alpha}' + pU^{uu}(\ )(W_i' - F_i')W_{i\alpha} - pU^{ut_c}(\ )W_{i\alpha}\right] \Big/ (D) \qquad \text{(A5)}$$

which can be rewritten as,

$$\frac{\partial t_c}{\partial \alpha} = \frac{\left[(1-p)U^s(\ ) + pU^u(\ )\right] W_{i\alpha}'}{(D)} + W_{i\alpha}\left[\frac{\partial t_c}{\partial W_o}\right] \qquad \text{(A5}'\text{)}$$

The first term in (A5') will be negative if $W_{i\alpha}' > 0$ i.e. the increase in returns to illegal activity increases the marginal "wage" in illegal activity. This term can be regarded as a substitution effect. The second term in (A5') is a wealth effect. If leisure is a normal good i.e.

$\frac{\partial t_c}{\partial W_o} > 0$ then this term will be positive, because $W_{i\alpha} > 0$ by definition. In general, therefore, it will be impossible to sign (A5$'$) unambiguously, because it is the sum of two effects which work in opposite directions. If, however, the increase in returns merely lifts the average wage rate ($W_{i\alpha} > 0$), whilst keeping the marginal wage rate constant ($W'_{i\alpha} = 0$), then (A5$'$) would reduce to a pure wealth effect and could be signed according to the conditions given on pp (75).

(a) <u>An increase in the severity of punishment</u>

$$\frac{\partial t_c}{\partial \gamma} = \frac{-\,pU^{uu}(\;)(W'_i - F'_i)F_{i\gamma} - pU^{u}(\;)F'_{i\gamma} + pU^{t_c u}(\;)F_{i\gamma}}{(D)} \tag{A6}$$

(A6) cannot be signed unambiguously too. If $W'_i - F'_i < 0$ and $U^{uu} < 0$ then the first two terms of the numerator will be negative, but the third term is positive. Variations on those two assumptions will not, however, remove the ambiguity. Even an increase in severity which left the marginal severity of punishment unchanged would not generate an unambiguous prediction for $\frac{\partial t_c}{\partial \gamma}$.

It seems reasonable to conclude, therefore, that the assumption that leisure is fixed is quite crucial in generating the unambiguous predictions of the time allocation model. By merely replacing it with an assumption of fixed working weeks it is no longer possible to derive unambiguous predictions about the effect upon t_i of changes in the various law enforcement and returns variables.

Chapter 3 : Econometric Studies of Crime : A Survey

In the previous chapter we examined the theoretical models of criminal behaviour developed by Becker (1968), Ehrlich (1973) and Block and Heineke (1975). We discussed the theoretical restrictions which these models place upon the supply of offences function, i.e. predictions of the effects of changes in wealth, legitimate and illegal returns and in the deterrence variables upon the supply of effort to criminal activity. In this chapter we consider a number of attempts to estimate supply of offences functions.[1]

The vast majority of these empirical studies have used aggregate data on recorded crimes, sanction levels and various socio-economic factors at either a national, regional, municipality, city or sometimes precinct level. An exception to this approach is the paper by Witte (1980) which uses micro (i.e. individual) level data. The economic model of criminal behaviour is founded upon individual decision-making, but the virtual absence of reliable data at that level has forced economists to estimate, what Ehrlich (1981) has described as, market-level relationships.

Blumstein, Cohen and Nagin (1978) have identified three broad approaches to research design in this area. These are controlled experiments, quasi-experiments and the analysis of natural variations. The approach most commonly used by economists is the analysis of natural variation in crime-rates and sanction levels occurring across geographical areas at a point in time. The use of data on natural variations is

---

1. We will not consider, however, the literature which has grown up following Ehrlich's attempt to estimate the deterrent effect of capital punishment (Ehrlich (1975a)). An extensive discussion of this subject is contained in Pyle (1983, Chapter 4).

virtually inevitable, because controlled experiments (quasi or otherwise) are relatively rare in this field of study. Largely, one suspects, for practical, legal or ethical reasons. Therefore, the studies we discuss try to determine whether variations in saction levels across areas can explain variations in recorded crime levels, other things remaining the same.

The format of this chapter is as follows. First, we consider a number of methodological problems concerning the estimation of crime supply functions. Some authors have claimed that the supply of offences function is just one equation in a simultaneous equation model of the interaction between criminals and the criminal justice system. If so, we will need to consider the specification of that model in detail. In that case too, we will have to consider the question of the identification of the supply of offences function. We must also consider a number of data problems which impact upon the estimation of the crime function. In particular we shall be concerned with the problems arising from measurement error in the crime variable. Second, we examine a number of empirical studies of the supply of offences function in some detail. Given the limitations of available space, this review must be a rather selective one.

(1) Methodological Preliminaries

(i) Simultaneous Determination of Crime and Sanctions

In the previous chapter we examined various economic models of criminal behaviour. From these it is possible to specify a supply of offences function of the form,

$$C = C(p, f, X) \qquad (1)^2$$

where C is the number of offences committed per period of time,

p is the probability of detection/conviction,

f is a measure of the severity of punishment (in monetary terms)

and X is a vector of variables such as income from illegal and legitimate activities, unemployment etc.

Ignoring, for the time being, the precise definitions of these variables, would it be sensible to undertake a multiple regression analysis with crimes as the dependent variable and sanctions and the other variables as independent variables? Unfortunately, the answer to that question may be no. It has been argued in the literature that not only is the number of offences dependent upon the certainty and severity of punishment, but these variables themselves might depend upon the number of offences that are committed. For example, when crime levels are high, the criminal justice system may respond by setting very high levels of punishment in an attempt to deter crime in future periods. Also, with fixed police resources, an increase in the number of crimes might reduce the probability of detection. If so, p and f in equation (1) cannot be treated as exogenous variables. They would be endogenous variables, their levels being determined by the number of crimes (C). Proper estimation would require specification of the complete model. A fairly general specification might be as follows,

$$C = C(p, f, X) \qquad (1a)$$

$$p = p(C, f, X) \qquad (1b)$$

$$f = f(C, p, X) \qquad (1c)$$

---

2. It is a characteristic of many of the empirical models that we will review in this chapter that they postulate the existence of an <u>aggregate</u> crime function with certain plausible but possibly ad hoc properties. The theoretical models of the previous chapter have been based upon individual decision-making units. The link between the models of chapter 2 and those examined here has received little attention.

This model, with everything depending upon everything else, would be impossible to estimate. It would be impossible to separate one relationship from any other. In order to use standard statistical procedures for estimating simultaneous models, it is necessary to impose a number of identification restrictions i.e. a priori assumptions about which variables enter which equation and which do not. The system above is not identified because all variables enter each equation. It would be identified if the variables entering on the right hand side of each of the equations were different. Are there valid reasons for excluding any of p, f or X from these equations? It may seem unlikely, for example, that f should be included in equation (1b), or that p should enter equation (1c). Similarly, there may be sound theoretical reasons for excluding some socio-economic factors (i.e. X variables) from determining p and f, but not from determining C or vice versa. If there are sound reasons for excluding some variables, then the identification problem will be resolved and it will be possible to estimate the equation system simultaneously.

However, the choice of which variables to exclude and from which equation is not an easy matter and cannot be decided by the data involved in estimating the model. It must be based upon sound theoretical reasoning. The main problem with estimating simultaneous crime-sanctions models seems to be the relatively small amount of basic theory around which to frame a choice of identifying restrictions. Some critics argue that this lack of theoretical underpinning must bring into question the reliability of some of the empirical estimates of supply of offences functions.

Blumstein, Cohen and Nagin (1978) have argued that, "Identification is not a minor technical issue. If a system is not properly identified, completely erroneous conclusions can be drawn from the estimated relationship" (p 26). With this in mind we briefly develop a simplified (i.e. two equation) example in order to show how the imposition of incorrect identification restrictions could lead to erroneous conclusions about the deterrent effect of increases in the apprehension/conviction rate.

An Example of the Identification Problem in Crime/Police Models

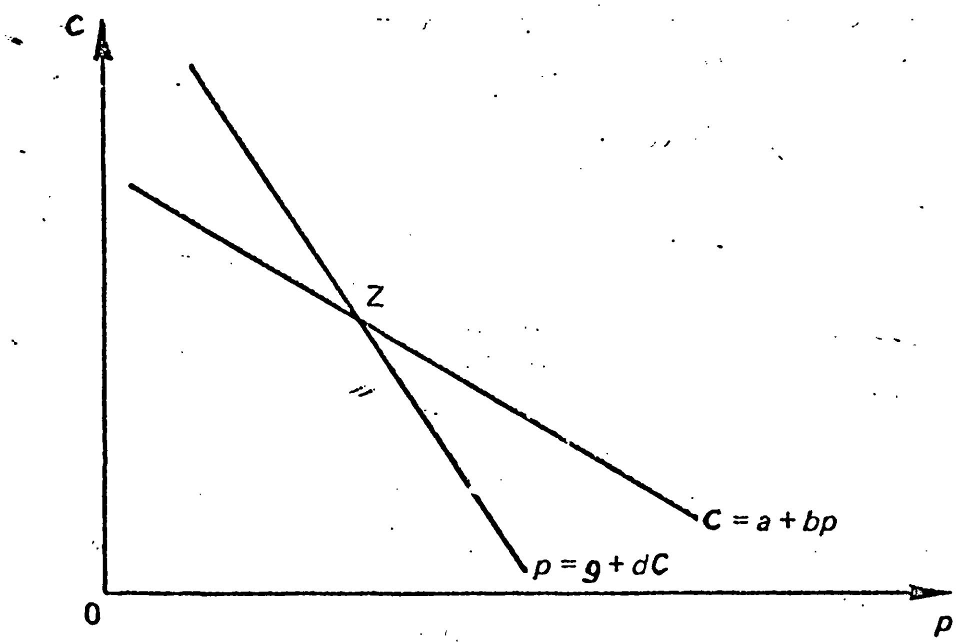
Consider the following simplified, linear model of the criminal justice system:

$$C = a + bp + \Sigma \qquad (2a)$$

$$p = g + dC + \mu \qquad (2b)$$

where C is the crime/offence rate and p is the probability of apprehension, a, b, g and d are parameters to be estimated and Σ and μ are stochastic disturbances. The model is depicted in Figure 3.1 below.[3]

Figure 3.1



As we can see from Figure 3.1, the solution of the non-stochastic versions of equations (2a) and (2b) will generate a point Z. When the stochastic

3. For expositional purposes we assume that $b < 0$ and $d < 0$. This is not essential for the argument.

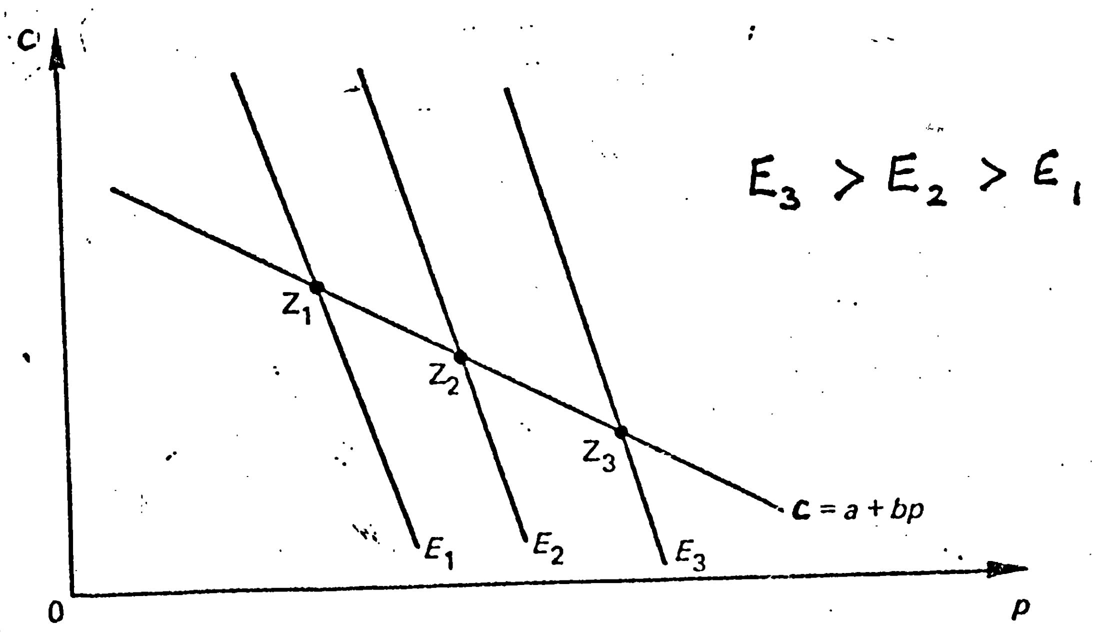
elements are introduced, we will observe a scatter of points around Z. However, this information is insufficient to enable estimation of either of the relationships, because there are an infinite number of linear systems that could generate points like Z.

However, estimation of the structural equations may be possible under certain conditions. This would require the imposition of a priori restrictions upon the system. Normally this involves assuming that certain variables affect one of the endogenous variables but not the other. However, variable exclusion would only aid in the identification of the equation from which that variable is excluded. For example, suppose that an exogenous variable, E - expenditure on police services - is thought to affect p, but not C directly. In that case equation (2b) will have to be rewritten as,

$$p = g + dC + eE + \mu \qquad (2c)$$

Additionally, assume that $e > 0$ i.e. increases in police expenditure are hypothesised to increase the probability of apprehension, ceteris paribus. Figure 3.2 depicts the non-stochastic version of this new model.

Figure 3.2



If we observed "equilibrium" points like Z_1, Z_2 and Z_3 then the structural equation for C (the supply of offences) would be uniquely determined. However, the equation for p (the police production function) is not identified by this restriction.

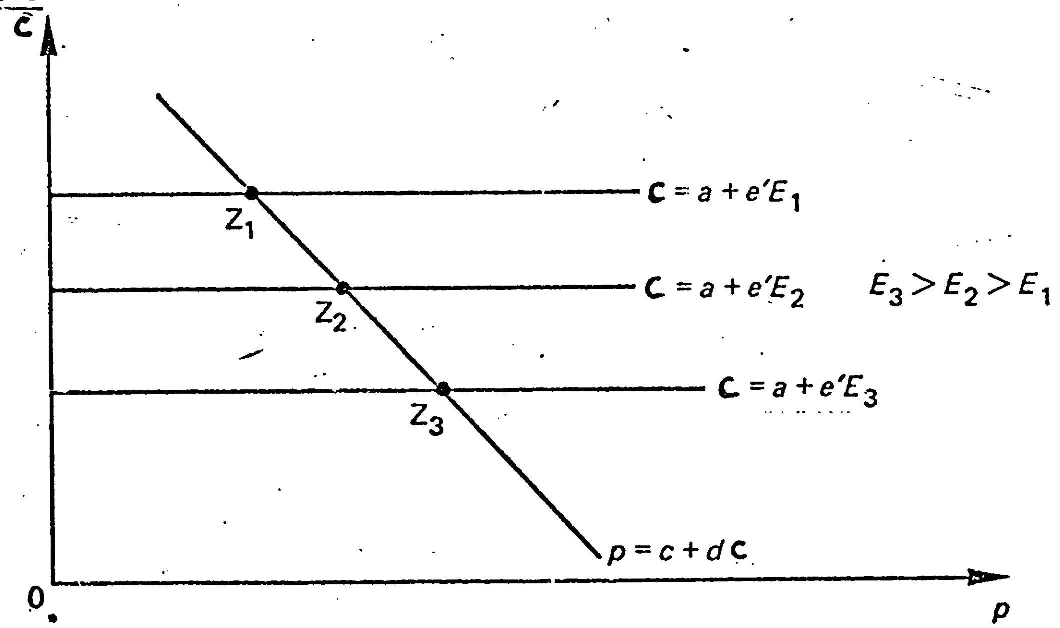
We must exercise caution here. Suppose that the <u>true</u> underlying relationships are different from those hypothesised by equations (2a) and (2c) above. Suppose that p <u>does not</u> affect C and that E affects C but not p (increased police expenditures do not affect detection rates, but deter crime through, say, increased police patrolling). In that case the "true" model is:

$$C = a + e'E + \Sigma \qquad (3a)$$

$$p = g + dC + \mu \qquad (3b)$$

This model is depicted in Figure 3.3.

<u>Figure 3.3</u>



The three points (Z_1, Z_2 and Z_3) showing an inverse relationship between the crime and detection rates lie on the police production function. A curve fitted through these points would <u>not</u>, therefore, represent a supply of offences function. In adopting the model specification given by equations (2a) and (2c), we would have been led to conclude that an increased probability of detection had a deterrent effect upon crime when, in fact, none existed.

Fisher and Nagin (1978) argued that "(t)he very real possibility of making erroneous causal inferences when a model is identified through erroneous assumptions underscores the point that identification is not a minor technical point of estimation" (p 371). Further, they argued, "it is essential that when exclusion restrictions are used for identification, the restrictions must be carefully justified on ... a priori grounds ..." (p 372). They claimed also that "In analysing the mutual association of crime and sanctions, the possibility of making erroneous causal inferences about the causal effect of sanctions on crime is particularly high" (p 372).

If there are good reasons for believing that crime has a negative causal effect upon sanctions, we might observe a negative relationship between the two even if sanctions did not deter crime. We must, therefore, exercise care when interpreting the studies reported in later sections of this chapter.

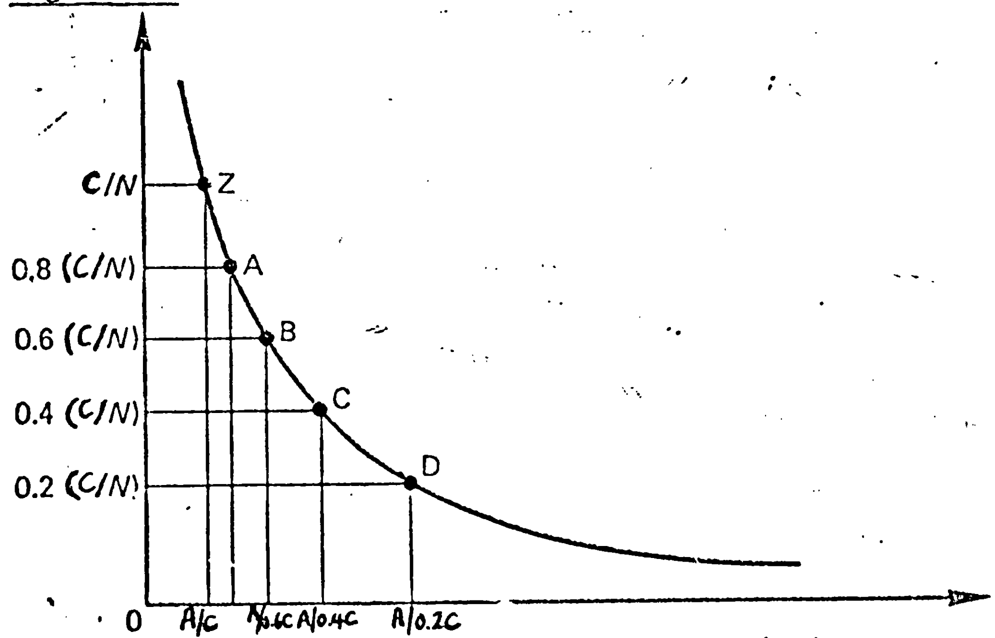
We have dealt in fairly general terms with the identification of a simple model. Identification in more complex models works on basically the same principles (see Fisher and Nagin, 1978 pp 374-8 or Stewart and Wallis, 1981, Chap IV). We now examine the problems caused by measurement error in the crime variable.

(ii) <u>Measurement Error in the Crime Variable</u>

Most empirical studies of crime have estimated a supply of offences function using recorded crimes (per capita) as the dependent variable and the probability of arrest and/or conviction as one of the sanction variables. The probability of arrest is normally defined as the ratio of the number of arrests to the number of recorded crimes. Ignoring the other variables, for ease of exposition, we can show that if there are variations across areas in the measurement error of the recorded crime variable then a spurious negative correlation between the crime rate and arrest rate may exist.

Suppose that we have data for a number of areas. Each area has an identical population size (N), the same true level of crimes (C) and exactly the same number of arrests (A). The example may seem far fetched, but it illustrates the point most clearly. If we were to plot the true per capita crime rate (C/N) against the true probability of arrest (A/C) then all the areas would be located at the same point (Z) in Figure 3.4 below.

Figure 3.4



However, suppose that there is some variation across areas in the recording of crimes. For example in some areas only 80% of crimes are recorded, in others only 60%, 40% and 20%, and so on. Recorded crime rates for these areas will, therefore, be only 0.8 (C/N), 0.6 (C/N), 0.4 (C/N) and 0.2 (C/N) respectively. If the total number of arrests remains at A then the arrest rate will also appear to differ across areas. Those areas reporting the lowest number of recorded crimes will have the highest arrest rates. The result is that a set of points like A, B, C and D in Figure 3.4 is generated. It would seem that there was a negative association between the crime rate and the arrest rate. However, that is a purely spurious association induced by measurement error in the recorded crime rate.

Of course, measurement error would be totally insignificant if a constant proportion of all crimes are recorded by the police. In that case the conclusions drawn from studies using the recorded crime rate would be the same as those using true crime levels. If, however, measurement error in recording crime statistics was not constant, then estimates of the deterrent effect of punishment would be inconsistent and biased. The extent of the inaccuracy would depend upon the magnitude and variance of the measurement error in the recorded crime statistics.

Taylor (1978) has shown, for a logarithmic specification of the supply of offences function, that measurement error has both multiplicative and additive effects upon the estimate of the deterrence elasticity. These two effects pull in opposite directions. One will tend to reduce the size of the coefficient attaching to the sanction variable, the other tending to increase it. Whether the overall effect is to increase or reduce the size of the measured deterrent elasticity, relative to its true level, depends upon whether the true deterrent elasticity is greater or less than minus one.[4] If its true value is between zero and minus one then measurement error

4. If its true value is exactly minus one then no bias occurs.

will tend to increase the absolute value of the measured deterrent elasticity. As we shall see, many empirical studies do in fact put the elasticity of offences with respect to probability of apprehension/detection between zero and minus one. Such studies will tend, therefore, to overstate the extent of the deterrent effect of arrest.

To be precise about the impact of measurement error it would be necessary to undertake detailed Monte Carlo simulation experiments with each of the empirical models reported in the next section. We could then see how different assumptions concerning measurement error in the crime variable affected the parameter estimates of the model. However, it should be clear, even from this limited discussion, that techniques exist in econometrics for dealing with measurement errors in variables. Therefore, the immediate response to the existence of such error need not necessarily be to engage in collecting new data by for example expensive victimisation or self-reporting studies. Such data may itself be subject to an unknown degree of error.

A related problem in using recorded crime and arrest data is that, because both may be used as indicators of police effectiveness there is an incentive for police forces to manipulate the data so as to produce reductions in crime rates and increases in arrest rates. However, this would only strengthen any spurious negative correlation between the two variables if there is variation across areas in the intensity with which this practice occurs.

We must offer one final word of caution concerning the interpretation of any observed negative association between crime and sanctions. Part of the association may reflect incapacitation effects rather than deterrence effects. Areas with higher imprisonment rates may have larger reductions in crime rates, because these areas are physically restraining a greater proportion of criminals from committing crimes. However, the incapacitation effect may be nullified by the entry of new criminals to replace those who have been imprisoned. Separation of the incapacitation and deterrence effects is complicated, but is important both for policy purposes and from a scientific perspective. As yet there seems to be little agreement as to whether the incapacitation effect is substantial (Nagin, 1978 and Wolpin, 1978a) or small (Ehrlich, 1981). Research into this subject is still in its infancy.[5]

(2) A Review of Empirical Studies

It is not the purpose of this section to review the whole of the literature concerning general deterrence i.e. the effect that punishment may have upon potential criminals. We focus instead upon the empirical work undertaken by economists following Becker's seminal theoretical analysis (Becker (1968)). Much of the earlier macro-level work, undertaken by sociologists and criminilogists, lacked a sound theoretical basis, used less powerful statistical methods and often either failed to control for differences in socio-economic factors between areas (examples of earlier studies are Gibbs (1963) and Tittle (1969)). It will also be impossible to discuss every study. A recent bibliography (Palmer (1977)) listed no fewer than 78 studies by economists of the deterrent effect of sanctions and the list continues to grow. We also concentrate on the supply of offences function. We will, however, briefly discuss estimates of the police "production function" which these studies have jointly produced. A more

5. In Chapter (6) we try to reach some tentative conclusions about the relative strengths of the deterrence and incapacitation effects for property crimes in England and Wales.

extensive discussion of law enforcement productions is contained in Pyle (1983, chapters 6 and 7).

(1) North American Studies

An important and impressive piece of empirical work in this area is that by Ehrlich (1973) for States in the U.S.A. in 1940, 1950 and 1960. The supply of offences function was specified as being,

$$\left[\frac{Q}{N}\right]_i = A\, P_i^{\,b_{1i}}\, T_i^{\,b_{2i}}\, W^{c_{1i}}\, X^{c_{2i}}\, NW^{e_{1i}} \exp(\mu)$$

where $\left[\frac{Q}{N}\right]_i$ is the per capita known crime rate in crime category i,

P_i is the number of offenders imprisoned (in that year) per known offence of category i,

T_i is the average time served by offenders in state prisons for offence i,

W is median family income (a measure of average potential gains from illegal activity),

X is the percentage of families whose incomes are below a half of the median income (a measure of the relative distance between legal and illegal earnings opportunities),

NW is the percentage of non-Whites in the population,

and μ is a random disturbance.

Note first, that the crime supply function was specified as linear in the logarithms of the variables and second, that the deterrence variables refer solely to imprisonment rates and the length of imprisonment. No variables are included to measure the probability of detection and/or conviction.

Ehrlich viewed the crime equation as part of a simultaneous model in which $\left[\frac{Q}{N}\right]_i$, P_i and $^E/N$ (per capita law enforcement expenditures) were endogenous variables.[6] The full model is given by the crime equation above and the following two equations,

$$P_i = B \left[\frac{E}{N}\right]^{\beta_1} \left[\frac{Q}{N}\right]_i^{\beta_2} \prod_j Z_j^{\delta_j} \exp(\xi) \qquad \text{("Production Function")}$$

$$\text{and} \quad \frac{E}{N} = \Gamma L^{\gamma} \left[\frac{Q}{N}\right]^{\gamma} \left[\frac{E}{N}\right]_{-1}^{1-\gamma} \exp(\varepsilon)$$

where L is average potential loss from victimisation and the Z_j's are socio-economic variables.

Some twelve pre-determined and socio-economic variables were used in the regression analysis. These included the variables W, X and NW mentioned above. In addition Ehrlich included per capita law enforcement expenditures lagged one period, the crime rate lagged one period, the unemployment rate for civilian urban males aged 35-39 years, the percentage of males aged 14-24 years, the percentage of the state population living in standard metropolitan statistical areas, the number of males per 100 females, a North-South dummy variable, the mean number of years of schooling of those aged 25 years and over and the total population of the state. Identification of the crime function was, therefore, based on excluding these additional nine socio-economic/demographic variables from the crime

---

6. Severity of punishment (measured by T_i) is assumed to be exogenous unlike the stylized model of section 1(i). Empirical work on crime has commonly made this assumption.

equation.[7]

Ehrlich examined each of the seven FBI index crimes (murder, rape, assault, robbery, burglary, larceny and auto-theft) separately. The crime equations for 1940 and 1950 were estimated by OLS (ordinary least squares), because data for police expenditures across states was not available for those years.[8] The 1960 data was used to derive OLS, 2SLS (two stage least squares) and SUR (seemingly unrelated regression) estimates of the first equation of the model. A result of this is that Ehrlich produced a mass of sometimes confusing and very occasionally conflicting results that are difficult to summarise succinctly. As an illustration consider his OLS and 2SLS results for all offences in 1960. Whilst the qualitative results are quite similar, i.e. in terms of the signs and significance of the regression coefficients, the sizes of some of the coefficients are quite different. This can be seen in Table 3.1 below.

---

7. There seems to be very little justification for excluding some of these variables from the crime equation, especially the unemployment and age structure variables. Indeed some of them were added at a later stage.

8. This prevented estimation of the full model. Further, as no data for L on a statewide basis was available no attempt was made to estimate the third equation of the model.

Table 3.1

Ehrlich's Estimates of the Supply of Offences Function, 1960 data

Coefficient	OLS estimate	2SLS estimate
b_1	- 0.526	- 0.991
b_2	- 0.585	- 1.123
c_1	2.065	1.292
c_2	1.801	1.775
e_1	0.207	0.265

All coefficients are at least twice their standard error.

The difference is most noticeable for the deterrence elasticities, which are both approximately - 0.5 for OLS, but approximately - 1 for 2SLS.[9] (It is interesting to recall at this point Taylor's result that if the true deterrence elasticity is - 1, then measurement error in the crime variable will not impart any bias to the measured elasticity)

In Table 3.2 we present Ehrlich's 2SLS parameter estimates for the supply of offences function for each of the seven FBI index crimes in 1960.

9. As the model is specified as being simultaneous, it would seem sensible to concentrate attention upon the parameter estimates derived by a simultaneous equation technique i.e. 2SLS or SUR. In fact as there is remarkably little difference between Ehrlich's 2SLS and SUR estimates, nothing is lost by concentrating upon one set of results rather than the other.

Table 3.2

Ehrlich's 2SLS estimates, 1960 data

	coefficient associated with variable				
Offence	b_1 (P)	b_2 (T)	c_1 (W)	c_2 (X)	e_1 (NW)
Robbery	- 1.303*	- 0.372	1.689	1.279	0.334*
Burglary	- 0.724*	- 1.127*	1.384*	2.000*	0.250*
Larceny	- 0.371*	- 0.602	2.229*	1.792*	0.142*
Auto-Theft	- 0.407*	- 0.246	2.608*	2.057*	0.102
Murder	- 0.852*	- 0.087	0.175	1.109	0.534*
Rape	- 0.896*	- 0.399*	0.409	0.459	0.072
Assault	- 0.724*	- 0.979*	1.650*	1.707*	0.465*

* Indicates that a coefficient is more than twice its standard error.

These results appear to lend considerable support to the pro-deterrence thesis.

A number of interesting points emerge from an analysis of Ehrlich's results presented in Table 3.2. First, certainty of imprisonment (P_i) seems more often to be a significant deterrent than its severity (T_i). Often too, its coefficient is considerably larger.[10] The absolute sizes of b_1 and b_2 vary considerably between crimes, indicating that the responses of criminals are possibly different in the various crime categories. This result must cast doubt upon the reliability of those studies which have used data for all crimes rather than for different types of crime.

The income variables (W and X) perform rather better in the equations for property crimes (i.e. burglary, larceny and auto-theft) than they do in the equations for violent crimes (except for assault). NW is significant in both the property crimes equations and also in some of the

10. However, there are some cases in which the elasticity of offences with respect to severity is larger than with respect to certainty (i.e. burglary and assault).

violent crimes equations. In three of the property crime equations (burglary, larceny and auto-theft), the absolute values of the coefficients c_1 and c_2 are larger (often considerably so) than the coefficients b_1 and b_2. This indicates that improvements in the relative income positions of lower income groups may have a considerably greater impact upon the level of property crimes than increases in the severity and/or certainty of punishment. Ehrlich argued, "this suggests a social incentive for equalising training and earning opportunities across persons, which is independent of ethical considerations" (p 112). Of course, whether it "pays" society to reduce crime by improving earnings and employment prospects rather than by increasing expenditures on law enforcement would require a full-scale cost-effectiveness study.

Ehrlich introduced three additional variables into the crime supply equation. These were the unemployment rate amongst civilian, urban males aged 14-24 years, the labour force participation rate of the same group and the percentage of all males in the 14-24 years age group. However, introduction of these variables "... had virtually no effect on the (previously) estimated elasticities ..." (p 107).[11]

Finally, Ehrlich briefly considered the extent to which crimes were either substitutes or complements for each other. He introduced into each of the crime equations variables relating to the certainty and severity of

---

11. Almost invariably, the coefficients of these variables were less than twice their standard errors (the only exceptions being the age variable in the assault equation and the labour force participation rate in the equations for robbery, murder and rape). The coefficient of the participation rate was found to be consistently negative for crimes against the person.

imprisonment for subsets of the other crimes. He found that robbery and burglary were complements and that burglary and theft were substitutes. However, he concluded that the "... absolute values of the coefficients associated with these variables are quite low relative to their standard errors" (p 107, footnote 52).

Ehrlich also estimated an aggregate production function (i.e. for all felony offences) using the cross-section of states in 1960. His results indicated that changes in per capita law enforcement expenditures were <u>insignificant</u> in explaining changes in P (the imprisonment rate). The per capita offence rate had a significant negative effect upon the imprisonment rate, i.e. higher levels of offences per capita lowered the rate of imprisonment. This was taken by Ehrlich to indicate the existence of a "crowding effect" upon the resources of the criminal justice system. However, there is no indication at what point the crowding takes place, i.e. whether higher offence rates made it more difficult for the police to apprehend offenders or for courts to deal with them or whether because prisons were already full, alternative, non-custodial sentences were imposed. Other significant variables were (i) population size (negative), (ii) racial mix (positive), (iii) mean years of education (positive) and (iv) the North-South dummy variable. It is not easy to interpret some of these results and in fact Ehrlich did not always attempt to do so. For example, he made no attempt to explain the significance of the positive relationship between the mean number of years of schooling and the percentage of offenders sentenced to imprisonment. One result was, however, clear i.e. increased expenditures on law enforcement had remarkably little effect upon imprisonment rates.

Avio and Clark (1976, 1978) estimated a similar model for property crimes using Canadian data. Their earlier study was based upon data for eight provinces for the years 1970, 1971 and 1972. Their later study employed 1971 data for census divisions in the province of Ontario. The model used in both studies had basically the same structure. It also comprised three equations. One to explain the recorded crime rate, another to explain the clearance rate (a police production function) and a third to explain government expenditures on law enforcement.[12] The supply of offences function was of the form,

$$O_i = a_i + \alpha_i P_i + \beta_i Q_i + \delta_i S_i + \sum_{j=1}^{n} \gamma_{ij} X_{ij}$$

where O_i is the recorded crime rate per 1000 population for crime i,

P_i is the clearance (arrest) rate for crime i,

Q_i is the conditional conviction rate for crime i, i.e. the ratio of convictions to charges,

S_i is the average prison sentence imposed for crime i, adjusted for remission and parole,

and the X_{ij}'s are socio-economic/demographic factors.[13]

In their study of provinces, Avio and Clark included in the X_{ij}'s the following variables,

(i) the percentage of families with less than half the median income,

(ii) the number of households with record players (a measure of victim stock),

12. However, Avio and Clark presented estimates for the supply of offences function only. The other two equations were used merely to suggest instrumental variables for the 2SLS estimation.

13. All variables are measured in natural logarithms. Note also that Q_i and S_i are treated as exogenous variables, although Avio and Clark did later experiment by making S_i endogenous.

(iii) the unemployment rate (sometimes restricted to that for males 14-24 years of age),

(iv) the labour force participation rate (sometimes restricted to males 14-24 years of age),

(v) the percentage of males aged 15-24 years,

and (vi) the percentage of North American Indians in the population.

In their study of Ontario census divisions the X_{ij}'s were

(i) the unemployment rate (UR),

(ii) the percentage of the population that was North American Indian (IND),

(iii) average family income (INC),

and (iv) the percentage of the population that was male and aged between 15 and 24 years (AGE)

In both studies the model was estimated by 2SLS for the crimes of robbery, break and enter, theft and fraud. We present in Table 3.3 results from the later study only (Avio and Clark (1978)), although in the ensuing discussion we shall refer to earlier results.

Table 3.3 Avio and Clark's Estimates of the Supply of Offences Function, 1971 data[14]

Crime	Variable						
	P	Q	S	UR	INC	AGE	IND
Robbery	- 1.146*	- 0.658	- 0.035	1.030*	2.318*	-	-
Break and Enter	- 1.020*	- 1.008	- 0.174	0.761*	0.153	3.191*	0.144
Theft	- 0.782*	0.575	- 0.012	0.671*	0.980*	1.195	- 0.033
Fraud	0.588	- 1.989	0.076	0.173	1.957*	1.534	- 0.003

* Indicates a t statistic greater than 2.

14. We have selected from the regressions presented in Table 2 of Avio and Clark (1978) those with the largest number of t - statistics greater than 2.

Avio and Clark used a larger number of deterrence variables than Ehrlich. This may be important if the successive stages of the Criminal Justice System (CJS) produce different deterrent effects. Further, they chose to measure imprisonment differently from previous studies. Instead of using data on time served by released prisoners, they used sentences imposed by the courts in that period (corrected for parole and remission possibilities). They argued that this represented a better measure of expected sentence length, because "... information on current sentences handed down is more readily available to prospective offenders than sentence information on released offenders. Many newspapers publish the results of current court proceedings, but newspapers do not systematically publish information on offenders released from incarceration" (p. 6). This argument seems plausible, although it begs the question how do prospective offenders formulate their expectations about punishment variables and what information sources they use. Avio and Clark also argued that data on the average time served might show a spurious negative correlation with crime rates. If the crime-rate fell the number of prisoners would fall and average sentence length served would tend to increase, because prisons would tend to be populated by long stay inmates. The negative association would be caused by the fall in the crime-rate, not the rise in sentence length.

Avio and Clark also considered the question of crime spillovers/displacement. This problem had been largely ignored previously (but see Mehay (1977) and later discussion). Displacement may occur when law enforcement agencies "crack down" upon crime in one area and criminal activity is displaced into adjoining areas. This may be an important consideration in studies covering small, contiguous areas, e.g. precincts, adjacent cities etc, where the population is thought to be mobile. Avio and Clark tested for displacement by incorporating into the crime supply function, "the minimum clearance rate among contiguous neighbouring census division areas ..." (p. 9). However, they concluded that "for all categories of property crime the test results indicate the insignificance of the neighbouring clearance rate ..." (p. 9).[15]

The main results of Avio and Clark's analysis confirm those of earlier studies with respect to most variables. However, two of the deterrence variables (the conditional probability of conviction and sentence length) were invariably statistically insignificant. The clearance rate was usually significant, except in the equation for fraud. As with Ehrlich's earlier study some variability was found in the size of the clearance elasticity across crimes. The conditional conviction rate was argued to be everywhere insignificant, although its t-statistic was in the region 1.6 to 1.7 for the crimes of robbery, break and enter, and fraud. The expected sentence length variable proved to be insignificant in all cases.[16]

The opportunity cost (UR) and victim stock (INC) variables were usually significant and had the predicted signs in all equations. The insignificance of the unemployment rate in the fraud equation is not altogether surprising. Indeed the unemployment variable here is probably an entirely inappropriate measure of opportunity cost.[17]

---

15. This is, of course, not the only possible, nor necessarily the best, test of the displacement hypothesis. More sophisticated formulations are offered by Mehay (1977) and Furlong and Mehay (1981).

16. An interesting ranking of elasticities (in absolute terms) seemed to be $\alpha_i > \beta_i > \delta_i$. This ranking is in fact predicted by the theoretical model. See Ehrlich (1975).

17. An interesting comparison with Ehrlich's results is possible too. The coefficients attaching to UR and INC are not usually greatly in excess of those attaching to P, but are larger than those attaching to Q and S. The unemployed have fewer opportunities to engage in fraud than the employed, unless of course they are defrauding the social security system!

The performance of the demographic variables (AGE and IND) is generally poor. Both are generally statistically insignificant, the one exception being AGE in the equation for break and enter.

Avio and Clark were concerned by the failure of expected sentence length to exert a significant deterrent effect. They considered a number of reasons why this may have been. One possibility was that sentence length was an endogenous variable positively related to crime levels. Whilst re-estimation of the model leant some support to this thesis, it did not improve the performance of S in the crime equation. Incorporation of variables measuring the probability of imprisonment and sentence variability failed to change the results. Avio and Clark concluded that, sentence length simply did not exert a deterrent effect in Canada, possibly because of the significant delays in court hearings allied to high rates of time preference amongst potential offenders.

We now briefly consider the results of Avio and Clark's earlier study (Avio and Clark (1976)) of Canadian provinces. We cannot place a great deal of reliance upon these results, because of the somewhat limited sample size. Even pooling time-series and cross-section data provided only 24 observations and added the potentiality for serial correlation of the residuals. The model was again estimated by 2SLS for the crimes of theft, fraud, break and enter and robbery.

Generally significant inverse relationships were observed between the crime rate and the clearance rate, and between the crime rate and the conviction rate (except for the crimes of fraud and break and enter). However, no significant deterrent effect attaching to sentence length was found. Both the income distribution and victim stock variables were found to be significant and positively related to all crime rates. The age distribution variable was significant in the fraud and robbery equations, whilst unemployment was significant in the theft and break and enter equations, but not elsewhere.

Sjoquist (1973) estimated a supply of offences function for aggregate per capita property crimes (i.e. reported robberies, burglaries and larcenies over $50) for 53 municipalities with populations in the range 25,000 to 200,000 in 1968. To avoid the displacement issue isolated cities were used. Several deterrence variables were included. These were the arrest rate, the conviction rate, the conditional conviction rate and average time served in State and federal prisons. Other variables used were (i) annual labour income of manufacturing workers (representing legal gains), (ii) the unemployment rate, (iii) the percentage of families whose annual income was less than $3000, (iv) retail sales per establishment (potential criminal gains), (v) the percentage of the population that was non-white, (vi) the mean number of school years completed, (vii) population density and (viii) population size.

The supply function, which was assumed to be linear in the logarithms of the variables, was estimated for various groupings of the independent variable set by OLS. Sjoquist found a negative and statistically significant relationship between the property crime rate and the arrest rate with an elasticity of approximately - 0.36. The conditional conviction rate was only significant when the arrest rate was not included. Average sentence length was rarely found to be a significant variable, especially when the unemployment and income distribution variables were included. The coefficients of the racial composition, schooling and unemployment variables were always positive and significant.

Important weaknesses of Sjoquist's study must, however, be his failure (i) to consider explicitly the possible simultaneous determination of offence rates and sanction levels and (ii) to estimate separate supply equations for the different crimes within the aggregate property crime index.

Phillips and Votey (1975) estimated a simultaneous model of crime generation using data for 50 Californian counties in 1966. Endogenous variables were the per capita aggregate felony rate (for all seven FBI index offences), the conviction rate and the number of law enforcement personnel. The crime rate was assumed to depend upon the conviction rate, the percentage of those convicted who were committed to state prison, probation with jail or probation (a measure of sentence severity), the fraction of these commitments that were probation with jail and an index of socio-economic and demographic factors.[18] The system of equations was assumed to be linear in the logarithms of the variables and was estimated by 2SLS.

Estimates of the crime equation reveal highly significant negative coefficients for the conviction rate and the measure of sentence severity. The socio-economic index was also significant and directly related to the per capita crime rate. Further analysis of the twelve demographic and socio-economic factors included in the index revealed that measures of economic conditions (poverty and frustrated economic ambition) exerted a much more

---

18. The conviction rate was assumed to depend upon the aggregate crime rate and the numbers of law enforcement personnel. The elasticity of the conviction rate with respect to the crime rate was approximately - 1.6, whilst with respect to the number of law enforcement personnel it was approximately 2.3.

pronounced effect upon crime rates than did the demographic variables.

Pogue (1975) estimated a three equation model in logarithmic form for data drawn from samples of Standard Metropolitan Statistical Areas (SMSAs) for the years 1962, 1967 and 1968. Separate equations were estimated for each of the FBI index crimes. The deterrence variable (the arrest rate) had a significant negative coefficient in all the crime equations except those for assault and auto-theft. However, its effect varied considerably across crimes (the elasticity ranged from - 0.86 for larceny to - 2.73 for murder). The only other variable which appeared to be consistently significant was the percentage of households with incomes below $3000 per year, which had a positive coefficient. Variations in unemployment levels and in median years of schooling seemed to have little effect upon inter-SMSA crime rates.

The arrest rate was assumed to depend upon both state and local government expenditures on the police, population size and population density of the area and the crime rate. The "production function" proved to have remarkably poor explanatory power. Pogue concluded that, "... the estimated effects of both State and SMSA police protection expenditures on clearance ratios are statistically insignificant and often negative ... (and) ... clearance ratios are not well explained by the variables included in the regression equation" (p. 24). He went on, "Similar results were obtained when number of police per capita was used as the index of police protection. Thus, these results provide no support for the hypothesis that clearance ratios and hence crime rates are influenced by the per capita levels of police spending and manpower in an SMSA" (p. 24).

An interesting application of the economic model is Landes' (1978) analysis of the incidence of the hijacking of U.S. aircraft between 1961 and

1976. He argued that in this case simultaneity was not a problem, because hijackings were not so frequent as "... to strain the enforcement capacity and make the probability of apprehension a negative function of the rate of hijacking" (footnote 11, pp. 6-7). The limited number of annual observations forced him to estimate supply functions using as the dependent variable data on (i) quarterly hijackings, (ii) the time interval between hijackings and (iii) the flight interval between hijackings.

Explanatory variables used were (i) the probability of apprehension, (ii) the conditional probability of incarceration, (iii) average sentence length, (iv) the conditional probability of death of a hijacker, (v) the quarterly number of flights, (vi) population size, (vii) unemployment and (viii) per capita personal consumption.[19]

The regression using quarterly hijackings was estimated using modified first differences to eliminate serial correlation of the residuals. The Cochrane-Orcutt technique was used to difference the variables. Variables were not transformed logarithmically, because in almost half of the periods no hijackings took place.

The results of the analysis of quarterly data showed that generally the deterrence variables were significant, except for the probability of offender's death. However, the other variables were generally insignificant.

Results of the regression analysis using time and flight intervals

---

19. Estimates of the probability of apprehension, the conditional probability of incarceration and average sentence length were generated in several different ways. These involved using either three-quarter moving averages or regression estimates based upon the three most recent values of the appropriate variable.

between hijackings showed that increases in the certainty and severity of punishment generally increased the interval between hijackings. In addition the non-deterrence variables also appeared to be significantly related to the intervals between offences. Increases in unemployment (representing a reduction in legitimate earnings opportunities) and population size (representing an increased supply of potential offenders) tended to reduce the intervals between hijackings, as did increases in per capita consumption (standing for improved legal opportunities). Clearly, this last variable is not working in its expected fashion.

Landes considered a crime for which under-reporting was likely to be insignificant and for which simultaneous interaction of the crime and deterrence variables was likely to be weak. Similar claims were made by Blumstein and Nagin (1977) in a study of draft evasion. Further, draft evasion is argued to be a good test of the hypothesis, because draft evaders are "... fully aware of the potential penalties for their crime and therefore had information necessary to respond to measures designed to deter crime" (p. 247). Data on draft evasion are also free from measurement error and do not confound possible deterrence and incapacitation effects.[20]

The study used US state-level data for the years 1970 and 1971. The dependent variable - the evasion rate - was measured by the number of evaders divided by the draft call in a state in that year. The sanction measures were (i) the proportion of defendants found guilty and (ii) the expected prison sentence for those going to trial. Additional explanatory variables were (i) the percentage of the population living in urban areas, (ii) the percentage of non-whites in the population, (iii) median education

20. An individual can only evade the draft once, so that the incapitation effect is by definition nil.

for persons over twenty-five years of age, (iv) median real family income, (v) the percentage of the population classified as poor and (vi) time and regional dummy variables.

Five different measures of the evasion rate were in fact used (because of ambiquities about the precise definition of evasion) in four different model specifications using both linear and logistic functional forms. This produced no less than 40 separate regression estimates! Blumstein and Nagin found a consistently negative and significant association between the evasion rate and probability of conviction, an association that was significant over a wide range of model specifications. However, length of punishment proved to be a far less effective deterrent.

Mathur (1978) estimated a three equation model using data of US cities with populations over 100,000 in 1960 and 1970. Equations for each of the seven FBI index crimes were estimated by 2SLS. The endogenous variables were the crime rate per 100,000 population, the imprisonment rate and per capita police expenditures. The crime rate was assumed to be a function of the imprisonment rate, the median term of imprisonment, median income, a measure of income inequality, the percentage of the population that was non-white, median years of schooling for those aged 25 years and over, the percentage of the population in white collar jobs, the unemployment rate and a North-South dummy variable.

Mathur concluded from his estimated model, "... that the deterrent hypothesis is alive and well and that punishment does work as a significant deterrent to crime" (p. 464). However, in 1960 only 6 of the 14 deterrence elasticities were negative and significant at the 10% level. In 1970 8 of the 14 were negative and significant. In all of the cases where significant elasticities were found, certainty of imprisonment exerted a larger deterrent effect than its severity. Mathur also found considerable differences in the sizes of the deterrence elasticities across crimes. The equations for murder and larceny seemed poorly determined. Of all the other variables hypothesised to affect crime levels, only the racial composition variable was found to be consistently significant (and positive). Unemployment was significant (at the 5% and 10% levels) in about half the cases.

Mathur's equation for the imprisonment rate included as explanatory variables, (i) median length of imprisonment, (ii) per capita police expenditure, (iii) the crime rate, (iv) population and population squared and (v) the percentage of non-whites in the population. Separate "production functions" were estimated for each of the seven FBI index crimes. Results for the estimated production functions can be summarised as follows. The crime rate usually had a negative coefficient, though in the 1970 sample it was only significant at the 10% level or better in two of the equations. There seems to be a fairly marked, significant inverse relationship between probability of imprisonment and its severity. However, the elasticity varies considerably across crimes (for example from - 0.58 for rape to - 2.10 for larceny in 1960). Strangely, increased police expenditures seem to reduce the probability of imprisonment for most crimes, except for murder where the coefficient is positive and significant. Invariably racial mix is positively and significantly related to the probability of imprisonment.

We now examine four studies of crime and law enforcement at the city/metropolitan level. These are (i) Thaler's study of property crime in Rochester, New York (Thaler (1977)), (ii) Furlong and Mehay's study of crime in Montreal districts (Furlong and Mehay (1981)), (iii) Mehay's study of crime in communities in the Los Angeles metropolitan area (Mehay (1977)), and (iv) Mathieson and Passell's study of crime in 65 precincts of New York City (Mathieson and Passell (1976)). An advantage of using data at a lower level of disaggregation is that it is easier to incorporate normally unpublished information on police deployment/resource allocation. A disadvantage is the inability to test for the effect of severity of punishment, which is invariably constant across areas. Also, the displacement effect is likely to be more of a problem in this case.

Thaler estimated a four equation model using 1970 census tract data in which the endogenous variables were (i) A_i - the number of individuals arrested who lived in census tract i, (ii) P_i - the number of patrol car hours spent in census tract i per acre, (iii) C_i - the clearance rate in census tract i [21] and (iv) O_i - the number of reported property offences in census tract i.

The supply of offences (O_i) was assumed to depend positively upon A_i - a proxy for the number of criminals living in the area - and negatively upon C_i (via a deterrence effect). The effect of P_i upon O_i was felt to be indeterminate a priori, because the preventative effect of patrolling might be offset by a reporting effect. The model was estimated by 2SLS,

21. The clearance rate was measured in two ways. One measure included offences taken into consideration (TICs), the other excluded TICs.

with variables measured in actual values.[22]

The results for the crime supply equation were largely as predicted, except that the clearance rate (excluding TICs) was not significant. The clearance rate including TICs was negatively and significantly related to offences. The effect of more patrolling was to increase the reported offence rate. Thaler concluded, therefore, that there was little evidence of a deterrent effect of patrol as such.

An important consideration at this level of disaggregation is the possibility of spillovers/displacement of crime. It is not apparent that Thaler gave explicit consideration to this problem. An author, who has considered this problem is Mehay (1977) in a study of 46 cities in the Los Angeles metropolitan region. The crime supply equation had as one of its

---

22. The other equations of Thaler's model were as follows. A_i was assumed to depend upon a number of socio-economic/demographic variables such as population density, age and sex structure of the population, racial mix, median education, unemployment, median income, the percentage of houses valued at over $20,000, the number of husband/wife households and the number of unrelated individuals in the population. P_i was assumed to depend upon the property crime rate, age/sex structure of the population, population size, the percentage of males who were married and the per capita non-property crime rate. C_i was assumed to depend upon the number of arrests, police density, the property crime rate, the percentage of houses valued in excess of $20,000, mean reported losses (and losses squared), average response time and the percentage of property offences that were robberies. We shall interpret this last equation as Thaler's "production function". Two production functions were, in fact, estimated. One using C_i including TICs, the other excluding them. The production function for "output" excluding TICs was poorly determined the only significant variables being house value (negative) and losses (also negative). When TICs were included the equation included a larger number of significant variables. These were the crime rate (negative coefficient), the number of arrests (positive), police density (positive), losses (negative) and the percentage of offences classified as robberies (positive).

arguments the per capita police patrol input differential between adjacent cities. He estimated crime supply equations for two aggregate offence groups - property crimes (burglary, robbery, grand theft and auto theft) and violent crimes (homicide, aggravated assault and forcible rape). Other explanatory variables were (i) the arrest rate, (ii) retail sales per 1000 population, (iii) the percentage of families below the official poverty line, (iv) the percentage of non-whites in the population and (v) the percentage of males aged 14 years and over who were married (a measure of family stability). No simultaneous interaction between offences and sanction variables was hypothesised, so the supply functions were estimated by OLS in linear form.

The property crime equation seemed quite well determined with all coefficients having appropriate signs and t - statistics of at least 2. The equation for crimes of violence was less well determined and in particular the deterrence variables were insignificant. Mehay found evidence of the existence of a spillover effect. Property crime rates in particular responded to differences between areas in police patrol inputs. However, the magnitude of the displacement effect was quite small. A ten per cent increase in the patrol input differential generating an increase of about one per cent in property crimes in surrounding areas.

Furlong and Mehay (1981) estimated a three equation model for 38 police districts in Montreal in 1973. The endogenous variables were (i) the per capita reported offence rate, (ii) the clearance rate and (iii) the number of police officers per 1000 of the population.[23] The offence rate was argued to depend upon (i) the clearance rate, (ii) the male unemployment rate, (iii) average household income, (iv) the percentage of males aged 15-24 years in the total population, (v) the median value of owner-occupied detached dwellings, (vi) average sales per retail store and (vii) a crime spillover measure. The last variable was measured by the differential between the average attractiveness of targets in contiguous districts and targets in the relevant district. The model was estimated by 2SLS for each of the crimes of robbery, break and enter, theft, all these crimes and finally for all property crimes plus homicide, rape and assault. Furlong and Mehay adjusted the resident population of an area to allow for daily travelling between districts. The 'dynamic' population measure thus produced was felt, by the authors, to be a more accurate measure of the actual population requiring protection. We discuss, therefore, Furlong and Mehay's results when variables were adjusted by this measure of population.

The clearance rate coefficient was consistently negative and significant for all crime categories (with an estimated elasticity of

---

23. The clearance rate was assumed to depend upon the number of police officers per 1000 population, population density, the ratio of investigators to total manpower, and the ratio of patrol manpower to total manpower. The number of policemen per 1000 population was assumed to depend upon the overall crime rate, population density, average sales per retail store, median value of owner-occupied detached dwellings, average household income and calls for service, most of which are not crime-related. Separate "output" equations were estimated for each crime category. On the whole the output equations were poorly determined with all t-statistics being less than 2. The number of policemen per 1000 population normally increased the clearance rate (except for robbery), although only for the crime category break and enter was the t-statistic greater than 1.4. The ratio of investigators to total manpower was rarely anywhere near being significant. Only in the robbery equation was its t-statistic greater than 0.6. However, the patrol manpower ratio was slightly more effective and only for robbery was the t-statistic less than 1.5 and in that equation its coefficient was, in fact, negative.

approximately − 0.6, which varied little across crimes). The spillover measure was significant for all crimes except robbery, although its magnitude was usually very small. The unemployment variable had a positive and highly significant coefficient. In addition its elasticity (approximately 1.5) was often considerably larger than that for the clearance rate. Furlong and Mehay concluded that "... property crime is considerably more responsive to economic conditions than to apprehension risk" (p. 52). Other variables proved to be less consistent. The coefficient of income (a measure of legitimate gains) was positive and significant in three of the five equations. This may have arisen because of collinearity with the two illegal gains indicators - retail sales and the value of owner-occupied housing. The age variable had a consistently significant, but negative coefficient. The authors concluded that, "Perhaps Canadian youth do not share the same propensity for crime as their counterparts in the US, when other factors are held constant" (p. 53).

Mathieson and Passell (1976) built a three equation model to explain inter-precinct variations in robbery and homicide rates in New York City in 1971. Endogenous variables were (i) the crime rate, (ii) the arrest rate and (iii) the number of policemen per district. The crime rate was assumed to depend upon the arrest rate, median income, the percentage of families with incomes over $25,000 and median income in adjacent districts. The coefficient of the deterrence variable was found to be negative and significant. The elasticity was quite large, being in the range − 1.96 (homicide) to − 2.95 (robbery). This contrasted sharply with previous results and may be due to rather high mobility between New York precincts.[24]

So far, all the studies we have examined offer considerable support to both the pro-deterrence hypothesis and the economic theory of criminal behaviour. The number of studies by economists which have reported no support for the deterrence hypothesis is very small. One such study is that of Forst (1976), who found "... the crime rate to be virtually insensitive to cross-state variation in either the probability or length of incarceration" (p. 479). Forst tested a model of crime determination against data for 50 States in the USA in 1970. Forst's model contained two endogenous and three predetermined variables. The endogenous variables were the aggregate crime rate and the probability of incarceration. The predetermined variables were per prisoner expenditures on the correctional system, per capita expenditures on police and per capita expenditures on the correctional system. The crime rate was hypothesised to depend upon (i) the probability of incarceration, (ii) the average prison sentence, (iii) per prisoner expenditures on the correctional system, (iv) the population migration rate, (v) population density, (vi) the proportion of households that were not husband-wife households, (vii) median family income, (viii) a measure of income dispersion, (ix) the adult unemployment rate, (x) the proportion of residents aged 18 to 20 years, (xi) the proportion of males in the population, (xii) the proportion of residents who were non-white and (xiii)

24. The arrest rate was assumed to depend upon police manpower per reported crime and the percentage of families who had lived in the same residence for five or more years. Police manpower was related to the number of reported crimes, population size, miles of street and a dummy variable for business districts. Separate production functions were estimated for each crime. The number of policemen per reported crime had a positive and highly significant coefficient in the robbery equation, although its elasticity was quite low (approximately 0.22). However, in the homicide equation the police manpower variable was insignificant. In neither equation was the "neighbourhood stability" variable close to being significant.

average temperature. The simultaneous part of the model was estimated by 2SLS. Various functional forms were tried, the ones reported being unweighted regressions of simple linear combinations of the explanatory variables.[25]

Examination of the estimated crime equation shows none of the deterrence variables to be statistically significant. The only significant variables are those relating to migration, population density, "broken" homes and income dispersion. Forst contrasted his results with those of Ehrlich (1973). He claimed that Ehrlich had overlooked a number of important social and demographic variables affecting crime. Inclusion of these variables drastically reduced the significance of the deterrence variables.

A partial test of this thesis can be found in Forst's re-estimation of his crime equation using a restricted set of explanatory variables. It was noticeable that the elasticities attaching to the deterrence variables increased quite substantially. However, they were still somewhat smaller than these reported by Ehrlich. Forst speculated that these reduced elasticities may have been caused by (i) a genuinely reduced impact of punishment upon offenders in 1970 compared with 1960, (ii) reduced measurement error in the crime variable in the later year or (iii) criminals shifting towards those crimes less deterred by punishment.

---

25. The probability of incarceration was argued to depend upon the crime rate, per capita police expenditures, population density and a North-South dummy variable. The crime rate had a negative and significant coefficient with an elasticity of - 1.02. Per capita police expenditure was also significant with a positive coefficient, though its elasticity was only 0.52. Population density was insignificant, whilst the dummy variable was highly significant.

Forst concluded that "The evidence suggests strongly that Ehrlich's crime-deterrence variables are, to a large degree, substitutes for demographic factors that are real determinants of crime but that are not included in Ehrlich's 'supply of offences' equation" (p. 490). Given the rather ad hoc arguments for including many of these social and demographic variables, this conclusion seems rather strong.[26]

One other study which failed to find support for the existence of a deterrent effect was Cloninger (1975). Contrary to the arguments we have advanced above he claimed, "... there are too many reasons why empirical tests would not or could not reveal the existence of a deterrent effect if it did exist" (p. 334). Cloninger's work was based upon an analysis of data for 113 southern US cities with populations of over 25,000. Cloninger's deterrence variable was law enforcement officers per capita. He was unable to find any significant impact of variations in law enforcement, so defined, upon crime-rates. As he quite correctly argued, "The only time when evidence of a deterrence effect has been found ... has been when arrests and convictions per offence have been used as the enforcement variable ... (When) either expenditure per capita or officers per capita has been used as the enforcement variable, no evidence of a deterrence effect has been found" (pp. 327-8).

Whilst agreeing with Cloninger's remarks, it should be clear that a "test" of the deterrence/economic hypothesis cannot be made using law enforcement expenditures. The choice theoretic model of criminal behaviour specifies a crime supply function in which the deterrence variables are probability of apprehension/conviction and severity of punishment. The

---

26. Why, for example, should per prisoner expenditures on the correctional system be thought to influence the crime rate?

effectiveness of police inputs in producing deterrence and, therefore, in reducing crime is another question. It concerns the police production function, which is another equation of the model.

We conclude this section by briefly exploring two aspects of the more recent research into the determinants of crime. These concern (i) whether crimes are substitutes or complements for each other and (ii) the analysis of individual (rather than macro-level) criminal behaviour.[27]

Possible substitute/complement relationships between crimes were briefly alluded to by Ehrlich (1973). The question is important for policy purposes. For example, an increase in the punishments given to convicted burglars may, ceteris paribus, reduce the number of burglaries, but if it induces a movement into the robbery "business", then the overall level of crime may not fall and its seriousness might even increase!

Holtmann and Yap (1978) studied inter-relationships between the crimes of robbery, burglary and larceny using state-level data for the USA in 1970. They constructed a simultaneous model with each offence rate and the probability of imprisonment for each offence as endogenous variables. The model was estimated by 2SLS. Each crime equation included the following deterrence variables, (i) the probability of imprisonment for the offence itself, (ii) the probabilities of imprisonment for each of the other two offences and (iii) average time served for the offence.[28] In addition the

---

27. For example, car theft and bank robbery may be complementary crimes if bank robbers steal their get-away cars. Whereas burglary and bank robbery may be substitutes, though not necessarily perfect ones, in competing for the criminals available time.

28. Times served for the three crimes were strongly correlated across states and so all three sentence lengths were not used.

following socio-economic and demographic variables were included, (i) median family income, (ii) the percentage of families earning below one half of median family income, (iii) the percentage of the population that was non-white, (iv) the unemployment rate for those aged 14-24 years and (v) the earnings of male service workers aged 16 years and over.

The results were interesting. For example, the estimated equation for burglary showed that whilst an increased probability of imprisonment for burglary did deter burglaries, increases in the probability of imprisonment for robbery and larceny both tended to <u>increase</u> burglary offences.[29] This suggests that burglary is regarded by robbers and thieves as a substitute activity. Also, introduction of these variables greatly increased the size of the "own-price" deterrence elasticity (i.e. the effect of the imprisonment rate for burglary upon burglary offences). The non-deterrence variables were generally significant and had their expected signs. However, unemployment was significant only in the equation for larceny.

The results from the other two crime equations were not so good. For example, in the larceny equation the only significant deterrence variable was the probability of imprisonment for burglary. This had a negative coefficient thus suggesting a complementary relationship between the two crimes, which is contrary to the earlier result. Economic theory presumably would suggest that cross-price substitution effects are symmetric. Non-symmetry may be possible, because an income or wealth effect is included in the estimated parameters. However, it is not apparent that Holtmann and Yap gave explicit consideration to this issue and, therefore, to the adequacy of their illegal and legitimate gains measures.

---

29. Average time served for burglary proved to be statistically insignificant.

Heineke (1978c) offered a more rigorous treatment of the relationship between criminal and legitimate activity. The crimes considered were burglary, larceny and robbery. Heineke assumed that each individual's indirect utility function was approximated by a trans-log function. He then derived each individual's commodity demand and activity supply functions. By integrating over the wealth distribution he obtained aggregate commodity demand and activity supply functions. The supply of effort to each activity then depends upon the expected returns to all different forms of "work" and upon the individual's wealth position. In estimating the equations of the model expected returns to the three criminal activities were approximated by average amounts stolen, adjusted for expected punishment.

The model's equations were then estimated using data for a cross-section of SMSA's over the period 1967-72.[30] The most striking result of Heineke's study was "... the apparent lack of interdependence between many sources of income. Own expected returns seemed to play a far larger role in the determination of both legitimate and illegal activity levels than did the returns in any competing or complementary activities" (p. 188). This is not to say, however, that the cross-elasticities were statistically insignificant. The cross effects between robbery and larceny, for example, were highly significant and supported the view that they are complementary activities. The wealth effects for illegal endeavour were all negative and quite large.[31]

However, Heineke was at pains to point out that the data upon which

---

30. Altogether there were 137 observations.

31. The inferiority of illegal activity is in stark contrast with the predictions of some of the models examined in Chapter 2.

these estimates were based was rather rough and ready. Undoubtedly, only the collection of better data will allow firm conclusions about substitution effects between crimes to be drawn. However, work in this area has already pointed to some interesting and so far relatively under-researched aspects of criminal behaviour.

All of the studies we have examined so far in this chapter have used aggregate statistics relating to whole areas. Manski (1978) considered the advantages of testing the economic model against individual-level data to be substantial. His argument was that it was difficult to draw inferences from macro-level studies because of the problems caused by measurement error and simultaneity. He also questioned whether the conditions necessary to aggregate individual preferences into a macro-level function could be achieved. For example, if individuals exhibit considerable heterogeneity in their circumstances, then it may not be possible to derive a macro function which adequately captures the behaviour of the whole population. With individual-level data the simultaneity question simply does not arise. Whilst an individual's actions may be affected by changes in sanctions variables, his isolated behaviour is unlikely to have any significant effect upon the criminal justice system. Manski further argued that specification of individual crime functions did not require some of the ad hoc reasoning which characterised modelling of macro crime functions.

Of course, a very considerable practical disadvantage facing individual-level studies is the virtual absence of sufficiently detailed information upon the criminal/non-criminal career choices of individuals. Manski felt that specifically designed longitudinal data might be required to answer some critical issues concerning deterrence and rehabilitation.

He was hopeful that self report studies of criminal behaviour might fill the gap. Unfortunately, existing self report studies fail to ask questions about the circumstances in which crimes were committed and are subject to an element of measurement error.

Individual based studies have conceptual disadvantages too. Whilst they might throw light upon how an individual is deterred by punishment, they cannot tell us how the aggregate crime rate will be affected. That requires a macro-level (i.e. general equilibrium) approach.

One attempt to test the economic model of crime using individual-level data was made by Witte (1980). She estimated a crime supply equation using information on the post-release activities of a random sample of 641 men who had been in prison in North Carolina in either 1969 or 1971. The activities of the men were monitored for an average of 37 months after release from prison. Only information on officially reported criminal activity was considered. Witte monitored both the number of arrests per month since release and the number of convictions per month since release. As for some individuals these offence measures were zero, she used probit analysis to relate the crime measures to a series of deterrence and socio-economic variables. These variables were (i) the accumulated work release funds received after release, (ii) the number of months until first job after release, (iii) the hourly wage rate after release, (iv) the conditional conviction rate prior to release, (v) the conditional imprisonment rate prior to release, (vi) average life-time period of imprisonment prior to release, (v) age at release, (vi) age at first arrest, (vii) the number of times the offender had been arrested and convicted, (viii) a dummy variable for race, (ix) a dummy variable for serious alcoholics, (x) a dummy variable for drug addicts, (xi) a dummy variable indicating supervision of parole, (xii) a dummy variable separating married from unmarried males and (xiii) a measure of the number of times the person had violated prison rules in his last period in prison.

Witte's results only partially validate the economic model of crime. Whilst she found evidence "... to support the contention ... that deterrence works ..." (p. 79), that support is relatively weak. Many of the deterrence elasticities are found to be insignificantly different from zero. However, she did find that the way that deterrence works seemed to vary markedly across types of crimes. Individuals who specialised in "consumption" offences (e.g. drug use) were substantially deterred by length of imprisonment. Individuals who specialised in non-serious "income" offences (e.g. small thefts) were most affected by the <u>probability</u> of being sent to prison. However, for individuals who specialised in serious "income" offences (e.g. drug pushing, robbery etc) <u>none</u> of the deterrence variables seemed to work.

As regards the "taste" variables, Witte concluded that "(t)hese results indicate that an old, non-white individual who had little previous criminal record, did not use drugs, was supervised on release, and behaved well in prison will have fewer arrests and convictions ..." (p. 82).

Of course, Witte's sample does not satisfy the criteria set out by Manski. It is biased in the sense of only considering convicted offenders. However, even here there is some support for the economic approach, in that the model itself would suggest that deterrence effects are likely to be smaller and less significant amongst convicted offenders than the population as a whole.

(ii) British Studies

Despite the very considerable interest shown by economists in the USA in questions of crime and law enforcement, the number of contributions using British data is remarkably small.[32] It is possible to find only a handful of published studies. These are the empirical analyses by Carr-Hill and Stern (1973, 1977 and 1979), by Wolpin (1978a and 1978b) and by Hilton (1979). Of these we will not consider Wolpin's study of the deterrent effect of capital punishment nor Hilton's rather sketchy analysis of a small sample of police force areas.[33] We shall, therefore, concentrate upon the work of Carr-Hill and Stern and Wolpin's time-series analysis of crime and punishment in England and Wales between 1894 and 1967.

Carr-Hill and Stern estimated a three equation model for a cross-section of police force areas in England and Wales for each of the years 1961, 1966 and 1971. The endogenous variables were the aggregate crime rate, the clear up rate (sometimes the conviction rate was used instead) and the number of policemen per capita.[34]

Their model was specified as being linear in the logarithms of the variables. In its partially reduced form, it is

---

32. The number of British economists involved is even smaller as two of the major studies using data for England and Wales were undertaken by Wolpin, an American.

33. Wolpin's analysis of capital punishment is discussed in detail in Pyle (1983, Chapter 4). Hilton's attempt to unravel the recording problem is interesting, but flawed by a number of mathematical errors. He also used a severely limited set of socio-economic/demographic variables when estimating the crime equation.

34. Like most other studies Carr-Hill and Stern did not attempt to model the determination of the severity of punishment, but treated it as an exogenous variable.

$$y = \alpha_1 p + \alpha_2 c + \sum_{i=3}^{7} \alpha_i X_i^1 + \alpha_0 + \varepsilon_1$$

$$p = \beta_1 y + \beta_2 c + \sum_{i=3}^{7} \beta_i X_i^2 + \beta_0 + \varepsilon_2$$

$$c = \gamma_1 y + \gamma_2 p + \sum_{i=3}^{6} \gamma_i X_i^3 + \gamma_0 + \varepsilon_3$$

where y is the per capita indictable offence rate (i.e. all indictable offences),

p is the clear up rate for all indictable offences (sometimes, the conviction rate),

and c is the number of policemen per capita.

The X_i^j ($j = 1, 2, 3$) are socio-economic, demographic and other variables which differ from one equation to another (see below). The α_i, β_i and γ_i are parameters to be estimated and the ε_j are random disturbance terms. All variables are measured in logarithms.

In the first equation, the X_i's are:

(i) f - the percentage of those convicted who were given a custodial sentence (a measure of the severity of punishment)

(ii) a - the percentage of males aged between 15 and 24 years in the population,

(iii) s - the proportion of the population categorized as working class,

(iv) t - total rateable value of the area. (A measure of illegal gains) This variable was sometimes replaced by the proportion of the area that was urbanised (% urban),

and (v) e - total police expenditure per police officer.

In the equation explaining the clear up rate (p), the X_i's included a, s, e and in addition

(i) N - the total population of the area,

and (ii) V - the proportion of offences classified as being violent.

In the third equation, that explaining the number of policemen per capita (c), the X_i's were V, population density (1961 and 1966 only), % urban (1971 only), M - the proportion of the population classified as being middle class and U, the unemployment rate.

Carr-Hill and Stern identified the crime equation by excluding several of the socio-economic variables from it. In this case the excluded variables were V, N, M and U.[35]

It is difficult to present a succinct summary of Carr-Hill and Stern's work. The model was estimated for 1961, 1966 and 1971 separately and for different groupings of police forces e.g. urban only, urban and rural pooled etc.[36] They found evidence of structural breaks between 1961 and 1966 and

---

35. The appropriateness of such an identifying restriction has already been questioned in Section I(i) of this chapter and we shall take it up again in the next chapter. This is a general criticism of previous studies and should not be interpreted as an attack upon Carr-Hill and Stern alone.

36. The model was estimated by full information maximum likelihood methods.

again between 1966 and 1971. For simplicity we present in Table 3.4 a comparison of the estimated crime equations for the 1966 and 1971 urban and rural pooled, restricted samples.[37] Carr-Hill and Stern noted "... that significance levels are lower in 1971 than in 1966. We presume that this is largely due to the lower number of observations. Thus, for 1971 we accept coefficients with asymptotic T values of above unity as being significantly different from zero ... For 1966 results we adopt the more stringent requirement of asymptotic T values above 2" (Carr-Hill and Stern, 1979, pp. 135-6). In 1971 none of the coefficients in the crime equation had an asymptotic T value greater than 2.

Table 3.4

Carr-Hill and Stern's Estimates, 1966 and 1971 : Crime Equation

Variable / year	p	c	f	a	s	% urban	e
1966	- 0.59*	0.74*	- 0.17	0.63*	0.11	0.45*	0.40*
1971	- 1.05*	0.64*	- 0.21*	0.12	0.26*	0.07*	-

* indicates T value greater than 1 but less than 2 in 1971 sample, and a T value greater than 2 in 1966 sample.

Carr-Hill and Stern's work also lends support to the deterrence thesis and to earlier results using the economic model. The variables p and f "... appear as important with the coefficients appropriately signed" (p. 136). However, unlike Ehrlich's results for all offences for example (see Table 3.1), they found that the elasticity with respect to certainty was considerably greater than with respect to severity. The gap between them had also increased quite dramatically between 1966 and 1971. They pointed out,

37. "Restricted" means that some of the insignificant (or more insignificant) variables have been dropped from the regression equation in order to improve goodness of fit.

however, that if there is a fixed element in punishment then their estimate of the severity elasticity will understate its true effect. However, the gap was so large in 1971 that they felt that even allowing for this was unlikely to close the gap.

An interesting aspect of Carr-Hill and Stern's work was their finding that more policemen per capita tended to increase the recorded crime rate. They attributed this to the creating and reporting effects of having more police manpower, which outweighed the preventing effect. Expenditure per police officer also tended to increase the recorded crime rate, at least in 1966, presumably through a similar effect.

They found that urbanised areas had higher crime rates, ceteris paribus. The effects of the age and social-class variables were mixed, although generally areas with larger proportions of young males and working class people in the population tended to have higher crime rates. The age variable may have become less significant in 1971, because of changes in police crime recording practices.

Like Ehrlich, Carr-Hill and Stern included the offence rate as a determinant of the clear up rate or conviction rate, because "(f)or a given number of police, in a given area at a given time, with existing detective skills and under existing legal constraints, cannot solve an indefinitely large number of offences. That is, if the offence rate is higher in that area than an otherwise comparable area, we should expect the proportion solved to be lower" (p. 62).

It is perhaps slightly unusual that Carr-Hill and Stern should have included both the number of policemen per capita and expenditure per police officer as inputs in the "production function". They argued that "... the number of policemen (per capita) is not by itself capturing sufficient information. Man hours worked vary between areas ... The seniority structure and the number of supporting staff will vary from district to district. Also the equipment available to different forces varies ... We therefore decided to use expenditure per policeman together with the number of policemen per capita to represent police input" (p. 65).

The expenditure variable is, however, difficult to interpret, because it includes not only the effects of variations in equipment inputs but also labour inputs. It might have proved more illuminating if Carr-Hill and Stern had separated the capital and labour inputs more explicitly. Furthermore, the expenditure data was largely current expenditure and did not take into account either the use of existing major capital goods or the purchase of new ones. Information is readily available for numbers of civilian employees, numbers and types of vehicles etc and so a more traditional production function could have been estimated in this case. In Carr-Hill and Stern's formulation of the production function it is impossible, for example, to isolate the separate contributions of capital and labour.

Population size was used, by Carr-Hill and Stern, to measure possible economies of scale. The argument being that as a result of amalgamations to promote efficiency, larger police forces would have higher clear up rates.

We examine the justification for the inclusion of other variables in the production function in the next chapter and so will not discuss that subject here.

The effect of the recorded crime rate upon police "output" was somewhat erratic. Sometimes its coefficient was positive and significant, at other times it was negative and significant, but on occasions it was insignificant. Carr-Hill and Stern's overall conclusion was that "... a larger or smaller workload does not change the detective efficiency of the police" (p. 227). This is perhaps a strange conclusion. A more reasonable one might be that changes in the offence rate have different effects upon the efficiency of police forces at different times e.g. when they are operating at or near (detective) capacity compared with times when they have surplus capacity. Alternatively, they might have been led to question their model specification.

What of the effects of the two input variables, policemen per capita and expenditure per police officer? The results were somewhat erratic for the expenditure variable, but rather more consistent for the manpower variable. Carr-Hill and Stern concluded "(b)roadly speaking, the number of policemen ... seems to be a more important variable than expenditure on the police. The role of the latter is confined (as regards significant coefficients) to ... a negative (effect) on the clear up rate in 1971". However, the behaviour of the coefficient on policemen per capita was rather more predictable. "(A)gain, speaking broadly, in 1961 an increase in the number of police in an area ... had a negative effect on the clear up rate in urban areas. In 1966 ... more police decreased the clear up rates; and in 1971 more police ... decreased the clear up rate" (pp. 237-9).

The largely insignificant effects of police expenditure upon clear up rates mirrors the effect reported by Ehrlich. However, as we have suggested above, the expenditure variable is a relatively poor indicator of capital services utilised by the police. Before one can conclude that increased expenditure on the police service is wasteful in terms of increasing the clear-up rate we need to have more refined measures of capital and labour services. The negative effect of more manpower upon clear-up rates is perhaps more puzzling. Carr-Hill and Stern explain this in terms of what they call the "creating" effect of having more policemen in an area, i.e. "... increased public awareness of the police and crime may have led to more reports of minor events which are difficult to solve or not worthwhile solving" (p. 239). Again, however, this is a result that might have led them to question their model specification.

As with the offence, expenditure and manpower variables the effects of the socio-economic and demographic factors varied between groupings of areas and across time periods. We do not propose to examine the effects of these variables and refer the reader instead to Carr-Hill and Stern (1979, Chapter 7) for a full discussion of these results. The one exception we make is to note that the effects of both the age structure and social class composition variables were, with only minor exceptions, virtually negligible whether clear-up rates or conviction rates were used as the "output" variable.

Carr-Hill and Stern, unlike some other studies we have discussed, did not attempt to disaggregate the crime variable. In view of previous findings that deterrence elasticities varied considerably across crimes this is perhaps an important omission.

However Wolpin's analysis of crime and punishment in England and Wales between 1894 and 1967 did attempt to examine separate types of crime. Another important objective of this work was the attempt to isolate the deterrent component of imprisonment from its incapacitation element. On this Wolpin concluded that approximately one-half of the total effect of imprisonment could be ascribed to deterrence.

Wolpin estimated separate supply functions for the crimes of larceny, burglary, robbery, auto-theft, malicious wounding and felonious wounding. He also estimated aggregate supply equations for all offences against the person and for all offences. He doubted, despite all the evidence to the contrary, that increased crime rates would adversely affect apprehension/ conviction probabilities, particularly over the long-run. He, therefore, estimated the supply functions by OLS. Later in the paper, he did attempt to incorporate a simultaneous relationship between crime and punishment. Whilst increases in the offence rate did have a significant negative effect upon the probability of conviction - contrary to Wolpin's expectation - there was relatively little change in the sizes and significance of the coefficients of the deterrence variables in the supply offences function. We shall, therefore, discuss Wolpin's OLS estimates of the individual offence functions. This also enables us to discuss the effect of socio-economic and demographic variables upon crime. Wolpin's reported simultaneous equation results do not show these effects.

Explanatory variables in the crime supply functions were (i) the clearance rate, (ii) the conditional conviction rate, (iii) the conditional imprisonment rate, (iv) the conditional recognizance rate, (v) the conditional fine rate, (vi) the average length of imprisonment imposed by courts, (vii) the proportion of males aged 10 to 25 years, (viii) the unemployment rate, (ix) the proportion of individuals aged 15 years and over enrolled in schools other than Universities, (x) the proportion of individuals residing in non-rural areas, (xi) an index of real weekly wages of manual workers in manufacturing, (xii) real G.D.P. per capita, (xiii) a dummy variable for pre- and post- World War Two years and (xiv) a time trend.

Wolpin claimed that "(i)n most cases, the parameter estimates for law enforcement effects are negative". In fact this is something of an overstatement. Whilst 39 of the 45 estimated deterrence elasticities were indeed negative, only 18 were negative and significant at the 5% level using a one tail test. Similarly, the elasticity ordering predicted by the theory is satisfied in only two of the eight cases. Wolpin found quite considerable differences in the sizes of the deterrence elasticities across crimes. For example, the elasticity of crimes with respect to the clearance rate varied from - 0.27 for all offences against the person to - 1.35 for auto-theft. On the whole the deterrence variables seemed to work rather less well for crimes against the person than for property crimes.

The performance of the non-deterrence variables was somewhat mixed. The coefficient of the age variable was positive and significant in the property crime equations, but not elsewhere. The unemployment variable's coefficient, whilst being positive and significant in the overall crime equation, was significant only in the equation for burglary when examined against individual crimes. The coefficient of the schooling variable was generally significant and consistently negative for all crimes (with the possible exceptions of the group all offences against the person and burglary). The degree of urbanisation tended to significantly increase the overall crime rate, larcenies and burglaries, but to reduce malicious woundings! GDP per capita (proxy for illegal gains) was <u>negatively</u> related to burglaries and car thefts, but directly related to malicious woundings. The real wage in manufacturing (a legal gains variable) was positively associated with robbery and the two wounding categories. Clearly these last two variables sometimes behaved contrary to expectation.

Wolpin estimated a simultaneous, three equation model for aggregate offences only. In that model the conviction rate was argued to depend upon (i) the number of policemen per capita, (ii) the per capita crime rate, (iii) the proportion of defendants given legal aid, (iv) the imprisonment rate, (v) the lagged conviction rate, (vi) the number of registered motor vehicles per capita and "all of the environmental variables used in the offence equation" (p. 834). The third equation of the model related the number of policemen per capita to its value in the previous period, the lagged offence rate, the number of registered motor vehicles per capita, total local government expenditures and also to all the environmental variables in the offence equation. The "production function", like so many others, shows the crime rate to have a negative and significant coefficient (with an elasticity of - 0.38). The number of policemen per capita had a positive and significant coefficient (elasticity = 0.60). The imprisonment rate was inversely and significantly related to the conviction rate.

3. Conclusion

In this section, we will attempt to summarise fairly briefly the results of the rather large body of empirical material that has been surveyed.[38]

On the whole the evidence provides reasonably strong support for the economic model and the deterrence hypothesis. All of the studies reviewed

---

38. We must once again stress that whilst this survey has been fairly long it is by no means an exhaustive one. We have tried to undertake a fairly representative survey focussing on several major, innovative and sometimes controversial studies. Those studies that have been excluded should not be assumed to be any less worthy, however. Of course, we have deliberately chosen to ignore entirely that group of studies which have dealt with the issue of capital punishment. Pyle (1983, Chapter 4) offers a comprehensive survey of that literature, which we do not repeat here.

here (with the exception of Forst) have found a consistently negative and often highly significant association between crime-rates and arrest and clearance rates. This result has been established for a wide variety of different data sets covering different crimes, time periods and geographical areas.

The relationship between crime-rates and the probability of imprisonment has been examined using a rather smaller number of different data sets. The results here are slightly less emphatic. Whilst many studies reveal a significant inverse relationship, some have failed to find one.

The evidence in favour of a deterrent effect of the severity of imprisonment is possibly least well established. Even here, however, there are a number of studies (see Ehrlich, Phillips and Votey and Landes discussed above) that have found a significant inverse relationship between sentence severity and crime rates.

Most studies found the elasticity of crimes with respect to the probability of apprehension, to be larger than with respect to the probability of imprisonment which in turn was larger than with respect to the length of imprisonment. Such a ranking is consistent with the predictions of the economic model (see Ehrlich (1975a)). Most studies also point to quite large differences in deterrence elasticities across crimes.

The various factors incorporated to measure opportunity costs and illegal gains (e.g. measures of unemployment, victim stock, racial composition and age structure) have performed reasonably well, though not always consistently across studies. However, there is now a substantial body of evidence to support the argument that potential criminals respond to "positive" incentives and not just to negative ones. Indeed, some studies indicate that criminals are more responsive to these factors than to the deterrence variables.

Finally, it seems that attempts to explain variations in violent crime have been almost as successful as explanations of variations in crimes against property. Violent criminals seem, on the whole, to respond to incentives. Whilst their precise responsiveness may not always be the same as that of other criminals, the economic model seems to work in this area too.

Naturally, our relatively brief summary of results must be subject to some qualifications, mainly because of data exigencies and uncertainties about the simultaneity of relationships and their estimation. As we said in section (1), the identification problem is not a trivial question. Logically prior to consideration of the identification problem is the issue of whether or not the relationship between crime and sanction variables is simultaneous. Simultaneity is certainly plausible, although it is far too early to provide a definitive answer to that question. The determinants of sanction levels is a relatively under researched subject and knowledge about the relationship between sanction levels and crime is limited.

However, if valid identification restrictions are employed then an analysis that allows for simultaneity will be more general than one that does not. The way in which the models discussed above have been identified has been the subject of some criticism (see Fisher and Nagin (1978)). Fisher and Nagin take issue with investigators such as Ehrlich, Carr-Hill and Stern and Avio and Clark, who have identified their models by excluding from the crime function some variables included elsewhere in the model.

Fisher and Nagin argued that identification of the crime function by excluding various socio-economic variables and lagged endogenous variables was invalid. They claimed that "... it is simply not plausible to assume that such (socio-economic) variables do not have a direct effect on crime, while also assuming that each does directly affect either sanctions or police expenditures" (p. 373). Their argument here is that we, as yet, do not know enough about which socio-economic factors affect crime and which affect sanctions. Further, they argued "our conclusion is that it is most unlikely that the authors ... have successfully identified and consistently estimated the deterrent effect of sanctions" (p. 374).

Ehrlich (1979), not unnaturally, disagreed with Fisher and Nagin on this point. He claimed that a study by Vandaele (1978), showed the robustness of his (Ehrlich's) 1973 results to modifications of the identification restrictions of his model. Also, he argued that higher offence levels are likely to call forth higher levels of sanctions, once expenditures have adjusted. In a cross-section study the likelihood of such adjustment is high, because of the persistent pattern of crime and enforcement across states, cities etc. Therefore, the evidence showing an inverse relationship between crime and sanctions unambiguously reveals a crime supply function and not a production function for sanctions.[39]

In the following chapter we offer a simultaneous equation model to explain inter-area variations in rates of property crimes, the clear up rate for property crimes and the number of policemen in the area. We will then return to the discussion of the choice of appropriate identifying restrictions for that model.

---

39. It is interesting in view of this comment to note that Ehrlich's own estimated "production function" shows a strong, highly significant negative effect of the crime-rate upon the imprisonment rate.

CHAPTER 4 A MODEL OF PROPERTY CRIMES IN ENGLAND AND WALES

In Chapters 2 and 3 we reviewed the literature on both the economic theory of criminal choice and various econometric studies of the supply of offences function. We indicated that there has so far been very little published empirical work using data for England and Wales. We now wish to begin the task of formally modelling the determination of the rate of (recorded) property crimes in England and Wales. In this chapter we present the basic model used to explain (i) the levels of recorded property crimes, (ii) the detection rates for property crimes and (iii) the number of policemen on average daily strength. We also briefly examine the data sources used in order to estimate the model. First, however, we must examine the choice of unit of observation (the police force area) as this affects not only the model's specification, but also the interpretation of the empirical results.

1. An Aggregate Study

Since the economic theory of criminal choice, developed in Chapter 2, is based upon individual utility maximising behaviour, the selection of the police force area as the unit for analysis perhaps requires some justification.

Testing the "economic model" against data for individuals represents a virtually impossible task. One obvious reason is the absence of any information at that level. We do not have, for example, information on the amounts of time individuals devote to illegal activity or their perceptions of the likely returns to both legitimate and illegal activity. To obtain such information would require the construction of inordinately expensive sample surveys.

Some investigators (e.g. Witte, 1980 - this has been discussed in Chapter 3) have tried to resolve this difficulty by analysing data for convicted offenders. This approach has some similarities with that used in criminology for some time, i.e. the attempt to generate inferences about the population at large from a study of known criminals. We do not wish to be too critical of such an approach, but it is debatable whether such a technique could be regarded as a valid test of the economic approach.[1] Besides, it does not necessarily circumvent data problems. Even Witte was forced to use data on recorded crimes.

Economists have tended to test the economic model using aggregate data on levels of crime and criminal justice variables. In other words they have estimated "market level" relationships rather than individual supply functions. Such an approach has been fairly standard throughout most of applied microeconomics and so we do not propose to spend too long in justifying its adoption here. However, a few points need to be made.

The analysis of aggregate crime is both interesting and important for its own sake, irrespective of whether or not it provides an adequate test of the economic theory of criminal choice. The search for reasons why recorded crime rates differ across areas is of no small importance. It is precisely such data that are used in everyday discussions of

---

[1] The main criticism being that convicted offenders are hardly a random sample of the population.

crime to justify all kinds of pronouncements about criminal justice policy in particular and social policy in general. Likewise, the causes of differences in detection rates, and whether they are related to differences in police resources, is a subject of very considerable importance. The analysis of individual data could not, without much ingenuity, possibly answer such questions.

Further, the analysis of individual data may not be able to tell us how individuals <u>in the aggregate</u> might behave if any of the parameters affecting their decision were to change. The answer to that problem requires a general equilibrium analysis. Whilst this is not the same as an aggregate analysis it does point to the dangers of individual level studies even if adequate data were available.

We do not wish to imply that micro-level studies are pointless. On the contrary they may be extremely valuable in their own right and may also indicate those variables which should be included in macro studies. The two kinds of study are likely to prove highly complementary. However, economists tend to be more interested in macro studies if only because they are interested in how individuals in the aggregate respond to changes in policy variables and other forces.

Evidence on the effect of changes in police resources upon detection rates can only really come from a study of aggregate data relating to police force areas (or divisions/subdivisions within such areas). It could not come from an analysis of individual behaviour. Also, the allocation of police resources is likely to be related to the aggregate level of crime itself, so that a meaningful study of the police production process must be at a fairly high level of aggregation.

However, the use of aggregate data does pose some problems, The aggregation problem, as it is called, is likely to affect the estimates of the crime supply functions. Here we are aggregating both over individuals and crimes. In fact it is fairly easy to show that unless some fairly stringent conditions hold then the "aggregate" parameters may not be good estimates of the underlying "micro" parameters. Some simple examples may serve to illustrate this point.

The models of Chapter 2 predict that the amount of time an individual will devote to criminal activity (t_i) will depend upon the probability of being caught and punished (p), the severity of punishment (f) and returns to both legitimate activity (w_1) and illegal activity (w_i), i.e.

$$t_i = f\ (p,\ f,\ w_1,\ w_i)$$

The first problem is that we do not observe t_i directly, but only indirectly through c, the number of crimes each individual commits.[2] If c is a monotonic function of t_i then we could write individual j's supply of offences function as,

$$c_j = g\ (p,\ f,\ w_{1j},\ w_{ij})$$

where the subscript j identifies variables which are specific to individual j.

Further, assume, for reasons that will become apparent later, that individual j's supply function is linear. Then, ignoring the stochastic term

$$c_j = \alpha_0 + \alpha_1 p + \alpha_2 f + \alpha_3 w_{1j} + \alpha_4 w_{ij}$$

If the parameters α_i (i = 0, ... 4) and the variables p and f are the same for all individuals, but the w_{1j} and w_{ij} vary

[2] It is a feature of the theoretical models in this literature that they are usually framed in terms of t_i, whilst empirical models concentrate upon c or, at least, its aggregate value. However, see Baldry (1974,1976) for an attempt to build a theoretical structure in terms of c explicitly.

across individuals, then if we aggregate over all individuals we obtain,

$$\bar{c} = \alpha_0 + \alpha_1 p + \alpha_2 f + \alpha_3 \bar{w}_1 + \alpha_4 \bar{w}_i$$

where $\bar{c}$ is the per capita crime rate, $\bar{w}_1$ is average earnings in legitimate activity and $\bar{w}_i$ is average returns in illegal activity. In this case the parameter estimates of the aggregate function would be exactly those of the individual (micro) functions. However, we have had to make some stark assumptions in order to get here.

For example, if the micro functions are non-linear, then consistent aggregation may not be possible. Suppose the micro functions are log-linear, so that

$$\log c_j = \log \alpha_0 + \alpha_1 \log p + \alpha_2 \log f + \alpha_3 \log w_{1j} + \alpha_4 \log w_{ij}$$

If we continue to assume that the α_i, p and f are constant across individuals, but that the w_{1j} and w_{ij} vary, then the aggregate function will be

$$c^* = \alpha_0 p^{\alpha_1} f^{\alpha_2} (w^*_{1j})^{\alpha_3} (w^*_{ij})^{\alpha_4} \qquad (1)$$

where the starred variables are <u>geometric means</u> of the individual variables.

Consistent aggregation is still possible. However, in order to estimate the macro function "correctly" we need data on the geometric means of the crime and earnings variables. Normally such data simply do not exist. Instead we must work with arithmetic means and their relationship to the geometric means is not always straightforward.[3] For example, the simple device of logarithmic transformation of equation (1) above is of no help whatsoever.

Even if geometric means were available they would present other problems. For example, should any one of the c_j be zero then the geometric mean will be zero too. If only one individual in each area did not engage in criminal activity then the dependent variable in the macro study will be a vector of zeros and estimation of the aggregate function will be meaningless. As such an eventuality is distinctly likely, estimation with geometric means looks a bleak prospect. Besides which, geometric means are of remarkably little intrinsic interest.

So far, we have assumed that the parameters of the supply functions are the same for all individuals. If, however, the slope coefficients vary across individuals then the estimated aggregate relationship, even in a linear model, will not normally produce parameter estimates that are directly equivalent to the micro coefficients (see Green, 1964, Chapter 12).

Finally, we briefly consider aggregation over crimes.

---

[3] Green (1964, Ch.8) argues that if the variables obey the log normal distribution then the geometric and arithmetic means may be closely associated. In this case,

$$\log c^* = 2 \log \bar{c} - \tfrac{1}{2} \log (\bar{c}^2 + \sigma_c^2)$$

where c^* is the geometric mean of the observations on c, $\bar{c}$ is their arithmetic mean and σ_c^2 is the variance of observations on c_j.

Similar relationships hold for the variables w_l and w_i. If all the variables are independently distributed then estimation of the micro parameters would require information not just on the means of the variables, but also their variances. If, however, they are jointly log-normally distributed we would need additional information on the covariances of the variables. It is rare that economic data of that kind are available.

Suppose that the supply function for the t th crime is given by,

$$c_t = \alpha_{0t} + \alpha_{1t}p_t + \alpha_{2t}f_t + \alpha_{3t}w_1 + \alpha_{4t}w_i \qquad t = 1, 2, \ldots T$$

The subscript j has been dropped, because for the time being we are not concerned with aggregation over individuals. If we sum the supply functions over the first T_1 crimes, we obtain the following aggregate function (provided that p and f are the same for all crimes within the group),

$$c^1 = \alpha_0^1 + \alpha_1^1 p + \alpha_2^1 f + \alpha_3^1 w_1 + \alpha_4^1 w_i$$

where $c' = \sum_1 C_t$, $\alpha_0' = \sum_1 \alpha_{0t}$, $\alpha_1' = \sum_1 \alpha_{1t}$, $\alpha_2' = \sum_1 \alpha_{2t}$,

$\alpha_3' = \sum_1 \alpha_{3t}$ and $\alpha_4' = \sum_1 \alpha_{4t}$

Aggregation can then proceed across individuals in the manner indicated above.

Obviously there is more to consistent aggregation than we have been able to develop in the last few pages. However, it should be apparent that the necessary conditions for consistent aggregation are quite restrictive. It would seem that only in a few cases could one use evidence from aggregate relationships to reach firm conclusions about individual behaviour. We will need to bear this in mind when interpreting the empirical results later.[4]

In reviewing the empirical literature (see Chapter 3) it became apparent that no one, with the possible exception of

---

[4] It has been argued by Grunfeld and Griliches (1960) that when the micro functions have been incorrectly specified, estimation of the macro relationship may be preferable. This would be the case when, for example, the correctly specified micro function contains a macro variable. On the whole this seems, however, to be a rather poor justification for estimation of aggregate relationships even if one can think of situations in crime/criminal justice models when it might apply.

Heincke (1978c), had actually considered the aggregation problem in relation to crime supply equations.[5] We may stand accused of arguing " ... here is a (great) difficulty. Let us look it firmly in the face and pass on."[6] However, we should say in our defence that we have looked it in the face and shall continue to do so. Most investigators have behaved as if the problem did not exist.

2. Model Specification

The primary interest of the following research lies in the explanation of variations in levels of recorded property crimes per 100,000 population over a cross-section of police forces in England and Wales. However, in order to do this we must also examine the determination of several other variables using a simultaneous equations approach. The necessity for this lies in the belief that in the aggregate the crime rate and the detection rate are simultaneously determined (see Chapter 3). If this belief is correct we cannot treat the detection rate, which is expected to be a determinant of the level of offending, as an exogenous variable at the macro level. The level of police resources, and especially manpower, may also be endogenous to the system. We have seen above how police resources might affect the crime rate and the detection rate, but these variables in turn might influence either the demand for or the supply of police manpower.[7]

---

[5] Baldry (1976) briefly mentions the question before dismissing it as an unsuitable topic for discussion in the present state of the subject's development.

[6] Green (1964, p.vii) attributes this quote to Sir Dennis Robertson.

[7] Areas with high crime rates (or low detection rates) might have a greater demand for police protection, ceteris paribus. Likewise the supply of manpower might be adversely affected by the level of crime and/or detection rates, because of the effect upon workloads and morale.

Most previous econometric studies have acknowledged these possibilities by building simultaneous equation models aimed at explaining (i) the recorded crime rate, (ii) the detection rate and (iii) the level of police employment. Some studies have also attempted to explain levels of punishment and, very occasionally, the recording decision, i.e. the proportion of all offences that are recorded by the police.[8] It is perhaps surprising that few studies have paid any attention to the under-recording of crime. We share Carr-Hill and Stern's view that " ... there is a substantial interest and importance in trying to understand the process by which actual offences ... become recorded" (Carr-Hill and Stern, 1979, p.15). Given the absence of any useful victim survey data and the extremely formidable problems involved in collecting such material, we are forced to use recorded crime statistics. It seems then essential to try to formally model the link between actual and recorded crime rates. Later in this chapter we will attempt to do this.

In fact the model we shall develop is based upon one originally formulated by Carr-Hill and Stern.[9] However, we have altered the specification of that model in a number of important ways in an attempt to remove some of its stranger results, e.g. that increases in police manpower lead to falling detection rates (see Chapter 3 for a more extensive discussion of this model).

The model consists of five basic <u>types</u> of equations.

---

[8] Though the vast majority of studies have contented themselves with an explanation of recorded crime statistics.

[9] It would be wrong to give the impression that Carr-Hill and Stern have sole property rights in such a model. Most of the models used in the econometric work have a similar structure. The distinguishing feature of Carr-Hill and Stern's approach is their attempt to model the recording decision.

First, a series of supply of offences functions. Second, several police "production functions" determing detection rates. Third, a manpower <u>supply</u> equation. Fourth, a number of crime recording equations and fifth, and finally, a series of identities. Each <u>type</u> of equation, except the manpower supply equation, has a separate equation for each of the four groups of crimes considered.[10]

(i) <u>Supply of offences functions</u>

Each of these equations has as its dependent variable the "true" number of property crimes (type i) per 100,000 population. As one of the objectives of the research was to examine whether the economic approach to crime could explain variations in property crime rates across areas we have used that model to guide the selection of explanatory variables. However, at the aggregate level the relationship between crime rates and deterrence variables, for example, may be masked by the presence of certain "nuisance" variables such as the age and sex composition of the population. Also, other theories of crime determination might indicate additional variables which are thought to have an effect at this level. Accordingly, like other investigators, we have included a number of explanatory variables not normally included in the microeconomic analysis of criminal choice.

Both the economic approach and deterrence theories of crime argue that increases in the certainty and/or severity of punishment are likely to deter potential criminals. We have, therefore, included measures of both as explanatory variables in the supply of offences functions.

---

[10] The four offence groups are (i) burglary, (ii) robbery, (iii) theft and handling of stolen goods and (iv) the sum of these three groups, which is labelled all property offences.

Certainty has been measured by the "true" probability of detection for the offence in question. Clearly, the variable influencing individuals' decisions is the perceived probability of detection. There is some evidence to suggest that experienced criminals have a much better idea of the chances of being detected than do inexperienced ones (see Carr-Hill and Stern, 1979, Chapter 2). However, what determines the perceived probability of detection is less clear cut. We decided, as a first approximation, to assume that criminals are well informed about the probabilities of detection, or at least behave as if they know what they are. So, the perceived detection rate was measured by its "true" value.[11] In Chapter 6 we shall return to the question of measuring perceptions of detection rates and investigate some alternative hypotheses. In the first version of the model we will assume that criminals' perceptions of the certainty of punishment are accurately represented by the "true" detection rate.

Likewise the measure of the severity of punishment should represent individuals' perceptions of that variable. Again, however, we are forced by lack of data to measure these perceptions by the actual punishments imposed by courts. Again, this is a less than perfect measure. The penalty for unsuccessful criminal activity may include, for example, the shame associated with court appearance, loss of respectability, adverse publicity etc. However, whilst these costs are likely to vary across individuals they may show relatively little variation across areas. So that ignoring these costs may not be too serious an omission.

---

11 However, as we cannnot observe the true detection rate directly, we will have to find a way of replacing it in the crime supply equations (see section 3(i) and Appendix to this chapter).

There is, of course, no unique definition of the severity of punishment. We have, therefore, measured it in a number of ways. These are (i) the probability of being sentenced to imprisonment if found guilty, (ii) the average length of imprisonment imposed upon those sentenced to immediate imprisonment and (iii) the average size of fine.[12] Given the multifaceted nature of punishment it may be sensible to measure its severity in a number of ways rather than by using one index.

In fact most of the results reported in Chapter 6 concentrate upon the imprisonment variables. We have measured length of imprisonment by the period imposed by the courts rather than a more commonly used measure, the average prison sentence served by offenders released in the current year. We regard our measure as a superior indicator of the expected length of imprisonment, because information on court proceedings is more commonly reported in the media than is information on sentences actually served. As such it is more likely to be available to potential offenders. Also, if sentence lengths are changing then sentences served by currently released offenders may not be a good guide to currently imposed sentences. We would have preferred to amend sentence lengths for expected remission and parole possibilities, but such information is not generally available. However as such remission is likely to be constant across areas this is

---

[12] Whilst fines and imprisonment are not the only forms of punishment for property offences, they represent a substantial proportion of all disposals. For example, in 1975 some 51% of males and 26% of females convicted of burglary received these two forms of punishment. In the same year 73% of male robbers, 44% of female robbers, 68% of male theives and 59% of female thieves were similarly punished. The proportionate use of imprisonment versus fines varies across crimes. Imprisonment is most commonly used for robbery, then burglary and least for theft. The proportionate use of fines is the exact reverse.

unlikely to prove a major stumbling block.[13]

It might be argued that severity of punishment should not vary across areas if courts (i.e. Magistrates' Courts and Crown Courts) treat like cases in a like manner. Any observed variation in severity of punishment across areas would then be due to differences in the seriousness of crimes. There seems, however, to be a fairly substantial body of research which points to there being considerable discrepancies in sentencing practices, particularly in the Magistrates' Courts. For example, Radzinowicz and King (1977, pp.225-6) argue "(t)hat ... discrepancies in sentencing exist there is no doubt. They have been demonstrated again and again, in terms of areas, of courts, of individual judges and magistrates ... It can make quite a difference whereabouts in the country you commit your crime.".

We do not wish to labour this point as it is now fairly well documented, but we should briefly justify our decision to include severity of punishment as a variable.[14] All apprehended criminals will make an initial appearance in a Magistrates' Court, normally in the police force area in which the offence was committed. In most cases they will be tried and sentenced there. A minority of offenders will opt for trial at the Crown Court or will be sent there for trial or sentencing. We will, therefore, concentrate on discretion in sentencing in the lower courts. First, Magistrates have a wide range of possible disposals from which to choose, such as

---

13 Decisions on remission and parole are taken centrally by the Home Office Prison Department and not by boards sitting in local police force areas.

14 Whilst micro <u>theory</u> argues for its inclusion, if it does not vary across areas then its inclusion in the <u>empirical</u> model would be erroneous.

immediate imprisonment, a detention centre order, a probation order, an attendance centre order, a community service order, a fine, a parental bindover, etc. Second, for each type of sentence there are fairly wide limits, e.g. Magistrates can impose a probation order ranging anywhere between six months and three years, the length of imprisonment can be any time between five days and six months and so on. To some extent their discretion is limited by the nature of the offence and the age of the person convicted, but the most recent exhaustive analysis of sentencing practice in Magistrates' Courts concluded that " ... differences between courts and their use of the various disposals available cannot be accounted for wholly in terms of differences in intake and other external factors and that courts do have very different ways of dealing with similar types of offenders" (Tarling, 1979, p.).[15]

The case for treating severity of punishment as a variable and not constant across areas seems, therefore, to be reasonably strong. Certainly the data on rates and lengths of imprisonment for the three kinds of property crimes seem to show quite significant variation across police force areas (see Table 3.1).

---

15 Tarling's conclusion was based upon a detailed analysis of sentencing practice in a random sample of 30 Magistrates' Courts in urban areas during the period 1971-5. Part of the study involved interviewing Clerks to the Justices and Chairmen of Benches to see whether they attempted to achieve consistency with neighbouring courts as well as within their own court.

"Differences in intake" refers to the differences in the type of offence and characteristics of the offender appearing before the court. "Other external factors" include things such as the use of police cautioning in the division, resources available to the local probation service etc. which were expected to influence sentencing practice.

TABLE 3.1 Variation in sentencing across police force areas, 1975.

	Mean	Standard deviation	Coefficient of variation
1. Burglary			
(i) Percentage of offenders sentenced to immediate imprisonment	10.3	2.5	0.24
(ii) length of imprisonment (days)	447.3	80.6	0.18
2. Robbery			
(i)	40.2	12.5	0.31
(ii)	1149.3	194.9	0.17
3. Theft and Handling Stolen Goods			
(i)	3.6	0.7	0.20
(ii)	253.9	38.7	0.15

Source: Unpublished Home Office statistics.

In early versions of the model we have treated severity of punishment as an exogenous variable. However, the discussion of the last few pages raises the question whether variations in sentencing practice are systematically related to other variables in the model, i.e. should it be treated as an endogenous variable.[16] In Chapter 5 we report the results of an attempt to model sentence severity.

A study of variations in crime rates across areas must also consider the possibility that crime may be displaced from one area into adjacent areas. This is more likely to be a problem when relatively small, contiguous areas are used as the unit of observation and where the population can move

16 For example, courts might give harsher penalties if the crime rate is high or possibly they might impose lower fines if unemployment is high. Tarling (1979) found little support for the former hypothesis but some for the latter.

fairly easily between areas. However, relatively few econometric studies have considered the problem of spillovers explicitly (see Chapter 3). The possibility was dismissed entirely by Carr-Hill and Stern, who claimed that they were unlikely to occur " ... in view of the small monetary value of most thefts." (p.106). We propose, however, to test the displacement hypothesis rather more formally. Unfortunately it is an exceptionally difficult hypothesis to test. Presumably criminals living in area j would commit crimes in an area k rather than j if the net expected returns in area k were larger and outweighed the costs of transport between areas. The differential net return would be given by

$$w_{ik} - p_k f_k - (w_{ij} - p_j f_j) - T_{kj}$$

where w_{im} is the return to crime in area m (m = k,j)

p_m is the probability of being detected in area m

f_m is the size of punishment in area m

and T_{kj} is the cost of travelling between areas k and j

In practice it is difficult to construct a single variable to measure all of these effects. For example, information on transport costs could only be guessed at. The problem is further compounded when individuals can choose between more than two areas. However, in Chapter 5 we report the results of incorporating a measure of the relative attractiveness of areas. In the early versions of the model we have adopted a drastically simplified approach to modelling displacement effects. We have compressed them into a single variable, the certainty of punishment in adjacent areas, i.e. the "true" probability of detection in adjacent areas.

Both the economic model and various criminological theories predict that variables other than deterrence variables are likely to affect crime rates. Of particular interest to an economist, however, are the influence of illegal gains, legitimate earnings opportunities and the probability of unemployment in legitimate activity. In consequence we have included all three variables in the supply of offences function.

The crime supply equations also include measures of the age and sex composition of the population. Criminological research suggests that, on the whole, crimes tend to be committed by young males. (See, for example, Radzinowicz and King, 1977, pp.29-35.) Therefore, areas with a disproportionately large percentage of young males in the population might be expected to have higher crime rates. Likewise, previous econometric studies indicate that areas with larger concentrations of non-whites and/or immigrants tend to have higher crime rates. It is not altogether clear, however, whether this is because such people are more likely to commit crimes or because they are more likely to be the victims of crimes. If the former, it seems reasonable to assume that they are engaging in crime because their legitimate earnings potential is so much inferior to other residents. If that is the case then the earnings and unemployment variables should be picking up this effect and to include a demographic variable measuring racial mix would seem to be redundant. A practical difficulty is that the UK Census does not collect data on the number of non-white residents in each area. All that is collected is information on the numbers of people born outside the UK, which counts only first generation immigrants. Given the uncertainty surrounding the legitimacy of the inclusion of a racial variable and the imperfections in its measurement we preferred not to include such a variable.[17]

More formally, therefore, we can write the supply of offences functions as,

$$PC^*_i = f_i\ (CL^*_i,\ I_i,\ S_i,\ CL^*_{iA},\ R,\ U,\ W,\ A) \qquad i = 1,2,3,4$$

where the variables are defined as follows:

- PC^*_i is the "true" (unobserved) crime rate of type i,
- CL^*_i is the "true" (unobserved) probability of detection for crimes of type i,
- I_i is the probability of being imprisoned for crimes of type i if found guilty,
- S_i is a measure of the length of imprisonment for crimes of type i,
- CL^*_{iA} is the "true" (unobserved) probability of detection in adjacent areas for crimes of type i,
- R is a measure of potential gains from criminal activity,
- U is a measure of unemployment,
- W is a measure of earnings opportunities in legitimate activity,
- A is a measure of the age and sex composition of the population.

In writing the supply of offences functions this way we are assuming that crimes of type i are not affected by the punishment variables relating to crimes of type j. In other words we are assuming that no substitute or complement-type relationships exist between the various types of crime. It is not assumed, for example, that an increase in either the certainty or severity of punishment for robbery will lead potential robbers to switch to committing burglaries instead. We saw in Chapter 3 that few previous studies have investigated such inter-relationships directly. Where this has been done the results are somewhat mixed. In version 1 of the model we

---

[17] At an early stage we did experiment by including the proportion of residents (i) born in the New Commonwealth and (ii) born in the West Indies as explanatory variables. Neither proved to be statistically significant.

do not consider such switching to be a possibility. However, in Chapter 5 we investigate that possibility rather more formally.

For the time being, too, we leave the precise functional form of the supply of offences function unspecified.

(ii) <u>Police production functions</u>

In an aggregate model of crime determination the probability of detection cannot necessarily be treated as an exogenous variable. It is likely to be determined simultaneously with the crime rate. The second set of equations of the model, therefore, concern the modelling of the detection rates for property crimes. Whilst the equations themselves are not of primary interest they are an essential part of the model and they are not entirely without policy significance.

It is worth pausing here to consider how we propose to measure the probability of detection. In fact, we shall use two statistical proxies for this variable. These are (i) the clear-up rate and (ii) the conviction rate. The former is the ratio of the number of offences cleared up to the number of recorded offences.[18] The latter is the ratio of the number of convicted offenders to the number of recorded offences.

Clearly both variables have their disadvantages. Clear-

---

18 <u>Criminal Statistics 1975</u> defines offences cleared up as " ... those for which a person is arrested, summoned or cautioned; those attributed by the police to children under the age of criminal responsibility; those taken into consideration by a court when sentencing an offender who is found guilty of another charge; and some offences of which a person is known or suspected to be guilty but for which he cannot be prosecuted (e.g. because he has died)". (p.18).

up statistics have been heavily criticised by some sociologists and criminologists (see, for example, Bottomley and Coleman, 1981). One basic criticism is that they may simply reflect particular strategies pursued by police forces. Another is that the police may be under considerable "political" pressure to manipulate clear-up statistics, either to show that they are winning the battle against crime (high or rising clear-up rates) or to indicate a need for substantial increases in establishment (low or falling clear-up rates). Of course, if all forces are under the same kinds of pressures there is no reason to believe that clear-up rates will be biased estimators of the probability of detection. Interestingly, Burrows and Tarling (1982, p.6) found " ... the clear-up (rate to be) a remarkably robust measure". They reached this conclusion after a careful study of statistics on crime clearances. They derived several "refined" clearance measures, e.g. by excluding offences taken into consideration, and found the refined measures were highly correlated with the overall (unrefined) clear-up rate.[19] They concluded that " ... notwithstanding extremely wide differences between forces in the methods used to clear crime, and in their other strategies, ... these tend to have more of a random impact on force rates, rather than producing extensive systematic bias." (p.7).

Whilst the overall clear-up rate may show relatively little systematic bias across areas, it may still not be an especially good indicator of the probability of detection.

---

19 The correlation coefficient was often above 0.9. Only one correlation coefficient was less than 0.84. This was for clearances excluding those taken into consideration and otherwise dealt with. The correlation coefficient was then 0.75.

This is because it includes offences taken into consideration by courts when sentencing offenders. If, for example, someone commits five crimes during a period of time and is apprehended for one of them then the "objective" probability of detection will be $1/5$. However, if the individual asks for the other four offences to be taken into consideration when he is being sentenced, the police will count these offences as being cleared up. The clear-up rate will then be 100% and will be a relatively poor measure of the probability of detection. Accordingly, we attempted to find an alternative estimator of this variable. Unfortunately, it was impossible to obtain information on numbers of offences cleared by being taken into consideration. Instead we have used the ratio of the number of <u>offenders</u> convicted to the number of <u>offences</u> committed. In the example above the conviction rate (as we shall term this new measure) would be $1/5$, which accurately reflects the probability of detection. In fact the conviction rate for offenders who commit multiple offences will always be a superior measure of the probability of detection to the clear-up rate. However, if offenders commit only one offence its superiority is not so apparent.

Having considered how we propose to measure the probability of detection, we must now examine those factors which are expected to influence it. It is fairly standard in the econometric literature on crime to treat this relationship as a "production function", i.e. the detection rate is regarded as an output of the police service. It seems natural, therefore, to hypothesise that it will be influenced by the amounts of capital and labour inputs used in the police service, e.g. the levels of police and civilian manpower, the amounts of vehicles, buildings and other capital equipment and so on.

The main problem here concerns the appropriate way to measure the capital inputs. This is not an uncommon problem in estimating production functions, of course. There just is not a readily available index of either the capital stock or, more importantly, of capital services used by the police. We were able to obtain, after much effort, information on one aspect of the capital stock, i.e. the number of police vehicles.[19a] We did experiment with this variable, using it as a proxy for the amount of capital services used. However, for various reasons the experiment was not altogether successful and so we decided to drop the capital input from the model.[20]

We had hoped to treat police and civilian manpower as separate inputs in the production function and also to separate police manpower into numbers of uniformed and detective officers. However, civilian manpower was found to be highly correlated with police manpower (r = 0.96) and to eliminate multi-collinearity was dropped at an early stage in the model selection process. We were unable to distinguish between uniformed and detective manpower, because the definitive information source (manpower returns kept by Her Majesty's Inspectorate of Constabulary) were denied to us. Material published in the Annual Reports of Chief Constables was too imprecise to be used.

Accordingly, inputs of police resources were encapsulated in one variable, the number of police officers on average

---

[19a] This series was obtained by delving through the Annual Reports of Chief Constables kept in the Home Office and Scotland Yard Libraries and by writing individually to those Chief Constables whose Annual Reports did not publish vehicle stock information.

[20] The number of vehicles was found to be highly correlated with numbers of police officers (r = 0.95), for example.

daily strength.

The detection rate is also assumed to depend upon (i) the crime rate itself and (ii) the number of serious traffic accidents. The argument for including the crime rate is that with fixed amounts of resources a rise in the crime rate would exert pressure upon those resources and might, therefore, lead to a drop in the detection rate. The existence of such an effect has not always been accepted (see, for example, Wolpin, 1978a).[21] It is probably fair to say that such an attitude has usually been taken by investigators trying to justify the use of a single equation estimation technique. There is clearly some disagreement over the inclusion of this variable, and so it seemed reasonable to include it and to test for its effect.

We included the number of serious traffic accidents as an additional workload measure. Traffic policing absorbs a substantial minority of police resources (perhaps 10-15% - see Home Office, 1973-4). Such resources are not generally available for solving crimes, especially property crimes. We would have preferred a more direct approach, i.e. separating traffic police manpower from other police manpower. However, we were unable to gain access to sufficiently accurate information on the division of manpower by functional category. We were, therefore, forced to consider a number of indicators of traffic policing workloads such as miles of trunk road, traffic flow, traffic accidents etc. As a first approach we selected the number of <u>serious</u> traffic accidents, all of which require investigation and reduce the amount of manpower available for

---

21 Wolpin's argument was that in the long-run police resources would be adjusted so that an increase in the crime rate, over the long-run, would not lead to a fall in the detection rate. In a cross-section study a similar argument might be thought to apply if there is a stable pattern of crime across areas.

solving property crimes.

A number of other studies have included in the production function several socio-economic and demographic variables, e.g. the social class composition of the population, average earnings, the unemployment rate, the age structure of the population, population size (see, for example, Burrows and Tarling, 1982). The justification for including these variables seems rather thin. In fact, Burrows and Tarling in an exhaustive analysis of the effects of such variables, concluded that " ... social variables were generally not significantly related to clear-up rates" (p.10).[22] We have refrained from including such variables on the grounds that we do not feel that their inclusion is warranted.

Both Carr-Hill and Stern (1979) and Burrows and Tarling (1982) found that 'crime-mix' was a significant factor associated with the overall detection rate. However, both of these studies used an aggregate crime measure. As we propose to examine sub-sets of crimes within that aggregate the inclusion of such a variable would be superfluous. We can, therefore write the equations for the detection rates as,

$$CL_i = g_i\ (P,\ T,\ PC_i) \qquad i = 1,2,3,4$$

where CL_i is the observed detection rate for crimes of type i,
P is the number of police officers,
T is the number of serious road traffic accidents,
and PC_i is the recorded crime rate in category i.

Implicit in the specification of the production functions

---

22 Burrows and Tarling used Carr-Hill and Stern's model for this exercise. They simply "played around with" the production function of that model to examine the effect of the introduction of social class and other variables.

are several fairly restrictive assumptions. For example, increases in crimes of type j are not expected to influence detection rates for crimes of type i. In fact this assumption was later relaxed and had little effect upon the results, possibly because of the high correlations between the individual crimes (see Appendix to Chapter 5). Also, we have not attempted to allocate police manpower to specific crime categories, because such information is not available. We believe that this somewhat ad hoc approach can be tolerated because our primary interest lies in the estimation of the crime supply equations rather than the production functions.

(iii) Police manpower equation

We have argued in the previous section that the amount of police manpower will affect the detection rate. Some previous studies have also argued that the number of police officers would have a direct effect on the crime rate, through, say, street patrols. However, we have not used this argument ourselves, but have stressed the indirect effect through the detection rate. However, we need to consider whether to treat the number of police officers as an endogenous variable.

An economic sub-model could be built which would distinguish the demand for and supply of police officers and posit an equilibrium condition. Employment would then be related to various factors such as relative earnings, employment conditions and so on. Most of the American literature has argued that the manpower equation reflects the demand for police officers, presumably on the grounds that supply adjusts to meet demand. However, in England and Wales there are grounds for believing that the "market" for police officers is not in equilibrium, but that employment is supply constrained. If this is the case, then the manpower equation should be a supply function.

What evidence is there of an excess demand for police officers, particularly in the period 1975-6? One possible indicator of excess demand can be found by comparing the authorised establishment of the police service with its actual strength. In 1975 actual strength was some 8,869 officers below establishment, whereas in 1976 this gap had narrowed to some 7,404 officers below establishment.[23] These figures do not provide conclusive proof that the police service in general suffered from a shortage of manpower. For example, the shortage might have been confined to a small number of areas or police forces might have been denied the necessary finance to recruit up to their establishment.

Closer examination of the manpower situation in each of the 41 police force areas that form the basis of our later work reveals, however, that manning levels were generally below establishments and not concentrated in a small number of areas (see Appendix to this chapter). It is true that the extent of undermanning varied from area to area, but only one police force area (Hampshire in 1976) had actually recruited up to its authorised establishment. Many had strength deficiencies in excess of 5% of their allowed manpower levels.

The hypothesis that police forces were financially constrained to employ less than their authorised establishment also finds relatively little support. During the 1960s and 1970s there were a series of official enquiries into the police service and a constant theme running through the

---

[23] Actual strengths for 1975 and 1976 were 107,138 and 109,476 respectively. Authorised establishments for the same two years were 116,007 and 116,880 respectively.

reports of these enquiries was a concern with recruitment and wastage. For example, the Seventh Report from the Expenditure Committee (1974) entitled Police Recruitment and Wastage talked of the " ... chronic malaise of the undermanning of police forces throughout England and Wales" (para 3)[24], a situation for which, in part at least, they blamed deteriorations in the pay and conditions of the police service relative to other occupations.[25] Undermanning was so serious in the mid-1970s that in August 1977 the Home Secretary appointed A Committee of Inquiry on the Police "(t)o review the machinery for negotiating those matters relating to pay and conditions of the police service ..." (para 1). The report, subsequently known as the Edmund-Davies Report, recommended substantial pay increases for police officers in the hope of both increasing recruitment and reducing wastage.

The evidence suggests that during the period of the 1970s there was very considerable concern that the police service was unable to obtain sufficient manpower. The binding constraint was not demand, but a shortfall in supply. It would be surprising, therefore, that in such a situation the government had imposed financial restraints upon police authorities preventing them from recruiting up to their authorised establishments. In fact the government took great care to ensure that police manpower was protected and that sufficient funds

---

24 A similar view had been expressed by the earlier enquiry into Police Manpower, Equipment and Efficiency (Home Office, 1967) which remarked, "It is well known that the police service of England and Wales has for years suffered a chronic shortage of manpower" (para 3).

25 The situation was apparently so bad in some years in the 1960s that authorised establishments were set not in relation to "needs", but in relation to the likely supply of manpower that would be forthcoming. (See, First Report of The Estimates Committee, 1966-7, Police.)

were made available to enable police authorities to recruit up to their establishment.[26]

It seems reasonable then to model the manpower equation as a supply function. But what factors influence the supply of manpower to the police service? The various reports referred to earlier frequently stressed the role of pay in the police service relative to that in other occupations. Recruits to the police service are drawn predominantly from people (very largely men)[27] living within the area, so that the relevant earnings variable for comparison purposes is average (male) earnings in the locality. It would obviously be desirable to restrict the earnings measure to those occupations which compete most closely with the police service for labour, but this was not possible.

In addition to relative earnings in employment the level of unemployment might be expected to influence both recruitment to and wastage from the police service. If the local labour market is relatively slack (high unemployment) then the supply of manpower would be expected to increase. On the arguments of the last paragraph it is the male unemployment rate that is the most relevant indicator. However, data deficiencies limited us to using the unemployment rate for both males and females.

---

26 "Provision is made for the continuing build-up of police strengths towards authorised establishments ... Should numbers exceed the estimated growth, provision will be made for additional expenditure within authorised establishments". Public Expenditure to 1979-80 (Cmnd 6393, p.80, para 18.) This position was reaffirmed in The Government's Expenditure Plans (Cmnd 6721 - II, p.65, para 17) published the following year.

27 In 1975 94.5% of the stock of police officers were male. In 1976 the figure was 93.5%. As a percentage of recruits males are slightly less predominant, being 84.4% in 1975 and 80.2% in 1976. These figures have been calculated from material in the Report of Her Majesty's Chief Inspector of Constabulary 1976 HC 414.

The supply of manpower is also expected to be influenced by the number of individuals qualified for entry. Two areas offering the same relative pay and with the same unemployment rates might have very different supply situations if they have substantially differently sized labour forces. The potential stock of recruits to the police service is very largely the number of people (males) in the relevant age range with the minimum entrance requirements regarding height, eyesight and education. The minimum age for entry is 19 years and the maximum age (for those without service in the armed forces) is 30 years of age. There are no formal educational requirements in terms of CSEs, 'O' levels etc., although recruits are required to pass a standard entrance test. The national minimum height stipulation can be raised if Chief Constables wish, but only four have actually done so. The medical test is determined by the Chief Constable, though most now accept recruits who wear spectacles.[28] As it is impossible to obtain information on the distribution of the local populations by height and quality of eyesight, the stock of potential recruits to the service has been measured by the number of males aged 20 - 29 years.

We have so far not considered how working conditions are likely to affect the supply of manpower to the police service. Long hours of work, irregular shift patterns, heavy workloads and low morale are all reasons advanced to explain shortages of manpower. Unfortunately, it is difficult to obtain reliable information on the extent of variation across police

---

[28] See Memorandum by the Home Office to the Seventh Report from the Expenditure Committee, 1974, <u>Police Recruitment and Wastage</u> HC 310.

forces in some of these conditions. Carr-Hill and Stern (1979) have argued that the crime rate and the detection rate might be used as indicators of workload and morale and that the rate of violent crime in an area might be used to indicate the potential dangers of being a policeman in that area. However, as all of these variables are rather imperfect proxies for the factors they purport to measure, we have refrained from including them in version 1 of the model. However, later versions of the model did include some indicators of workload and the results are reported in Chapter 5.

The manpower supply equation can, therefore, be written more formally as,

$$P = h(E, U, M)$$

where P is the number of police officers,
E is average male earnings in other occupations relative to those in the police service,
U is the unemployment rate,
and M is the number of males aged 20 - 29 years.

(iv) <u>The recording equations</u>

We have modelled the crime supply equations in terms of the "true" (or actual) number of crimes per 100,000 population. Unfortunately we do not know precisely what that number is. Estimation could only proceed if we could find some way of approximating it. We do know the number of <u>recorded</u> crimes per 100,000 population. However, it is generally accepted that not all offences actually become recorded.[29] To use recorded crime statistics we need to model the relationship between recorded and actual crime. If we are confident that we have modelled this relationship satisfactorily then we can have

---

29 See, for example, <u>The British Crime Survey</u> (discussed in Chapter 1).

some confidence that the parameter estimates of the crime equations have something to say about the determination of the actual rather than the recorded crime rate.

A possible method of estimating the true number of offences might be to multiply the number of recorded offences by an "under-recording factor" derived from, say, a victim survey. However, we would need the results of victim surveys in each of the areas included in the later empirical analysis. Unfortunately such data simply do not exist. Besides, it is questionable how accurate such survey responses really are. Respondents may suffer, for example, from lapses of memory, or may lack knowledge of whether an act is a crime. Alternatively, they may not understand the question or may be suspicious of the motives of the questioner.

Lacking the resources to instigate separate victim surveys in each police force area in England and Wales we were forced to consider an alternative way of resolving the problem. An operational approach was suggested by Carr-Hill and Stern (1979). They argued that the proportion of offences that will be recorded may depend upon (i) the number of policemen per capita, (ii) the proportion of working class people in the population, and (iii) the percentage of young males in the population. The number of policemen per capita was expected to influence the ease with which members of the public could report an offence and also to affect the number of offences directly observed by the police. The social class and age structure variables were assumed to influence police officers' attitudes to the recording of incidents which they observed, i.e. they were less likely to overlook certain offences in areas with high proportions of young males and working class people. Of course, in such areas the public are less likely to trust the police and be aware of their rights, so that reporting (as distinct from recording) may be lower. These effects would seem, therefore, to work in opposite directions.[30]

The approach suggested by Carr-Hill and Stern is potentially highly fruitful and we intend to develop our argument along these lines. However, in modelling the reporting/recording process we should bear in mind the kinds of crimes that will be the focus of attention in the later empirical work. These are the crimes of burglary, robbery and theft and handling of stolen goods. Victims of such acts are highly likely to realise that a crime has been commmitted, although one can obviously think of examples where people may not realise it, e.g. they think that they have mislaid something when in fact it has been stolen, or their house was burgled without forced entry and nothing of value was taken. However, such examples are likely to be (extremely) rare.

The initiative in reporting such crimes seems to lie largely with the victim. Witnesses (whether members of the public or police officers) are likely to be few. What incentive is there for the victim to report the crime to the police? Possibly the most important one is the recovery of his property. If the victim believes the police will be either essential or even just helpful in recovering his goods then (s)he will probably report the offence. There may be some circumstances where reporting will take place even if the victim holds out little hope of his (her) property being returned. For example, if the goods have been insured against theft,

---

[30] Shaw and Williamson (1972) found that public attitudes to the police varied according to the social class and age of those interviewed.

the victim's insurance company may insist that the crime be reported before they will settle the claim. Of course, reporting is costly. It involves the victim in spending time contacting the police, answering questions, reading and filling in forms, writing to insurance companies and so on. If the cost of reporting is likely to exceed the value of the benefit resulting from reporting, rational individuals will not bother to report an offence. As the time involved in reporting an offence is likely to be fairly constant across crimes, then reporting is likely to increase directly with the value of property stolen.[31]

We would, therefore, expect the proportion of crimes reported to the police to depend upon (i) how successful the police were in solving crimes, (ii) the average value of property stolen, and (ii) the proportion of households insured against theft, etc. There is some support for these views in the British Crime Survey. When asked why the police were not contacted after a crime individuals often responded that the offence was too trivial to warrant reporting (in 49% of cases involving household offences and 38% of those involving personal offences). The second most important reason for not reporting a crime was a feeling that the police could do nothing. This was mentioned in 34% of cases involving household offences and 16% of those involving personal offences. Additionally, a small percentage of victims did not report crimes because they felt that the police would not be inter-

---

[31] However, the <u>value</u> of the time involved in reporting will rise directly with income. Therefore, richer individuals should be less likely to report an offence of £x than poorer individuals, <u>ceteris paribus</u>.

ested (in 9% of household offences and 3% of personal crimes).[32]

In addition the police have some discretion in the recording of offences that are actually reported to them. For example, they may not believe the complainant or further investigation may reveal that a crime did not take place or they may simply feel that recording would not be worthwhile.

Clearly, the process by which a crime eventually becomes recorded or not is rather complex. Some of the factors influencing the decision to report and/or to record are too complex and subtle to be modelled successfully at the macro level. It would be difficult, for example, to obtain information across areas on the extent to which individuals feared the police or felt that the police would not be interested. Accordingly, the modelling of the recording decision is bound to be somewhat simplistic.

We can perhaps isolate some of the factors which might influence variations in recording across areas. One such factor is the detection rate. As we have seen, crimes are often not reported because it was felt that the police could not solve them. Another possible factor is the wealth of the area. Wealthy people are more likely to insure their property and so are more likely to report a crime in order to claim upon insurance. Also, the average value of property stolen in such areas is likely to be higher, so that the "benefits" of reporting are likely to be larger. On the police side it seems that a crime is more likely to be recorded if they are

---

[32] Similar arguments have been advanced in other victim surveys. The General Household Survey 1979, for example, claimed that the two most important reasons for not reporting burglaries were " ... the police (were) thought to be ineffective ... or there was no hope of recovering the goods." (pp.72-3) See also Bottomley and Coleman (1981).

not hard pressed. When they are over-worked the police may not be prepared to record certain minor crimes which they feel they have little chance of solving or about which they have doubts.

Accordingly we could specify the recording equation as,

$$\frac{PC_i}{PC_i^*} = k_i\,(CL_i,\ Z,\ L) \qquad i = 1,2,3,4$$

where $\frac{PC_i}{PC_i^*}$ is the proportion of offences of type i reported,

CL_i is the detection rate for crimes of type i,

Z is a measure of the wealth of an area,

and L is a measure of the workload in the police force.

However, in version 1 of the model the arguments of the functions $k_i(\quad)$ are restricted to CL_i alone. In Chapter 5 we report the results of a more elaborate specification.[33]

Finally, we need to consider how to eliminate the unobserved variable CL_i^* (the "true" detection rate) from the supply of offences functions. This can be done by using an ingenious method suggested by Carr-Hill and Stern (1979). The "true" detection rate is given by,

$$CL_i^* \equiv \frac{D}{PC_i^*} \qquad i = 1,2,3,4$$

where D is the number of crimes solved/detected per 100,000 population.

The measured detection rate is,

$$CL_i \equiv \frac{D}{PC_i} \qquad i = 1,2,3,4$$

so that $$PC_i^* \times CL_i^* \equiv PC_i \times CL_i$$

---

[33] The detection rate may, of course, be inversely related to workload (see the argument of section (ii) of this chapter) in which case inclusion of both variables would be superfluous.

These identities can then be used along with the recording equations to eliminate the unobserved variables from the crime equations. However, use of this method imposes a cost in terms of the functional form of the model. It must be linear in the logarithms of at least two of the variables (PC_i and CL_i). However, this is not too great an inconvenience, because it enables direct comparison with earlier studies and easy computation of elasticities. Version 1 of the model assumes a logarithmic linear specification for the whole model. In Chapter 5 we report the results of an alternative functional specification.

3. The Complete Model

(i) Specification and partial solution

We can now set out more formally version 1 of the model, which assumes a log-linear specification of the equations.

(1) Crime Supply Equations

$$\log PC_i^* = \alpha_{0i} + \alpha_{1i} \log CL_i^* + \alpha_{2i} \log I_i + \alpha_{3i} \log S_i + \alpha_{4i} \log R + \alpha_{5i} \log A + \alpha_{6i} \log U + \alpha_{7i} \log CL_{iA}^* + \alpha_{8i} \log W + \mu_{1i}$$

(2) Police Production Functions

$$\log CL_i = \beta_{0i} + \beta_{1i} \log P + \beta_{2i} \log T + \beta_{3i} \log PC_i + \mu_{2i}$$

(3) Police Manpower Equation

$$\log P = \gamma_0 + \gamma_1 \log M + \gamma_2 \log E + \gamma_3 \log U + \mu_3$$

(4) Recording Equations

$$\log PC_i - \log PC_i^* = \delta_{0i} + \delta_{1i} \log CL_i + \mu_{4i}$$

(5) Identities

$$\log D_i \equiv \log PC_i^* + \log CL_i^* \equiv \log PC_i + \log CL_i$$

The α_{ji}, β_{ji}, γ_j and δ_{ji} are parameters to be estimated and the μ_{ji} are random disturbances (i = 1,2,3 and 4). The variables are defined in sections 2(i) to 2(iv) above.

The model given by equations (1) to (5) above cannot be estimated directly, because of the presence of the unobserved variables PC_i^*, CL_i^* and CL_{iA}^*. However, these can be eliminated by substituting equations (4) and (5) into equation (1). This produces a partial reduced form of the model. The modified version of equation (1) (see Appendix to this chapter) is,

$$\log PC_i = \alpha_{0i}^1 + \alpha_{1i}^1 \log CL_i + \alpha_{2i} \log I_i + \alpha_{3i} \log S_i + \alpha_{4i} \log R + \alpha_{5i} \log A + \alpha_{6i} \log U + \alpha_{7i}^1 \log CL_{iA} + \alpha_{8i} \log W + \mu_{1i}^1 \qquad (1a)$$

where

$$\alpha_{0i}^i = \alpha_{0i} + \delta_{0i} (1 + \alpha_{1i} + \alpha_{7i})$$

$$\alpha_{1i}^1 = \alpha_{1i} + \delta_{1i} (1 + \alpha_{1i})$$

$$\alpha_{7i}^1 = \alpha_{7i} (1 + \delta_{1i})$$

$$\mu_{1i}^1 = \mu_{1i} + \mu_{4i} (1 + \alpha_{1i} + \alpha_{7i})$$

The model then consists of equations (1a),(2) and (3). However, before it can be estimated we need to establish that the model is identified and also find statistical proxies for the variables of the model.

(ii) <u>Identification of the model</u>

It is relatively easy to show that the model satisfies the rank condition, and by implication, the order condition for identification. The proof of this statement can be found in the Appendix to this chapter. In fact each equation is over-identified.

(iii) Data sources

In estimating the model we have concentrated upon crimes against property, i.e. the offences of burglary, robbery and theft and handling of stolen goods. The justification for doing so is our feeling that potential property criminals are more likely to respond to "incentives" and/or are more likely to be economically motivated than potential violent criminals. The variables PC_i have, therefore, been measured by the number of recorded offences of burglary, robbery and theft and handling of stolen goods per 100,000 population. A fourth category, the aggregate of these offences,was also used. Recorded crime statistics are published annually for police force areas in England and Wales in Criminal Statistics.

The probability of detection (CL_i) was measured in two ways. First, by the clear-up rate, i.e. the percentage of recorded property offences deemed by the police to have been solved. Clear-up statistics for police force areas are not published, but were obtained from the Home Office. The second measure used was the ratio of persons found guilty of committing property offences (including those cautioned) to the number of recorded property offences. We call this the conviction rate. Numbers of persons found guilty of property offences were obtained from Criminal Statistics.

The conditional probability of being imprisoned (I_i) was measured by the ratio of the number of offenders sentenced to immediate imprisonment to the number of persons found guilty of offences (including those cautioned). The necessary information was also obtained from unpublished Home Office statistics. The length of imprisonment (S_i) was measured by the average sentence (in days) imposed by the courts upon those offenders sentenced to immediate imprisonment. Information on sentence lengths was also obtained from unpublished Home Office statistics.

The probability of detection in adjacent areas (CL_{iA}) was measured by either the average clear-up rate or the average conviction rate for contiguous police force areas, depending upon which of these measures was used as the detection rate.

Expected returns in legitimate activity were represented by two variables. These were the unemployment rate for males and females (U) and the average weekly earnings of the lowest paid ten per cent of males aged over twenty-one years (W). Increases in U are expected to reduce the opportunity costs of engaging in crime and so increase crime rates. The selection of the particular measure of W was based upon the presumption that it is low paid workers who are on the margin between criminal and legitimate activity. (This hypothesis is further investigated in Chapter 5). An increase in their average weekly earnings is expected to reduce the number of offences committed. Data for both of these variables were obtained from <u>British Labour Statistics</u>.

Potential gains from crime (R) depend upon the stock of real and financial assets available to be stolen. As a proxy for this stock and for illegal gains we have used total rateable value per hectare. These data were obtained from <u>Rates and Rateable Values in England and Wales, 1975-6</u>. Finally, in equations (1a), we have included the percentage of the population that was male and aged fifteen to twenty-four years (A). This variable was derived from data published in OPCS <u>Population Projections</u> statistics.

P was measured by the number of policemen on average daily strength. The data were obtained from Police Force and Regional Crime Squad Statistics. T was approximated by the number of fatal and serious road casualties per year, as information on serious road accidents was not readily available. Information on casualties was obtained from Road Accidents G.B. The stock of potential recruits to the police service (M) was measured by the number of males aged twenty to twenty-nine years. The data were also obtained from OPCS Population Projections statistics. Finally, $\dot{E}$ was measured by average weekly earnings of males aged over twenty-one years. This information was obtained from British Labour Statistics.

Appendix To Chapter 4.

(1) Under-manning by Police Force Area:

(a) At 31st March 1975

Police Force Area	(1) Authorised Establishment	(2) Actual Strength	(3) Absolute Short-fall (1) - (2)	(4) (3) as % of Authorised Establishment
Avon & Somerset	2868	2587	281	9.8
Bedfordshire	890	795	95	10.7
Cambridgeshire	1024	983	41	4.0
Cheshire	1770	1630	140	7.9
Cleveland	1411	1296	115	8.2
Cumbria	1078	1022	56	5.2
Derbyshire	1559	1456	103	6.6
Devon and Cornwall	2673	2579	94	3.5
Dorset	1089	1050	39	3.6
Durham	1373	1275	98	7.1
Dyfed-Powys	866	859	7	0.8
Essex	2436	2198	238	9.8
Gloucestershire	1101	959	142	12.9
Greater Manchester	6628	5584	1044	15.8
Gwent	928	921	7	0.8
Hampshire	2845	2706	139	4.9
Hertfordshire	1472	1328	144	9.8
Humberside	1910	1688	222	11.6
Kent	2454	2265	189	7.7
Lancashire	2880	2861	19	0.7
Leicestershire	1603	1581	22	1.4
Lincolnshire	1174	1140	34	2.9
Merseyside	4317	3858	459	10.6
Norfolk	1218	1160	58	4.8
Northamptonshire	844	831	13	1.5
Northumbria	3322	3104	218	6.6
North Wales	1216	1173	43	3.5
North Yorkshire	1277	1235	42	3.3
Nottinghamshire	2066	2034	32	1.5
South Wales	2886	2849	37	1.3
South Yorkshire	2752	2340	412	15.0
Staffordshire	2066	1932	134	6.5
Suffolk	1071	978	93	8.7
Surrey	1442	1270	172	11.9
Sussex	2661	2588	73	2.7
Thames Valley	2960	2781	179	6.0
Warwickshire	876	783	103	11.8
West Mercia	1650	1491	159	9.6
West Midlands	6419	5298	1121	17.5
West Yorkshire	5104	4387	717	14.0
Wiltshire	979	897	82	8.4

(b) At 31st March 1976

Police Force Area	(1) Authorised Establishment	(2) Actual Strength	(3) Absolute Short-fall (1) - (2)	(4) (3) as % of Authorised Establishment
Avon & Somerset	2868	2821	47	1.6
Bedfordshire	926	841	85	9.2
Cambridgeshire	1061	1043	18	1.7
Cheshire	1770	1740	30	1.7
Cleveland	1411	1361	50	3.5
Cumbria	1079	1032	47	4.4
Derbyshire	1559	1555	4	0.2
Devon and Cornwall	2673	2649	24	0.9
Dorset	1108	1093	15	1.4
Durham	1373	1351	22	1.6
Dyfed-Powys	916	903	13	1.4
Essex	2436	2352	84	3.4
Gloucestershire	1101	1040	61	5.5
Greater Manchester	6628	5953	675	10.2
Gwent	964	962	2	0.2
Hampshire	2845	2847	- 2	0
Hertfordshire	1472	1403	69	4.7
Humberside	1939	1754	185	9.5
Kent	2465	2440	25	1.0
Lancashire	3080	3066	14	0.5
Leicestershire	1705	1644	61	3.6
Lincolnshire	1182	1156	26	2.2
Merseyside	4342	4110	232	5.3
Norfolk	1264	1201	63	5.0
Northamptonshire	914	893	21	2.3
Northumbria	3322	3227	95	2.9
North Wales	1276	1222	54	4.2
North Yorkshire	1328	1303	25	1.9
Nottinghamshire	2124	2118	6	0.3
South Wales	3069	2973	96	3.1
South Yorkshire	2761	2517	244	8.8
Staffordshire	2066	2035	31	1.5
Suffolk	1085	1031	54	5.0
Surrey	1442	1397	45	3.1
Sussex	2785	2774	11	0.4
Thames Valley	2960	2877	83	2.8
Warwickshire	876	825	51	5.8
West Mercia	1650	1592	58	3.5
West Midlands	6417	5556	861	13.4
West Yorkshire	5104	4607	497	9.7
Wiltshire	994	958	36	3.6

(c) Frequency distribution of under-manning in Police Fcrce Areas

percentage below Authorised Establishment	At 31.3.76 No. of police force areas	At 31.3.75 No. of police force areas
less than 1%	7	3
more than 1% but less than 2%	9	4
more than 2% but less than 5%	14	9
more than 5% but less than 10%	9	15
more than 10%	2	10
	41	41

Sources for Table 1: Police Force and Regional Crime Squad Statistics
Actuals 1974-5 and 1975-6

(2) Partial Solution of Model:

From equations (5) of the model (see p.172) we have

$$\log CL_i^* = \log PC_i + \log CL_i - \log PC_i^*$$

and $$\log CL_{iA}^* = \log PC_{iA} + \log CL_{iA} - \log PC_{iA}^*$$

If we substitute for $\log CL_i^*$ and $\log CL_{iA}^*$ in equations (1) we obtain

$$\log PC_i^* = \alpha_{oi} + \alpha_{1i} [\log PC_i + \log CL_i - \log PC_i^*] + \alpha_{2i} \log I_i + \ldots\ldots$$

$$\ldots\ldots + \alpha_{7i} [\log PC_{iA} + \log CL_{iA} - \log PC_{iA}^*] + \alpha_{8i} \log W + \mu_{1i}$$

which simplifying gives

$$\log PC_i^* = \frac{1}{1 + \alpha_{1i}} \Big\{ \alpha_{0i} + \alpha_{1i} [\log PC_i + \log CL_i] + \alpha_{2i} \log I_i + \ldots\ldots$$

$$\ldots\ldots \alpha_{7i} [\log PC_{iA} + \log CL_{iA} - \log PC_{iA}^*] + \alpha_{8i} \log W + \mu_{1i} \Big\}$$

From equations (4) we have

$$\log PC_i^* = \log PC_i - \delta_{0i} - \delta_{1i} \log CL_i - \mu_{4i}$$

and $$\log PC_{iA}^* = \log PC_{iA} - \delta_{0i} - \delta_{1i} \log CL_{iA} - \mu_{4i}$$

Substituting for $\log PC_i^*$ and $\log PC_{iA}^*$ in the above equation gives

$$\log PC_i = \alpha_{0i} + \delta_{0i} (1 + \alpha_{1i} + \alpha_{7i}) + [\alpha_{1i} + \delta_{1i} (1 + \alpha_{1i})] \log CL_i + \alpha_{2i} \log I_i +$$

$$\ldots\ldots + \alpha_{7i} (1 + \delta_{1i}) \log CL_{iA} + \alpha_{8i} \log W + \mu_{1i} + \mu_{4i} (1 + \alpha_{1i} + \alpha_{7i})$$

which are equations (1a) of the text.

(3) Identification of the Model

The partial reduced form of the model can be set out as follows

Equations	PC_i	CL_i	I_i	S_i	R	A	U	CL_{iA}	W	P	T	M	E
1a	1	α'_{1i}	α_{2i}	α_{3i}	α_{4i}	α_{5i}	α_{6i}	α'_{7i}	α_{8i}	0	0	0	0
2	β_{3i}	1	0	0	0	0	0	0	0	β_{1i}	β_{2i}	0	0
3	0	0	0	0	0	0	γ_3	0	0	1	0	γ_1	γ_2

Order Condition

To be identified each equation must exclude at least 2 variables appearing in the model.

Equation	No. of excluded variables	Order condition
1a	4	over identified
2	9	over identified
3	9	over identified

Rank Condition

Each equation is identified if and only if there is at least one non-zero 2 x 2 determinant contained in the array of coefficients with which those variables excluded from the equation appear in the other equations of the model.

For example, equation 1a excludes the variables, P, T, M and E. The relevant array of coefficients, is therefore,

$$\begin{bmatrix} \beta_{1i} & \beta_{2i} & 0 & 0 \\ 1 & 0 & \gamma_1 & \gamma_2 \end{bmatrix}$$

Six 2 x 2 determinants can be formed from this array and 5 are expected to be non-zero.

The array of coefficients attached to variables excluded from equation 2 is

$$\begin{bmatrix} \alpha_{2i} & \alpha_{3i} & \alpha_{4i} & \alpha_{5i} & \alpha_{6i} & \alpha'_{7i} & \alpha_{8i} & 0 & 0 \\ 0 & 0 & 0 & 0 & \gamma_3 & 0 & 0 & \gamma_1 & \gamma_2 \end{bmatrix}$$

Whilst there are 36 possible two by two determinants, many will in fact be zero. However there are still some 20 non-zero determinants.

Finally the array of coefficients formed by variables excluded from equation 3 is

$$\begin{bmatrix} 1 & \alpha'_{1i} & \alpha_{2i} & \alpha_{3i} & \alpha_{4i} & \alpha_{5i} & \alpha'_{7i} & \alpha_{8i} & 0 \\ \beta_{3i} & 1 & 0 & 0 & 0 & 0 & 0 & 0 & \beta_{2i} \end{bmatrix}$$

Again many of the 2 x 2 determinants will be zero. However, there are still 21 possible non-zero 2 x 2 determinants.

We can conclude that, by the rank condition, the model given by equations (1a), (2) and (3) is over-identified.

Chapter 5 : Results of Model Estimation

In this chapter we present the results of the estimates of the model that was set out formally in Section 3 of the previous chapter. We do not discuss the interpretation of these results in any detail in this chapter. That is done in the following chapter.

The model consists of three equations. One explains the recorded crime rate, another explains the detection rate and a third is used to explain the level of police employment. The model has been estimated using data for a cross-section of police force areas in England and Wales in each of the years 1975 and 1976. The two sets of cross-section data were also pooled to produce a further set of results. As four crime groups were used (the offence groups of burglary, robbery, theft and handling stolen goods and an aggregate of all of these offences) a large volume of statistical results has been produced. In order to simplify their presentation we report first the results for the group all property offences. We then disaggregate this group into its constituent crimes and examine the result for each offence group. This approach has a distinct advantage in that the aggregate offence class has been used in order to test a number of alternative hypotheses about the determination of crime rates and detection rates. We are, therefore, able to present the results of these investigations when examining the estimates for all property crimes.

However, before presenting the results we need to say something about the estimation procedure adopted.

1. Estimation Procedure

The model of Chapter 4.3 is clearly simultaneous. It would obviously be inappropriate to estimate it by single equation methods. As we showed in the Appendix to chapter 4 the model is, theoretically at least, identified (indeed it is over-identified) and so can be estimated by standard simultaneous equation methods. We chose to estimate it by two stage least squares (2SLS). Whilst this is only a limited information technique, unlike three stage least squares or full information maximum likelihood, it has an advantage over these other estimation methods in this particular case. In 2SLS each equation is estimated separately, so that specification error in one equation of the model is not then transmitted throughout the model. We can, therefore, be rather more confident that specification error in one equation will not distort the parameter estimates of the other equations. This may be particularly advantageous in an area where uncertainty about model specification is likely to be quite high.[1]

As each equation of the model is over-identified, we have tested the validity of the over-identifying restrictions each time the model has been estimated. The null hypothesis is that all of the coefficients of the predetermined variables excluded from each equation are zero. The alternative hypothesis is that one or more of these coefficients is non-zero. The test, based broadly speaking upon the residual sums of squares with and without exclusion of the predetermined variables, is described briefly in the Appendix to this Chapter. The test statistic, which has an F distribution, is reported with each set of equation estimates. Where a test

1. Carr-Hill and Stern (1979, p. 160) argue that "(t)he specification of an econometric equation is ... always an act of faith" (my emphasis). However, in some areas it requires greater faith than in others.

is significant at the 5% level it is indicated by means of the symbol †.[2]

As a further check on the specification of the equations of the model we have computed the covariances and correlations between the residuals of each of the equations. The existence of strong positive or negative correlations between these residuals may indicate that a variable (or variables) has been omitted from the equation(s). Also, they may help to indicate what those variables might be. For example if areas with a higher (lower) detection rate, than predicted by the second equation, also had a higher (lower) crime rate than predicted by the first equation then a positive correlation would exist between the residuals in these equations. This may be because (un)successful police forces are more (un)willing to record crimes. This in turn may be explained, say, by the presence of a particularly efficient and dynamic senior management team.

Comparison of the residual variance with the variance of the variable to be explained also gives a very rough indication of the goodness of fit of the regression equation. However, with 2SLS the residual sum of squares can exceed the total sum of squares, so this comparison should not be pushed too far.

The model has been estimated for a cross-section of police force areas in England and Wales. As this provides only 41 observations[3] in any year we have increased the number of observations by pooling data for two years.

---

2. Equation 3 is not really simultaneous with the rest of the model as it does not contain any of the other endogenous variables. Accordingly no test of over-identifying restrictions is performed for that equation.

3. Two police force areas (the MPD and City) were excluded because data for some of the socio-economic and demographic variables were not available.

When reporting pooled regression estimates, it would also have been useful to be able to report the results of a test for structural change between years. However, the Chow test, based upon the residual sum of squares, is unreliable in the context of 2SLS estimation, because the estimation procedure does not minimise the residual sum of squares. In that case it is possible for the constrained sum of squares to be less than the sum of the residual sums of squares from the separate regressions. Accordingly, we are forced to report both the pooled results and the results for individual years separately.

The estimated equations have also been tested for heteroscedasticity by means of the Glejser test.[4] Whilst the Glejser test is possibly less powerful than the Goldfeld-Quandt test for heteroscedasticity it is rather easier to apply. However, as a cross-check we also used the Goldfeld-Quandt test for any explanatory variables that came close to failing the

---

4. The Glejser test is based upon the residuals from the model's equations, e_i. These are then used to estimate a second regression of the form,

$$|e_i| = \alpha_0 + \alpha_1 X_i^h$$

where h can take values $-1, -\frac{1}{2}, \frac{1}{2}$ or 1 and X_i is an explanatory variable. We have used as explanatory variables all the predetermined variables in the appropriate equation and population size. The hypothesis that $\alpha_1 \neq 0$ is then tested in the usual way i.e. using a t-test.

Glejser test.[5] All of the tests for the presence of heteroscedasticity proved to be negative and so, given the already large volume of statistical results, we do not report the results of these tests each time the model has been estimated.

The main results are presented in tabular form. Each table reports coefficient estimates, t-statistics, estimates of the variance-covariance matrix of residuals, the correlation matrix of residuals, variances of the dependent variables and test statistics for over-identifying restrictions. The t-statistics are reported in brackets underneath each coefficient. Coefficients significant at the 1%, 5%, 10% and 15% levels, using a one-tail test, have been indicated by means of a series of asterisks. Four asterisks indicate a coefficient that is significant at the 1% level, three asterisks indicate a coefficient significant at 5%, two asterisks for coefficient significant at 10% and one asterisk for coefficients significant at the 15% level. The reported t-statistics are, of course, asymptotic t-values and so should be treated with some caution given sample sizes of 41 or 82 observations.

We have used a one-tail test, because we are interested in testing whether coefficients have a particular sign. For example, in the crime equation we wish to test whether the deterrence variables (I_i, S_i and CL_i)

---

5. The Goldfeld-Quandt test is rather more time consuming because it requires the observations to be ordered according to the size of X_i. Then the central m observations are excluded and the sample is divided in two and the regressions re-estimated for each half of the new sample. A test is then performed on the two residual sums of squares to see whether they are significantly different.

have negative coefficients.[6] The critical values for the t-statistic are as follows,

	1.04	(15% level, one tail test)
	1.28	(10% " " " ")
	1.65	(5% " " " ")
and	2.33	(1% " " " ")

Information on the means and standard deviations of the variables is given in the Appendix to this Chapter. Also in the Appendix we present the correlation matrices of the variables. The actual data itself is contained in the Statistical Appendix at the end of the thesis.

In estimating the model we have used two measures of the detection rate (the clear up rate and the conviction rate. See Chapter 4.2.ii). Therefore, in presenting the results we show the model estimates for each measure of the detection rate separately. These are indicated by the headings CL (conviction rate) and CL (clear up rate) respectively.

The model was estimated using the ESP package on the University of Leicester CDC Cyber 73 computer.

2. All Property Offences

(i) Main Estimates

The first batch of results relate to an aggregate crime measure, i.e.

---

6. Formally we wish to test the following hypotheses,

α_{1i} , α_{2i} , α_{3i} , α_{8i} , β_{2i} , β_{3i} , γ_2 $<$ 0

α_{4i} , α_{5i} , α_{6i} , α_{7i} , β_{1i} , γ_1 , γ_3 $>$ 0 the number of offences of burglary, robbery and theft handling of stolen goods per 100,000 of the population. The detection rate is, therefore, the weighted average detection rate for all of these offences.

The principal results are given in Tables 5.1 - 5.6 inclusive.

The results given in Tables 5.1 to 5.6 inclusive are, overall, reasonably satisfactory. Each table contains 14 estimated coefficients and there are never less than eight coefficients which are significant at the 15% level or better. In total some two-thirds of the coefficients are significant at this level. However, the crime equation has the highest proportion of insignificant coefficients when the detection rate is measured by the clear up rate. More importantly it is the significance of the deterrence variables that is affected by the choice of measure of the detection rate. This point is explored more fully in Chapter 6.

On the whole the model passes the test of the correctness of over-identifying restrictions. The test statistic is reported in the final column of each table and is only once significant at the 5% level. This is when the production function, using conviction rates, was estimated for pooled data. Given that the model generally passes the test the question of the correctness of the over-identifying restrictions was not pursued further.

None of the correlation coefficients between the residuals is particularly strong (the largest value being 0.57).[7] However, some of them

7. Carr-Hill and Stern (1979, Chapter 7) chose, admittedly arbitrarily, a value for the correlation coefficient of 0.7 as being high and had some coefficents in excess of 0.9.

Table 5.1 1975 CL (conviction rate)

Dependent Variable	Explanatory Variable									Test Statistic
	log CL	log T	log S	log R	log A	log U	log CL_A	log W	intercept	
log PC	- 0.98** (1.52)	- 0.31** (1.43)	- 0.48*** (1.67)	0.14**** (3.18)	0.30 (0.36)	0.26*** (1.97)	0.21 (0.47)	- 0.37 (0.48)	13.27 (2.19)	2.30 (2,31)
	log P	log T	log PC						intercept	
log CL	0.19*** (2.19)	- 0 25**** (2.98)	- 0.45**** (3.06)						7.21 (6.44)	1.86 (7,31)
	log M	log E	log U						intercept	
log P	1.01**** (26.43)	- 0.19 (0.46)	0.35**** (5.26)						3.43 (2.10)	- -

variance/covariance matrix of residuals

0.026	0.010	0.005
	0.015	0.004
		0.013

variance

log PC	0.076
log CL	0.026
log P	0.292

correlation matrix of residuals

1.00	0.52†	0.28
	1.00	0.27
		1.00

Table 5.2 — 1975 CL (clear up rate)

Dependent Variable	Explanatory Variable									Test Statistic
	log CL	log I	log S	log R	log A	log U	log CL_A	log W	inter-cept	
log PC	- 0.07 (0.13)	- 0.17 (0.72)	- 0.20 (0.80)	0.19**** (3.80)	1.16** (1.56)	0.18* (1.23)	0.73** (1.64)	- 0.61 (0.69)	5.48 (1.14)	2.45 (2,31)
	log P	log T	log PC						inter-cept	
log CL	0.12*** (1.72)	- 0.25**** (3.50)	- 0.29**** (2.36)						7.01 (7.56)	1.14 (7,31)
	log M	log E	log U						inter-cept	
log P	1.01**** (26.43)	- 0.19 (0.46)	0.35**** (5.26)						3.42 (2.10)	- -

variance/covariance matrix of residuals

0.032	0.007	0.003
	0.011	0.005
		0.013

variance

log PC	0.076
log CL	0.016
log P	0.292

correlation matrix of residuals

1.00	0.37†	0.16
	1.00	0.39†
		1.00

Table 5.3 1976 CL (conviction rate)

Dependent Variable	Explanatory Variable									Test Statistic
	log CL	log I	log S	log R	log A	log U	log CL_A	log W	inter- cept	
log PC	- 0.67* (1.04)	- 0.26* (1.08)	- 0.19 (0.62)	0.16**** (3.93)	0.50 (0.67)	0.34**** (2.78)	0.33** (1.29)	- 0.21 (0.29)	8.95 (1.60)	0.03 (2,31)
	log P	log T	log PC						inter- cept	
log CL	0.42**** (3.82)	- 0.52**** (4.76)	- 0.36**** (2.75)						6.66 (7.25)	1.06 (7,31)
	log M	log E	log U						inter- cept	
log P	1.02**** (27.86)	- 0.36 (0.93)	0.40**** (5.65)						4.08 (2.50)	- -

variance/covariance matrix of residuals

0.020	0.003	0.004
	0.013	0.001
		0.013

variance

log PC	0.073
log CL	0.029
log P	0.296

correlation matrix of residuals

1.00	0.21	0.27
	1.00	0.04
		1.00

Table 5.4 1976 CL (clear up rate)

Dependent Variable	Explanatory Variable									Test Statistic
	log CL	log I	log S	log R	log A	log U	log CL_A	log W	intercept	
log PC	- 0.78 (0.93)	- 0.07 (0.35)	- 0.15 (0.52)	0.15**** (2.82)	0.84* (1.10)	0.20 (0.94)	0.90** (1.55)	- 0.21 (0.22)	6.45 (1.32)	0.09 (2,31)
	log P	log T	log PC						intercept	
log CL	0.25*** (2.13)	- 0.33**** (2.84)	- 0.24*** (1.74)						6.26 (6.49)	0.94 (7,31)
	log M	log E	log U						intercept	
log P	1.02**** (27.86)	- 0.36 (0.93)	0.40**** (5.65)						4.08 (2.50)	

variance/covariance matrix of residuals

0.034	0.015	0.006
	0.015	0.005
		0.013

variance

log PC	0.073
log CL	0.021
log P	0.296

correlation matrix of residuals

1.00	0.57†	0.30†
	1.00	0.35†
		1.00

Table 5.5

Pooled 1975/6 CL (conviction rate)

Dependent Variable	Explanatory Variable									Test Statistic
	log CL	log I	log S	log R	log A	log U	log CL_A	log W	inter-cept	
log PC	- 0.86*** (1.72)	- 0.29*** (2.06)	- 0.34*** (1.73)	0.15**** (5.65)	0.36 (0.61)	0.28**** (3.61)	0.32** (1.58)	- 0.15 (0.75)	10.75 (2.81)	1.70 (2,72)
	log P	log T	log PC						inter-cept	
log CL	0.19**** (2.91)	- 0.27**** (4.25)	- 0.35**** (3.36)						6.45 (8.64)	4.60† (7,72)
	log M	log E	log U						inter-cept	
log P	1.01**** (39.99)	- 0.05 (0.41)	0.38**** (8.17)						2.84 (5.22)	- -

variance/covariance matrix of residuals

0.022	0.006	0.005
	0.016	0.003
		0.013

variance

log PC	0.073
log CL	0.027
log P	0.291

correlation matrix of residuals

1.00	0.35†	0.29
	1.00	0.23
		1.00

Table 5.6 Pooled 1975/6 CL (clear up rate)

Dependent Variable	Explanatory Variable									Test Statistic
	log CL	log I	log S	log R	log A	log U	log CL_A	log W	intercept	
log PC	- 0.37 (0.71)	- 0.10 (0.35)	- 0.17 (1.02)	0.16**** (5.41)	1.07*** (2.14)	0.20*** (1.77)	0.75*** (2.29)	- 0.23 (1.00)	5.23 (1.99)	2.31 (2,72)
	log P	log T	log PC						intercept	
log CL	0.12*** (1.94)	- 0.22**** (3.71)	- 0.22**** (2.34)						6.26 (9.29)	2.17 (7,72)
	log M	log E	log U						intercept	
log P	1.01**** (39.99)	- 0.05 (0.41)	0.38**** (8.17)						2.84 (5.22)	- -

variance/covariance matrix of residuals

0.031	0.007	0.005
	0.013	0.005
		0.013

variance

log PC	0.073
log CL	0.018
log P	0.291

correlation matrix of residuals

1.00	0.36†	0.23
	1.00	0.42†
		1.00

are still significant at the 5% level. In fact 9 of the 18 correlation coefficients reported in Tables 5.1 to 5.6 are significant at that level. All nine are positive. Of these, five are between the residuals from the first and second equations, three are between the residuals from the second and third equations and only one is between the residuals of the first and third equations. Seven of the nine significant correlation coefficients occur when the detection rate is measured by the clear up rate. This may be a further reason for doubting the value of the clear up rate as a satisfactory proxy for the detection rate. The main source of correlations between the residuals lies, therefore, in a higher (lower) than predicted crime rate being associated with a higher (lower) than predicted detection rate. A possible reason for this was given in section 1 of this Chapter i.e. more efficient police forces record more property crimes than less efficient ones. This is, of course, a different argument from that which says that the public is more willing to report crimes in areas where the detection rate is high. That hypothesis is incorporated into the model via the recording equation. The positive correlation between the residuals is presumably due to another variable influencing both the detection rate and the crime rate in the same direction e.g. a particularly dynamic chief constable might encourage recording and improve detection rates. However, it is difficult to test this thesis directly.

(ii) Some Alternative Hypotheses

The "aggregate model" has been used to test a number of alternative hypotheses and we briefly report the results of these tests in this sub-section. As there are a large number of alternative hypotheses which could be investigated we focus upon a rather select group of these. Hopefully they are the major competitors with the main model. Each time the model was respecified care was taken to ensure that the model was identified.

First, previous investigators have often argued for the inclusion of the number of policemen (per capita) in the crime supply equation. There are a number of arguments behind this. One is that police presence has a direct deterrent effect upon crime, influencing criminals' perceptions of the probability of capture. An alternative explanation is that more police either encourage more reporting or discover more crimes. These two arguments point to the inclusion of P in the first equation, but yield contradictory predictions about the sign of its coefficient.

We have argued in Chapter 4 that we believe some of these arguments to be weak. Certainly the recording effect of more police is likely to be limited for property crimes.[8] Of course, more police may influence public willingness to report crimes if they associate greater police presence with greater willingness of the police to take the report seriously and do something about it.

In view of the number of arguments for including P in the crime equation and Carr-Hill and Stern's earlier finding that more police per capita generally increased the offence rate in both 1966 and 1971, we decided to test for the effect of P upon the crime rate. The results are shown in Tables 5.7 and 5.8, where for brevity we show only the re-estimates of the crime equation.

In each table we report four different specifications of the crime equation. In column 1 of each table the crime equation has been modified by

8. Support for this view comes from a study of "How crimes come to police notice" undertaken by J. Burrows at the Home Office. He argues, "(t)he fact that most crime is initiated by public reports makes it increasingly difficult to attach credence to the view that the police, by their actions, 'create' much crime". HORPU Research Bulletin No. 13, 1982, p. 14.

adding P as an explanatory variable. In neither case is its coefficient remotely near to being significant. Nor does its inclusion improve the significance of the other coefficients of the equation. In fact these generally deteriorate. In columns 2 and 3 of each table P_A, the number of policemen in adjacent areas, has also been added. If P affects individuals' perceptions of the probability of detection or victims' willingness to report offences then P_A should be included in order to control for spill-over effects. In column 2 P_A is treated as an exogenous variable, whereas in column 3 it is treated as an endogenous variable. The inclusion of P_A is not particularly successful, especially when it is treated as endogenous. Finally, we have re-estimated the model replacing P, the number of policemen, by the number of policemen per capita (PPC). The arguments for doing this do not seem strong, but such an approach has been adopted by previous investigators. The results are shown in column 4. Whilst the coefficient of PPC is significant in Table 5.7 its inclusion generally adversely affects the significance of the other coefficients of the equation.

Whilst this does not exhaust the possible ways in which P might be incorporated into equation 1, the results, so far, are not encouraging. Given the fairly sound arguments against its inclusion in the first place, we feel justified in not pursuing this investigation any further.

Table 5.7 Crime Equation

1975 CL (conviction rate)

Explanatory Variable	1	2	3	4
log CL	− 0.93** (1.28)	− 0.77* (1.09)	− 4.60 (0.38)	− 1.47*** (1.68)
log I	− 0.31** (1.40)	− 0.36** (1.57)	0.93 (0.23)	− 0.20 (0.69)
log S	− 0.47** (1.50)	− 0.46** (1.50)	− 0.49 (0.26)	0.10 (0.19)
log R	0.14**** (2.52)	0.17**** (2.77)	− 0.54 (0.26)	0.04 (0.45)
log A	0.37 (0.39)	0.32 (0.34)	2.06 (0.27)	− 0.15 (0.14)
log U	0.25*** (1.71)	0.22** (1.53)	0.95 (0.41)	0.04 (0.17)
log CL_A	0.22 (0.48)	0.28 (0.61)	− 0.99 (0.21)	− 0.70 (0.86)
log W	− 0.33 (0.41)	− 0.61 (0.72)	6.99 (0.31)	0.83 (0.67)
log P	0.01 (0.15)	0.02 (0.22)	− 0.09 (0.14)	
log P_A		− 0.11* (1.06)	2.96 (0.33)	
log PPC				2.36** (1.60)
intercept	12.67 (1.74)	13.82 (1.84)		10.05 (1.27)

Table 5.8 Crime Equation

1975 CL (clear up rate)

Explanatory Variable	1	2	3	4
log CL	0.13 (0.20)	0.24 (0.35)	5.38 (0.31)	- 2.14 (0.84)
log I	- 0.17 (0.68)	- 0.20 (0.80)	- 1.92 (0.33)	0.25E-2 (0.45E-2)
log S	- 0.17 (0.64)	- 0.19 (0.70)	- 1.26 (0.32)	1.61 (0.80)
log R	0.16**** (2.49)	0.18**** (2.48)	1.00 (0.36)	- 0.16 (0.42)
log A	1.36*** (1.68)	1.30** (1.56)	- 1.67 (0.15)	- 0.37 (0.16)
log U	0.17* (1.15)	0.18* (1.18)	0.53 (0.36)	- 0.88 (0.75)
log CL_A	0.62** (1.28)	0.51 (0.96)	- 4.61 (0.27)	- 0.56 (0.33)
log W	- 0.34 (0.35)	- 0.49 (0.48)	- 7.66 (0.31)	2.71 (0.67)
log P	0.07 (0.71)	0.08 (0.74)	0.35 (0.32)	
log P_A		- 0.09 (0.61)	- 4.14 (0.31)	
log PPC				6.58 (0.93)
intercept	3.21 (0.55)	4.52 (0.72)	68.47 (0.32)	- 2.31 (0.17)

Second, we investigated an alternative specification of the police manpower equation. We argued in Chapter 4 that the supply of manpower might be affected by both morale and conditions of service. So far, however, we have not attempted to incorporate any variables to measure such effects. Unfortunately, the choice of proxies for morale and conditions of service is not easy. One could argue that a low detection rate might adversely affect morale and that a high crime rate could cause a deterioration in working conditions (high workloads leading to large amounts of overtime etc). Accordingly we have included both PC and CL in the police manpower equation and the results are given in Table 5.9. The estimates of the other equations of the model are, of course, unaffected by this change and so are not reported again.

Table 5.9 Police manpower equation, 1975

Explanatory Variable	CL (conviction rate)	CL (clear up rate)
log M	1.02**** (20.38)	1.08**** (18.86)
log E	- 0.51 (0.81)	- 0.02 (0.02)
log U	0.14** (1.50)	0.34**** (3.94)
log PC	0.40**** (2.34)	0.11 (0.68)
log CL	0.91**** (3.23)	0.86**** (2.88)
intercept	- 1.04 (0.42)	- 1.69 (0.63)

Whilst the additional variables are both significant, the sign of the coefficient of log PC is different from that predicted. This may indicate that the manpower equation is picking up some elements of the demand for policing i.e. areas with higher crime rates demand more policemen. This possibility is not investigated further as the manpower equation is not of central interest to the later discussion. Also, given the nature of 2SLS estimation, any change in the specification of this equation, within limits, would not have any effect upon the estimates of the other equations of the model.

Third, the possibility that the severity of punishment, in particular the imprisonment rate, is endogenous rather than exogenous has also been investigated. The modelling of the imprisonment rate represents something of a journey into the unknown. However, we hypothesised that it is directly related to the crime rate and inversely related to the detection rate, ceteris paribus. The argument behind this is that courts in areas with high crime rates and/or low detection rates respond by imposing harsher sentences. Finally, we hypothesised that wealthy areas may be less tolerant of crime than poorer ones and so might tend to use imprisonment more frequently. Accordingly, we include log R as an explanatory variable in the equation for log I.

The results, reported in Tables 5.10 and 5.11, are not altogether successful. In particular the coefficient attaching to log PC in the equation for log I has the wrong sign. Also, making log I endogenous has a bad effect upon the coefficient estimates of the crime equation. The omens for treating log I as an endogenous variable, therefore, look poor. Rather than press on with trying to improve the modelling of log I we decided to treat it as an exogenous variable. We can perhaps draw some comfort from the observation that Carr-Hill and Stern's attempts to make the severity of punishment endogenous met with a similar lack of success.

Table 5.10 1975 CL (conviction rate)

log I endogenous

Dependent Variable	Explanatory Variable									Test Statistic
	log CL	log I	log S	log R	log A	log U	log CL_A	log W	intercept	
log PC	- 3.86 (0.67)	- 3.34 (0.60)	- 0.79 (0.66)	0.30 (0.91)	- 3.86 (0.47)	0.29 (0.60)	- 0.56 (0.26)	- 5.53 (0.57)	57.60 (0.69)	0.01 (1,32)
	log P	log T	log PC						intercept	
log CL	0.20*** (2.32)	- 0.26**** (3.08)	- 0.48**** (3.19)						7.45 (6.47)	1.95 (6,32)
	log M	log E	log U						intercept	
log P	1.01**** (26.43)	- 0.19 (0.46)	0.35**** (5.26)						3.42 (2.10)	- -
	log R	log CL	log PC						intercept	
log I	0.06** (1.39)	- 0.50** (1.57)	- 0.33*** (1.74)						5.57 (2.95)	2.75† (6,32)

variance/covariance matrix of residuals

0.337	0.032	0.008	0.007
	0.015	0.004	0.005
		0.013	0.005
			0.028

variance

log PC	0.076
log CL	0.026
log P	0.292
log I	0.032

correlation matrix of residuals

1.00	0.45†	0.11	0.71†
	1.00	0.27	0.24
		1.00	0.24
			1.00

Table 5.11

1975 CL (clear up rate)

log I endogenous

Dependent Variable	Explanatory Variable									Test Statistic
	log CL	log I	log S	log R	log A	log U	log CL_A	log W	inter-cept	
log PC	2.18 (0.57)	2.78 (0.60)	- 0.46 (0.57)	0.67E-2 (0.02)	3.82 (0.83)	0.61 (0.79)	- 0.12 (0.07)	5.19 (0.56)	- 29.05 (0.53)	0.18 (1,32)
	log P	log T	log PC						inter-cept	
log CL	0.13*** (1.79)	- 0.25**** (3.52)	- 0.31**** (2.42)						7.14 (7.45)	2.57† (6,32)
	log M	log E	log U						inter-cept	
log P	1.01**** (26.43)	- 0.19 (0.46)	0.35**** (5.26)						3.42 (2.10)	- -
	log R	log CL	log PC						inter-cept	
log I	0.05 (1.00)	- 0.47* (1.24)	- 0.25* (1.27)						5.16 (2.58)	2.91† (6,32)

variance/covariance matrix of residuals

0.236	- 0.004	- 0.003	- 0.051
	0.011	0.005	0.007
		0.013	0.004
			0.029

variance

log PC	0.076
log CL	0.016
log P	0.292
log I	0.032

correlation matrix of residuals

1.00	- 0.09	- 0.05	- 0.62†
	1.00	0.38†	0.36†
		1.00	0.23
			1.00

So far, the severity of punishment has been measured by the conditional probability of being imprisoned and the average length of prison sentence. However, most property crimes are offences of theft and handling of stolen goods. The most common form of punishment for such offences is a fine. Accordingly, we have incorporated the average fine (F) into the crime equations instead of the rate of imprisonment (I) and the length of imprisonment (S). It would have been preferable to have been able to construct an index of the severity of punishment based upon F, I and S and possibly other measures of punishment. However, it is not entirely clear how such an index should be constructed. The results, given in Tables 5.12 and 5.13, are not dissimilar from those given in Tables 5.1 and 5.2 with which they are comparable. If anything they may be slightly superior, in that there is a marginal improvement in the reported t-statistics.

Table 5.12 — 1975 CL (conviction rate)

Dependent Variable	Explanatory Variable								Test Statistic
	log CL	log F	log R	log A	log U	log CL_A	log W	intercept	
log PC	- 0.71** (1.28)	- 0.32*** (2.08)	0.15**** (3.42)	0.51 (0.63)	0.29*** (2.18)	0.32 (0.77)	- 0.01 (0.02)	7.88 (1.98)	1.94 (2,32)
	log P	log T	log PC					intercept	
log CL	0.15*** (1.73)	- 0.22**** (2.58)	- 0.41**** (2.79)					6.93 (6.20)	1.84 (6,32)
	log M	log E	log U					intercept	
log P	1.01**** (26.43)	- 0.19 (0.46)	0.35**** (5.26)					3.42 (2.10)	- -

variance/covariance matrix of residuals

0.026	0.008	0.008
	0.015	0.004
		0.013

variance

log PC	0.076
log CL	0.026
log P	0.292

correlation matrix of residuals

1.00	0.41†	0.46†
	1.00	0.30†
		1.00

Table 5.13 1975 CL (clear up rate)

Dependent Variable	Explanatory Variable								Test Statistic
	log CL	log F	log R	log A	log U	log CL_A	log W	intercept	
log PC	- 0.02 (0.04)	- 0.20* (1.27)	0.18**** (3.99)	1.20*** (1.70)	0.22*** (1.66)	0.66** (1.52)	- 0.35 (0.47)	3.68* (1.04)	1.94 (2,32)
	log P	log T	log PC					intercept	
log CL	0.11** (1.52)	- 0.24**** (3.33)	- 0.27*** (2.25)					6.92 (7.49)	1.35 (6,32)
	log M	log E	log U					intercept	
log P	1.01**** (26.43)	- 0.19 (0.46)	0.35**** (5.26)					3.42 (2.10)	- -

variance/covariance matrix of residuals

0.032	0.006	0.005
	0.011	0.005
		0.013

variance

log PC	0.076
log CL	0.016
log P	0.292

correlation matrix of residuals

1.00	0.34†	0.24
	1.00	0.40†
		1.00

We do not develop the use of average fines at this point, but they are included in the analysis of specific types of crime in the following section.

The final two tables of this section (Tables 5.14 and 5.15) report an alternative functional specification of the model, in which the socio-economic and demographic variables have not been logarithmically transformed. The model, in fact, only requires that CL_i, CL_{iA} and PC_i be transformed logarithmically (in order to use identities (5)). However, in the main estimates all variables were transformed. The alternative functional form is not particularly successful. Some coefficients have the wrong sign and the significance levels are generally low. We cannot see any overwhelming reason for rejecting the logarithmic specification of the model.

Table 5.14 1975 CL (conviction rate)

Dependent Variable	Explanatory Variable									Test Statistic
	log CL	log I	log S	R	A	U	log CL_A	W	inter-cept	
log PC	- 1.99*** (2.04)	- 0.28 (0.85)	- 0.87*** (2.01)	0.56E-4 (0.87)	- 0.09 (0.51)	- 0.04* (1.24)	- 0.10 (0.16)	- 0.02 (0.79)	19.92 (2.62)	2.20 (2,31)
	P	T	log PC						inter-cept	
log CL	0.88E-4*** (2.20)	- 0.15E-3**** (2.77)	- 0.48**** (3.11)						7.04 (5.76)	1.70 (7,31)
	M	E	U						inter-cept	
P	27.87**** (25.79)	- 14.26 (0.88)	105.44**** (3.81)						204.45 (0.21)	- -

variance/covariance matrix of residuals

0.058	0.023	- 14.54
	0.016	3.81
		14.25E5

correlation matrix of residuals

1.00	0.74†	- 0.05
	1.00	- 0.03
		1.00

variance

log PC	0.076
log CL	0.026
log P	15.00E5

Table 5.15

1975 CL (clear up rate)

Dependent Variable	Explanatory Variable									Test Statistic
	log CL	log I	log S	R	A	U	log CL_A	W	intercept	
log PC	0.11 (0.15)	0.15 (0.55)	- 0.27 (0.94)	0.12E-3*** (1.91)	0.18** (1.47)	0.03 (0.90)	0.44 (0.85)	0.03** (1.47)	4.52 (1.14)	7.27† (2,31)
	P	T	log PC						intercept	
log CL	0.61E-4*** (1.93)	- 0.16E-3**** (3.80)	- 0.28*** (2.27)						6.18 (6.37)	1.05 (2,31)
	M	E	U						intercept	
P	27.87**** (25.79)	- 14.28 (0.88)	105.44**** (3.81)						204.45 (0.21)	- -

variance/covariance matrix of residuals

0.044	0.006	- 45.03
	0.010	3.97
		14.25E5

correlation matrix of residuals

1.00	0.30†	- 0.18
	1.00	- 0.03
		1.00

variance

log PC	0.076
log CL	0.016
log P	15.00E5

Finally, in this subsection, we briefly report the results of some tests of other hypotheses without actually writing them down. First, we experimented with an alternative indicator of returns to legitimate activity. We used E (average male earnings) rather than W (earnings of the lowest paid ten per cent of males). The experiment was not successful. The coefficient of log E had the wrong sign, being positive, and was statistically insignificant. This may possibly be explained by collinearity between log E and log R ($r = 0.68$).

The use of CL_{iA} to pick up spill-over effects between areas is a relatively crude device. Whilst this variable often proved to be significant, it measures only one aspect of the displacement thesis i.e. the "stick" of likely detection. It altogether ignores the "carrot" of differences in illegal gains between areas. In order to make the test somewhat more sophisticated we included a new variable R_A, the average rateable value per hectare in adjacent areas. However, this variable proved to be statistically insignificant. We also constructed an index of the relative attractiveness of an area (to criminals) compared with surrounding areas. This index was based upon one used by Furlong and Mehay (1981).[9] However, this variable also proved to be insignificant. No doubt alternative indicators could be constructed, but we did not pursue this development any further.

---

9. The index is measured by A_j

$$= (1 - CL_j)\, R_j - \frac{1}{N_j} \sum_{k=1}^{N_j} (1 - CL_k)\, R_k$$

where CL_j is the detection rate in area j, R_j is rateable value per hectare in area j, CL_k is the detection rate in area k (contiguous with area j), R_k is rateable value per hectare in area k and N_j is the number of police force areas contiguous with area j.

Finally, we included in equation 3 a measure of average police earnings. This was derived by dividing the total police salary bill (plus rent allowances) by the average daily strength of the police service. This average police wage was used to construct an index of relative police pay by expressing it as a proportion of average male earnings (E). The new variable was then substituted into equation 3 in place of E. However, it proved to be rather less successful than even E. It is, of course, based upon a relatively crude measure of average earnings in police employment, but no more accurate measures were available.

To conclude, on the whole experiments with several alternative hypotheses proved remarkably unsuccessful. We feel reasonably confident, therefore, that the model set out in Chapter 4.3 is at least as good as any other in explaining variations in recorded property crime rates, detection rates and police employment across police force areas.

We turn now to examine the results generated by that model when the crime variable is disaggregated into the three main categories of property crime.

3. Separate Offence Groups

(i) The main estimates

The two stage least squares estimates of the crime supply equations are given in Tables 5.16 to 5.21 inclusive. Estimates of the police production functions are given in Tables 5.22 to 5.27 inclusive. At the foot of each table we present both the variance/covariance matrix and the correlation matrix of the residuals from the equations reported in that table. The correlation matrix of the residuals from the crime equations and the production functions is given in Table 5.28.

Even a cursory examination of Tables 5.16 to 5.21 is sufficient to reveal that there exists some variation across crime groups in the sizes and significance levels of the coefficients. This may be sufficient to present problems in explaining the determination of an overall crime aggregate. The production function estimates show rather less variation in the estimated coefficients, although it must be acknowledged that the "test" here is somewhat informal. Unfortunately, a formal test of the equality of the regression coefficients is not possible, for the same reason that a test for structural change proved impossible i.e. 2SLS does not proceed by minimising the sum of squared residuals from the structural equations. In such circumstances, the Chow test is unreliable.

All of the crime equations pass the test of the correctness of the over-identifying restrictions quite comfortably. However, some of the production functions fail the test at the 5% level and have been re-specified and re-estimated so as to pass this test. The production functions which failed the test were those for (i) burglary conviction rates (1975 and pooled 1975/6), (ii) theft conviction rates (pooled 1975/6) and (iii) burglary, robbery and theft clear up rates (all pooled 1975/6). In addition the production functions for burglary conviction rates (1976) and robbery clear up rates (1976) just failed the test at the 10% level and were also re-estimated. The re-estimated production functions are given in Table 5.29 and the amended correlations with the residuals from the crime equations are given in Table 5.30. All the re-estimated production functions pass the test of the correctness of the over-identifying restrictions quite comfortably at the 5% level and all but two now pass at the 10% level. Also, re-estimation of the production tends to sharpen the parameter estimates i.e. improve their asymptotic t-ratios.

The decision about which of the previously excluded pre-determined variables to include in the production function was largely based upon the need to pass the test of the over-identifying restrictions. However, we have also tried to find a satisfactory justification for including a variable. For example, the re-specified conviction rate equations all include a severity of punishment measure, either $\log I_i$ or $\log S_i$. One justification for this being that juries, for example, are less willing to convict defendants if the expected punishment is quite harsh. Certainly, the coefficients of these variables are all negative and highly significant, which may lend support to such a "trade-off" thesis. Likewise, in the re-estimated clear up rate equations it was found that the clear up rate in adjacent rates always appeared with a positive and significant coefficient. How might one explain this? One argument is that police forces are under considerable pressure (political?) to be seen to be solving (i.e. clearing up) as much crime as neighbouring police forces. In such circumstances forces surrounded by areas with high clear up rates will attempt to increase their own clear up rate. If this interpretation is correct, and if the process by which the clear up rate has been increased is dubious, then it would cast further doubt on the usefulness of the clear up rate as a measure of the detection rate.

The correlations between the residuals from the crime equations are all positive and generally statistically significant, although none is larger than 0.7 (a level judged by Carr-Hill and Stern (1979) to be high) and only about a half of them exceed 0.5. It seems that areas with higher(lower) than predicted crime rates of type i also experience higher(lower) than predicted crime rates of types j and k. Similar conclusions can be drawn from the correlations between the residuals from the production functions. Areas with higher(lower) than predicted detection rates for crimes of type i generally have higher(lower) than predicted detection rates for other crimes. An unexpectedly high detection rate for a particular crime category does not seem to be bought at the expense of a lower detection rate for one of the other two crimes.

Correlations between the residuals from the crime equations and the residuals from the production functions tend, on the whole, to be lower. Slightly less than a half of the 54 reported correlation coefficients are statistically significant and only ten of these exceed 0.5. Also, the "own" correlations tend to be strongest i.e. the residuals from the crime equation of type i are most strongly correlated with the residuals from the production function of type i.

The results, particularly for the crime equations, are a little disappointing. The number of statistically significant parameter estimates in Tables 5.16 to 5.19 is fairly low. For example, there is only one instance (1975, using conviction rates) when the number of statistically significant coefficients, excluding constants, is more than a half of those estimated. This may be due to the limited number of observations and/or lack of variability across the sample in some of the data series. Certainly, pooling the two years of data seems to help in this respect (see Tables 5.20 and 5.21), producing a quite dramatic increase in the number and proportion of significant coefficients. Another possible explanation of the relatively poor performance of the crime equations is that the measures of the severity of punishment (the imprisonment variables) may be inappropriate, particularly for the crime of theft and handling of stolen goods. Nearly 60% of individuals convicted of such offences receive a sentence of a fine, whereas less than 10% are sentenced to immediate imprisonment. Therefore, we decided to re-estimate the crime supply equations and police production functions using the average fine (instead of the imprisonment rate and the length of imprisonment) as a measure of the severity of punishment. In fact, we re-estimated only the equations for burglary and theft. A fine is a very rarely used sentence for the crime of robbery (less than 7% of convicted robbers received such a sentence in 1975). Indeed, in some areas in 1975 and 1976 the sentence was not used at all and in some others it was so rarely used that it would possibly be misleading to incorporate the average fine as a deterrence variable.

The re-estimated crime supply equations for burglary and theft are given in Tables 5.31 to 5.36 inclusive and the re-estimated police production functions in Tables 5.37 to 5.42. The introduction of the average fine in place of the imprisonment variables has a noticeable effect upon the proportion of significant coefficients in the crime supply equations.[10] The explanatory power of the theft equation is very considerably improved by the change.

The correlations between the residuals of the re-estimated equations can be found at the foot of Tables 5.31 to 5.42 inclusive and also in Table 5.44. We do not propose to say anything further about these as their pattern is very little changed by the alteration in the choice of variable to represent the severity of punishment.

Further discussion and interpretation of the results can be found in Chapter 6. However, before completing the presentation of the model estimates

---

10. In Tables 5.16 to 5.21 inclusive the proportion of significant coefficients in the burglary and theft equations is less than 47%. In Tables 5.31 to 5.36 that proportion increases to nearly 61%.

we shall briefly report the results of a preliminary investigation into the extent to which crimes of different sorts can be regarded as competing or complementary activities.

(ii) Substitution amongst crimes

So far this is a relatively little researched topic in the economics of crime, except for the contributions of Holtman and Yap (1978) and Heineke (1978c) which were discussed in Chapter 3.

Briefly, different forms of criminal activity might be regarded as substitutes or complements for one another if a change in the costs and/or benefits associated with one type of crime led to a change in the level of criminal activity of another kind. For example, suppose there is a rise in the costs (or fall in the benefits) associated with burglary, relative to those associated with theft. If this leads burglars to switch from burglary to theft then the two forms of activity could be regarded as substitutes. If it lead to a fall in both kinds of activity then they might be regarded as complementary activities.

It seems at least intuitively reasonable that substitution amongst the crimes of burglary, robbery and theft would be more marked than between one of these crimes and some other crime such as rape or murder. We have, therefore, attempted to test for the existence of such effects by including in the crime supply equations variables measuring the "costs" associated with the other forms of property crime and not just the "own" costs and benefits. Of course, the proxy variable for illegal gains is the same for each type of crime and so we have not been able to include separate benefit measures.

We, therefore, included in the supply function for crimes of type i either the detection rates or the imprisonment rates for crimes of type j and k. There is one immediately obvious problem in using detection rates. This is that they are fairly strongly correlated with one another (see Table A2 in the Appendix to this chapter), so that it may not be possible to isolate their separate effects.[11] This may partly explain the somewhat limited success of the inclusion of the other detection rates.

In Tables 5.45 to 5.48 inclusive we present the model estimates using cross-crime detection rates and in Tables 5.49 to 5.52 we present them with cross-crime imprisonment rates. These Tables should be compared with Tables 5.16 to 5.19. For convenience we reproduce only a shortened version of the equation estimates, which omits the variance/covariance and correlation matrices of the residuals and the test statistic for the correctness of the over-identifying restrictions.

On the whole the results are not very encouraging. The cross-crime deterrence variables are rarely significant. Using detection rates only six of the 24 coefficients are significant at the 15% level, whilst only one of the imprisonment rates is significant at the same level. Further, their effects are inconsistent over time e.g. the coefficient of the conviction rate for theft is negative and significant in the robbery equation in 1975, but positive and insignificant in 1976. In fact no elasticity is significant with the same sign in both years. Finally, inclusion of the cross-crime

---

11. The correlations between the detection rates normally exceed 0.5 and are frequently in excess of 0.7. The only ones below 0.5 are those between conviction rates for (i) burglary and robbery in 1976 and (ii) robbery and theft in both years. On the whole correlations between clear up rates are higher, but those between imprisonment rates are lower.

deterrence variables does not lead to any general improvement in the significance levels of other coefficients in the crime equations. Indeed, if anything, it leads to a marginal deterioration in their t-statistics.

Whilst this set of tests can not be regarded as exhaustive, the results produced do not lend much support to the idea of substitution effects amongst crimes. We have not felt it worthwhile to pursue this matter any further.

4. Some Brief Conclusions

In this chapter we have presented a large volume of statistical results arising from the estimation of the model of Chapter 4. We have not, so far, attempted to interpret these results in any depth. This is done in the next Chapter. Our remarks here are confined solely to a few points concerning the overall performance of the model.

The specification of the model seems reasonably satisfactory. The model's equations, for example, generally pass the test of the correctness of the over-identifying restrictions. The number of statistically significant coefficients is also fairly high, given the nature of the subject matter and the data available. The limited number of observations seems to present a problem here and it was hoped at one stage to increase their number by pooling data for more than two years. However, given the lack of a satisfactory test for structural change in 2SLS estimation and the extremely limited capacity of the ESP package as implemented on the University of Leicester computer, this was not pursued.[12] Attempts to respecify the model e.g. by using

12. Pooling two years' of data produces 82 observations on 27 variables, in the disaggregated case. The data set could only be handled by the ESP package if all the generations were performed on a separate programme and stored on a new data file.

alternative functional forms, using different measures of spillover effects, making the severity of punishment an endogenous variable etc, were not successful. On the whole, therefore, the model's performance is reasonably satisfactory and seems to be at least as good as that of Carr-Hill and Stern (1979).[13]

However, it is now time to attempt to draw some conclusions about the signs and sizes of particular coefficients in the model and how they relate to an economic explanation of property crime.

---

13. The most direct comparison is with Carr-Hill and Stern's estimates for the year 1971 given on pp. 206-7 (2SLS) and pp. 215 (FIML) of their book. We have not, unlike them, engaged in the somewhat dubious statistical practice of dropping statistically insignificant variables in order to "tighten" the estimates. We, therefore, do not attach much weight to their "restricted" estimates on pp. 174-180.

Table 5.16 Crime Equations, 1975

CL (conviction rate)

	BURGLARY (B)	ROBBERY (RB)	THEFT (TH)
log CL_i	- 1.41** (1.37)	- 0.31 (0.73)	- 0.78** (1.35)
log I_i	- 0.77*** (1.75)	- 0.41*** (1.74)	- 0.19* (1.05)
log S_i	- 0.40*** (1.73)	- 0.29 (0.87)	- 0.49*** (1.67)
log R	0.13** (1.49)	0.36**** (4.02)	0.16**** (3.75)
log A	- 0.55 (0.39)	0.78 (0.61)	0.62 (0.73)
log U	0.18* (1.09)	0.33** (1.55)	0.20** (1.56)
log W	- 0.88 (0.71)	0.22 (0.18)	- 0.45 (0.62)
log CL_{iA}	0.48* (1.22)	0.75** (1.43)	0.05 (0.12)
intercept	16.92 (1.56)	- 0.83 (0.13)	12.19 (2.34)
Test Statistic	2.19 (2,31)	2.19 (2,31)	1.48 (2,31)

variance/covariance matrix of residuals

0.044	0.022	0.020
	0.086	0.024
		0.025

variance

log B	0.137
log RB	0.364
log TH	0.062

correlation matrix of residuals

1.00	0.36†	0.62†
	1.00	0.53†
		1.00

Table 5.17 Crime Equations, 1975

CL (clear up rate)

	BURGLARY (B)	ROBBERY (RB)	THEFT (TH)
log CL_i	- 0.74 (0.94)	- 0.68 (0.85)	0.11 (0.19)
log I_i	- 0.26 (0.98)	- 0.49*** (2.10)	- 0.08 (0.39)
log S_i	- 0.37** (1.46)	- 0.19 (0.46)	- 0.24 (0.89)
log R	0.22**** (4.12)	0.35**** (2.61)	0.17**** (3.42)
log A	0.60 (0.62)	0.49 (0.31)	1.38*** (1.83)
log U	0.18 (0.84)	0.10 (0.37)	0.13 (0.91)
log W	- 0.64 (0.48)	- 0.27 (0.17)	- 0.67 (0.80)
log CL_{iA}	1.22**** (2.39)	1.57**** (2.58)	0.35 (0.72)
intercept	7.39 (0.93)	- 0.23 (0.03)	5.81 (1.26)
Test Statistic	1.98 (2.31)	0.49 (2,31)	1.59 (2,31)

variance/covariance matrix of residuals

0.050	0.047	0.027
	0.119	0.037
		0.033

variance

log B	0.137
log RB	0.364
log TH	0.062

correlation matrix of residuals

1.00	0.62†	0.68†
	1.00	0.59†
		1.00

Table 5.18 Crime Equations, 1976

CL (conviction rate)

	BURGLARY (B)	ROBBERY (RB)	THEFT (TH)
log CL_i	- 1.56* (1.11)	- 0.66** (1.41)	- 0.24 (0.48)
log I_i	- 0.79* (1.09)	0.17 (0.90)	- 0.02 (0.14)
log S_i	- 0.30 (0.98)	- 0.18 (0.62)	0.06 (0.22)
log R	0.09 (0.76)	0.35**** (2.56)	0.14**** (3.19)
log A	- 0.94 (0.52)	1.23 (1.02)	1.05** (1.39)
log U	0.36*** (1.83)	0.15 (0.62)	0.33*** (2.24)
log W	- 0.23 (0.19)	0.07 (0.05)	- 0.15 (0.19)
log CL_{iA}	0.20 (0.36)	0.51*** (1.98)	0.20 (0.68)
intercept	15.96 (1.16)	- 1.49 (0.33)	4.60 (1.27)
Test Statistic	1.02 (2,31)	0.73 (2,31)	0.12 (2,31)

variance/covariance matrix of residuals

0.054	0.003	0.010
	0.055	0.016
		0.025

variance

log B	0.128
log RB	0.336
log TH	0.060

correlation matrix of residuals

1.00	0.05	0.27
	1.00	0.43†
		1.00

Table 5.19 Crime Equations, 1976

CL (clear up rate)

	BURGLARY (B)	ROBBERY (RB)	THEFT (TH)
log CL_i	- 1.44 (0.99)	- 0.11 (0.16)	- 0.28 (0.43)
log I_i	- 0.35 (0.71)	0.09 (0.38)	0.36E-3 (0.25E-2)
log S_i	- 0.22 (0.53)	- 0.48*** (1.68)	0.01 (0.05)
log R	0.20**** (2.85)	0.49**** (3.57)	0.14**** (2.93)
log A	0.26 (0.18)	2.18** (1.36)	1.12** (1.57)
log U	0.33* (1.26)	0.36* (1.12)	0.23* (1.14)
log W	- 1.02 (0.51)	- 1.04 (0.62)	- 0.21 (0.25)
log CL_{iA}	1.20*** (1.80)	0.44 (0.92)	0.49 (0.93)
intercept	11.37 (0.92)	0.09 (0.02)	4.08 (1.06)
Test Statistic	0.36 (2,31)	1.41 (2,31)	0.18 (2,31)

variance/covariance matrix of residuals

0.092	0.012	0.028
	0.094	0.021
		0.028

variance

log B	0.128
log RB	0.336
log TH	0.060

correlation matrix of residuals

1.00	0.13	0.55†
	1.00	0.41†
		1.00

Table 5.20 Crime Equations, Pooled 1975/6

CL (conviction rate)

	BURGLARY (B)	ROBBERY (RB)	THEFT (TH)
log CL_i	− 0.94 (0.87)	− 0.19 (0.55)	− 0.33 (0.86)
log I_i	− 0.52** (1.32)	− 0.24** (1.48)	− 0.06 (0.66)
log S_i	− 0.35*** (2.17)	− 0.26** (1.34)	− 0.14 (0.84)
log R	0.15** (1.43)	0.44**** (5.90)	0.14**** (6.45)
log A	− 0.09 (0.07)	1.77*** (1.90)	0.98*** (1.82)
log U	0.28**** (2.88)	0.31*** (2.08)	0.23**** (2.55)
log W	− 0.17 (0.54)	− 0.86*** (1.69)	− 0.20 (0.96)
log CL_{iA}	0.46** (1.56)	0.62*** (2.27)	0.26* (1.23)
intercept	10.95 (1.41)	− 0.06 (0.02)	6.38 (2.33)
Test Statistic	2.24 (2,72)	0.25 (2,72)	1.63 (2,72)

variance/covariance matrix of residuals

0.034	0.018	0.017
	0.096	0.028
		0.026

variance

log B	0.131
log RB	0.348
log TH	0.060

correlation matrix of residuals

1.00	0.32†	0.58†
	1.00	0.57†
		1.00

Table 5.21 Crime Equations, Pooled 1975/6

CL (clear up rate)

	BURGLARY (B)	ROBBERY (RB)	THEFT (TH)
log CL_i	− 1.31 (0.87)	− 0.31 (0.62)	0.03 (0.06)
log I_i	− 0.25* (1.17)	− 0.26*** (1.72)	− 0.94E−2 (0.09)
log S_i	− 0.39*** (1.72)	− 0.25* (1.16)	− 0.09 (0.49)
log R	0.18**** (2.75)	0.42**** (5.76)	0.15**** (5.38)
log A	0.38 (0.34)	1.67** (1.58)	1.32**** (2.72)
log U	0.20 (0.87)	0.27** (1.30)	0.20*** (1.69)
log W	− 0.35 (0.97)	− 0.52* (1.15)	− 0.23 (0.97)
log CL_{iA}	1.31*** (1.83)	0.73*** (2.12)	0.38* (1.12)
intercept	8.81 (1.34)	− 0.92 (0.22)	3.60 (1.43)
Test Statistic	1.07 (2,72)	0.78 (2,72)	1.68 (2,72)

variance/covariance matrix of residuals

0.077	0.031	0.025
	0.113	0.036
		0.031

variance

log B	0.131
log RB	0.348
log TH	0.060

correlation matrix of residuals

1.00	0.33†	0.52†
	1.00	0.60†
		1.00

Table 5.22 Production Functions, 1975

CL (conviction rate)

	BURGLARY	ROBBERY	THEFT
log P	0.19** (1.61)	0.56**** (3.75)	0.18*** (2.15)
log T	- 0.27*** (2.31)	- 0.48**** (3.29)	- 0.24**** (2.93)
log PC_i	- 0.36**** (2.54)	- 0.68**** (6.22)	- 0.43**** (2.52)
intercept	5.88 (6.34)	4.83 (7.09)	6.95 (5.61)
Test Statistic	2.84† (7,31)	0.44 (7,31)	1.41 (7,31)

variance/covariance matrix of residuals

0.026	0.001	0.013
	0.059	0.001
		0.016

variance

log CL_B	0.041
log CL_R	0.130
log CL_T	0.025

correlation matrix of residuals

1.00	0.03	0.62†
	1.00	0.02
		1.00

Table 5.23 Production Functions, 1975

CL (clear up rate)

	BURGLARY	ROBBERY	THEFT
log P	0.11 (0.92)	0.10 (0.80)	0.11*** (1.81)
log T	- 0.22*** (1.85)	- 0.19** (1.51)	- 0.25**** (4.10)
log PC_i	- 0.16* (1.18)	- 0.28**** (3.00)	- 0.28*** (2.24)
intercept	5.52 (6.05)	5.27 (9.18)	7.01 (7.74)
Test Statistic	1.47 (7,31)	0.70 (7,31)	1.21 (7,31)

variance/covariance matrix of residuals

0.026	0.014	0.011
	0.042	0.009
		0.008

variance

log CL_B	0.031
log CL_R	0.053
log CL_T	0.015

correlation matrix of residuals

1.00	0.42†	0.72†
	1.00	0.47†
		1.00

Table 5.24 Production Functions, 1976

CL (conviction rate)

	BURGLARY	ROBBERY	THEFT
log P	0.48**** (2.62)	0.06 (0.30)	0.41**** (3.79)
log T	- 0.58**** (3.30)	- 0.12 (0.60)	- 0.51**** (4.60)
log PC_i	- 0.39**** (2.54)	- 0.42**** (4.47)	- 0.32*** (2.15)
intercept	6.09 (7.10)	5.37 (9.42)	6.31 (6.22)
Test Statistic	2.08 (7,31)	1.54 (7,31)	0.28 (7,31)

variance/covariance matrix of residuals

0.027	0.008	0.010
	0.046	0.001
		0.015

variance

log CL_B	0.052
log CL_R	0.119
log CL_T	0.028

correlation matrix of residuals

1.00	0.23	0.49†
	1.00	0.04
		1.00

Table 5.25 Production Functions, 1976

CL (clear up rate)

	BURGLARY	ROBBERY	THEFT
log P	0.28** (1.32)	0.20* (1.21)	0.26**** (2.64)
log T	- 0.33** (1.64)	- 0.39*** (2.28)	- 0.35**** (3.45)
log PC_i	- 0.13 (0.77)	- 0.24**** (2.96)	- 0.29*** (2.08)
intercept	4.85 (5.06)	5.81 (11.78)	6.66 (7.10)
Test Statistic	1.60 (7,31)	1.93 (7,31)	1.01 (7,31)

variance/covariance matrix of residuals

0.035	0.017	0.014
	0.035	0.011
		0.013

variance

log CL_B	0.041
log CL_R	0.069
log CL_T	0.019

correlation matrix of residuals

1.00	0.49†	0.66†
	1.00	0.51†
		1.00

Table 5.26 Production Functions, Pooled 1975/6

CL (conviction rate)

	BURGLARY	ROBBERY	THEFT
log P	0.18*** (1.73)	0.38**** (3.45)	0.20**** (3.17)
log T	− 0.27**** (2.84)	− 0.37**** (3.47)	− 0.28**** (4.39)
log PC_i	− 0.28**** (2.49)	− 0.55**** (7.42)	− 0.35**** (2.97)
intercept	5.43 (8.20)	5.09 (11.89)	6.40 (7.73)
Test Statistic	5.62† (7,72)	1.29 (7,72)	2.76† (7,72)

variance/covariance matrix of residuals

0.030	0.002	0.013
	0.052	0.000
		0.016

variance

log CL_B	0.041
log CL_R	0.130
log CL_T	0.026

correlation matrix of residuals

1.00	0.06	0.59†
	1.00	0.00
		1.00

Table 5.27 Production Functions, Pooled 1975/6

CL (clear up rate)

	BURGLARY	ROBBERY	THEFT
log P	0.04 (0.34)	0.04 (0.37)	0.13**** (2.45)
log T	- 0.13** (1.30)	- 0.18*** (1.93)	- 0.24**** (4.59)
log PC_i	- 0.02 (0.16)	- 0.22**** (3.34)	- 0.25**** (2.62)
intercept	4.45 (6.57)	5.53 (14.65)	6.59 (9.71)
Test Statistic	2.41† (7,72)	3.55† (7,72)	2.45† (7,72)

variance/covariance matrix of residuals

0.033	0.015	0.013
	0.040	0.011
		0.011

variance

log CL_B	0.035
log CL_R	0.060
log CL_T	0.017

correlation matrix of residuals

1.00	0.42†	0.67†
	1.00	0.51†
		1.00

Table 5.28

Correlations between residuals from crime equations and production functions

(1) 1975, CL (conviction rate)

Crime Equations	Production Functions: B	RB	TH
B	0.57†	0.11	0.46†
RB	- 0.09	0.48†	- 0.02
TH	0.21	0.07	0.48†

(2) 1975, CL (clear up rate)

Crime Equations	Production Functions: B	RB	TH
B	0.44†	0.49†	0.65†
RB	0.19	0.73†	0.37†
TH	- 0.05	0.20	0.31†

(3) 1976, CL (conviction rate)

Crime Equations	Production Functions: B	RB	TH
B	0.74†	0.39†	0.29
RB	- 0.04	0.34†	0.11
TH	- 0.09	0.02	- 0.01

Table 5.28 (continued)

(4) 1976, CL (clear up rate)

	Production Functions			
	B	RB	TH	
B	0.70†	0.29	0.66†	
RB	- 0.04	0.14	- 0.03	Crime Equations
TH	0.03	0.01	0.36†	

(5) Pooled 1975/6, CL (conviction rate)

	Production Functions			
	B	RB	TH	
B	0.38†	0.19	0.23†	
RB	- 0.25†	0.24†	- 0.04	Crime Equations
TH	- 0.13	0.00	0.12	

(6) Pooled 1975/6, CL (clear up rate)

	Production Functions			
	B	RB	TH	
B	0.60†	0.36†	0.65†	
RB	- 0.09	0.32†	0.09	Crime Equations
TH	- 0.13	0.05	0.22†	

Table 5.29 Modified estimates of production functions

	BURGLARY 1975 (conviction rate)	BURGLARY 1976 (conviction rate)	BURGLARY Pooled, 1975/6 (conviction rate)	THEFT Pooled, 1975/6 (conviction rate)
log P	0.20*** (1.88)	0.34*** (2.00)	0.21**** (2.38)	0.07 (0.98)
log T	- 0.19*** (1.80)	- 0.33*** (1.87)	- 0.19*** (2.29)	- 0.17**** (2.39)
log PC_i	- 0.53**** (3.90)	- 0.51**** (3.63)	- 0.51**** (4.90)	- 0.63**** (3.33)
log I_i	- 0.41**** (3.33)	- 0.44**** (3.28)	- 0.45**** (5.25)	
log R				0.07*** (2.05)
log U				0.19**** (2.36)
log S_i				- 0.24*** (1.99)
intercept	7.32 (7.87)	7.21 (8.65)	7.20 (11.08)	9.32 (6.25)
Test Statistic	1.31 (6,31)	0.84 (6,31)	2.13 (6,72)	1.15 (4,72)

correlations with residuals from other production functions

B	-	-	-	0.50
RB	0.05	0.35	0.15	0.05
TH	0.69	0.44	0.50	-

Table 5.29 (continued)

	ROBBERY 1976 (clear up rate)	BURGLARY Pooled, 1975/6 (clear up rate)	ROBBERY Pooled, 1975/6 (clear up rate)	THEFT Pooled, 1975/6 (clear up rate)
log P	0.29** (1.30)	0.11* (1.14)	0.10 (0.95)	0.12*** (2.23)
log T	- 0.46*** (1.93)	- 0.13** (1.40)	- 0.20*** (1.92)	- 0.21**** (3.75)
log PC_i	- 0.25**** (3.24)	- 0.22*** (1.86)	- 0.27**** (4.19)	- 0.29**** (3.07)
log CL_{iA}	0.42*** (2.19)	0.63**** (3.77)	0.50**** (3.23)	0.46**** (3.24)
log U	- 0.31*** (1.92)	- 0.06 (0.75)	- 0.21*** (2.22)	- 0.08** (1.58)
intercept	4.54 (4.56)	3.06 (4.21)	3.64 (4.80)	5.07 (6.26)
Test Statistic	1.14 (5,31)	0.64 (5,72)	2.19 (5,72)	1.06 (5,72)

correlations with residuals from other production functions

B	0.37	-	0.35	0.70
RB	-	0.35	-	0.42
TH	0.42	0.70	0.42	-

Table 5.30

Correlation between residuals of crime equations and modified production functions

(1) 1975, CL (conviction rate)

Production Functions (columns); Crime Equations (rows)

	B	RB	TH
B	0.79†	as Table 5.28	
RB	0.03		
TH	0.41†		

(2) 1976, CL (conviction rate)

Production Functions (columns); Crime Equations (rows)

	B	RB	TH
B	0.90†	as Table 5.28	
RB	0.00		
TH	0.11		

(3) Pooled 1975/6, CL (conviction rate)

Production Functions (columns); Crime Equations (rows)

	B	RB	TH
B	0.67†	0.19	0.49†
RB	- 0.12	0.24†	0.23
TH	0.13	0.00	0.53†

Table 5.30 (continued)

(4) 1976, CL (clear up rate)

Production Functions

	B	RB	TH
B		0.27	
RB		0.18	
TH		0.05	

Crime Equations

(others as Table 5.28)

(5) Pooled 1975/6, CL (clear up rate)

Production Functions

	B	RB	TH
B	0.80†	0.36†	0.66†
RB	0.02	0.43†	0.11
TH	0.09	0.10	0.29†

Crime Equations

Table 5.31 Crime Equations, 1975

CL (conviction rate)

	BURGLARY (B)	THEFT (TH)
log CL_i	- 0.87* (1.24)	- 0.58* (1.09)
log F_i	- 0.45*** (2.32)	- 0.26*** (1.97)
log R	0.17**** (2.43)	0.14**** (3.70)
log A	- 0.10 (0.09)	0.73 (0.91)
log U	0.36**** (2.35)	0.23*** (1.84)
log W	0.39 (0.46)	- C.19 (0.29)
log CL_{iA}	0.76*** (2.31)	0.27 (0.79)
intercept	5.72 (1.16)	7.59 (2.26)
Test Statistic	1.94 (2,32)	0.26 (2,32)

variance/covariance matrix of residuals

0.041	0.023	0.019
	0.086	0.022
		0.024

variance

log B	0.137
log RB	0.364
log TH	0.062

correlation matrix of residuals

1.00	0.38†	0.61†
	1.00	0.49†
		1.00

Table 5.32 Crime Equations, 1975

CL (clear up rate)

	BURGLARY (B)	THEFT (TH)
log CL_i	- 0.77 (1.03)	0.16 (0.30)
log F_i	- 0.27* (1.24)	- 0.18** (1.29)
log R	0.23**** (4.15)	0.17**** (3.56)
log A	0.48 (0.49)	1.39*** (1.98)
log U	0.29*** (1.67)	0.18** (1.40)
log W	- 0.36 (0.34)	- 0.57 (0.76)
log CL_{iA}	1.31**** (2.41)	0.34 (0.72)
intercept	4.19 (0.73)	4.40 (1.37)
Test Statistic	1.48 (2,32)	1.51 (2,32)

variance/covariance matrix of residuals

0.054	0.041	0.026
	0.119	0.036
		0.032

variance

log B	0.137
log RB	0.364
log TH	0.062

correlation matrix of residuals

1.00	0.52†	0.63†
	1.00	0.57†
		1.00

Table 5.33 Crime Equations, 1976

CL (conviction rate)

	BURGLARY (B)	THEFT (TH)
log CL_i	- 0.59* (1.19)	- 0.32 (0.66)
log F_i	- 0.44*** (1.76)	- 0.35** (1.32)
log R	0.17**** (2.77)	0.16**** (4.52)
log A	- 0.02 (0.02)	0.99** (1.45)
log U	0.41**** (2.92)	0.27*** (2.19)
log W	0.26 (0.29)	- 0.49 (0.71)
log CL_{iA}	0.65**** (2.72)	0.07 (0.25)
intercept	5.34 (1.35)	8.12 (1.83)
Test Statistic	0.79 (2,32)	1.44 (2,32)

variance/covariance matrix of residuals

0.033	0.019	0.013
	0.055	0.016
		0.022

variance

log B	0.128
log RB	0.336
log TH	0.060

correlation matrix of residuals

1.00	0.45†	0.49†
	1.00	0.46†
		1.00

Table 5.34 Crime Equations, 1976

CL (clear up rate)

	BURGLARY (B)	THEFT (TH)
$\log CL_i$	− 0.96* (1.07)	− 0.33 (0.53)
$\log F_i$	− 0.28 (0.84)	− 0.28 (0.97)
log R	0.20**** (3.35)	0.16**** (3.77)
log A	0.38 (0.36)	1.11*** (1.66)
log U	0.43*** (2.23)	0.19* (1.21)
log W	− 0.47 (0.39)	− 0.48 (0.64)
$\log CL_{iA}$	1.09*** (1.90)	0.32 (0.75)
intercept	6.26 (1.04)	7.01 (1.47)
Test Statistic	0.36 (2,32)	0.18 (2,32)

variance/covariance matrix of residuals

0.065	0.020	0.026
	0.094	0.021
		0.027

variance

log B	0.128
log RB	0.336
log TH	0.060

correlation matrix of residuals

1.00	0.26†	0.63†
	1.00	0.42†
		1.00

Table 5.35 Crime Equations, Pooled 1975/6

CL (conviction rate)

	BURGLARY (B)	THEFT (TH)
log CL_i	− 0.50* (1.14)	− 0.39 (0.99)
log F_i	− 0.44**** (3.31)	− 0.27*** (2.27)
log R	0.20**** (4.80)	0.14**** (6.84)
log A	0.26 (0.37)	0.92*** (1.75)
log U	0.37**** (3.89)	0.25**** (2.93)
log W	− 0.05 (0.20)	− 0.12 (0.57)
log CL_{iA}	0.72**** (3.95)	0.16 (0.82)
intercept	5.40 (2.08)	6.63 (2.84)
Test Statistic	1.36 (2,73)	1.59 (2,73)

variance/covariance matrix of residuals

0.036	0.026	0.017
	0.096	0.025
		0.023

variance

log B	0.131
log RB	0.348
log TH	0.060

correlation matrix of residuals

1.00	0.44†	0.60†
	1.00	0.53†
		1.00

Table 5.36 Crime Equations, Pooled 1975/6

CL (clear up rate)

	BURGLARY (B)	THEFT (TH)
$\log CL_i$	− 0.98* (1.04)	− 0.02 (0.05)
$\log F_i$	− 0.29*** (1.77)	− 0.18** (1.50)
$\log R$	0.20**** (4.43)	0.15**** (5.45)
$\log A$	0.41 (0.48)	1.29**** (2.76)
$\log U$	0.34**** (2.33)	0.20*** (2.16)
$\log W$	− 0.24 (0.73)	− 0.17 (0.73)
$\log CL_{iA}$	1.20*** (2.23)	0.28 (0.87)
intercept	5.16 (1.47)	4.12 (1.99)
Test Statistic	1.02 (2,73)	1.30 (2,73)

variance/covariance matrix of residuals

0.063	0.030	0.025
	0.113	0.034
		0.030

variance

log B	0.131
log RB	0.348
log TH	0.060

correlation matrix of residuals

1.00	0.36†	0.58†
	1.00	0.58†
		1.00

Table 5.37 Production Functions, 1975

CL (conviction rate)

	BURGLARY	THEFT
log P	0.22*** (1.89)	0.14*** (1.69)
log T	− 0.30**** (2.54)	− 0.21**** (2.55)
log PC_i	− 0.42**** (2.96)	− 0.36*** (2.15)
intercept	6.23 (6.71)	6.47 (5.33)
Test Statistic	1.38 (6,32)	1.11 (6,32)

variance/covariance matrix of residuals

0.026	0.002	0.013
	0.059	0.000
		0.016

variance

log CL_B	0.041
log CL_R	0.130
log CL_T	0.025

correlation matrix of residuals

1.00	0.05	0.65†
	1.00	0.01
		1.00

Table 5.38 Production Functions, 1975

CL (clear up rate)

	BURGLARY	THEFT
log P	0.12 (0.98)	0.10** (1.62)
log T	- 0.22*** (1.89)	- 0.24**** (3.98)
log PC_i	- 0.19** (1.33)	- 0.25*** (2.13)
intercept	5.66 (6.16)	6.85 (7.84)
Test Statistic	1.46 (6,32)	1.53 (6,32)

variance/covariance matrix of residuals

0.026	0.014	0.011
	0.042	0.009
		0.008

variance

log CL_B	0.031
log CL_R	0.053
log CL_T	0.015

correlation matrix of residuals

1.00	0.42†	0.74†
	1.00	0.47†
		1.00

Table 5.39 Production Functions, 1976

CL (conviction rate)

	BURGLARY	THEFT
log P	0.44**** (2.35)	0.38**** (3.34)
log T	− 0.54**** (3.02)	− 0.50**** (4.27)
log PC_i	− 0.37**** (2.41)	− 0.23** (1.50)
intercept	5.97 (6.99)	5.75 (5.44)
Test Statistic	1.16 (6,32)	1.10 (6,32)

variance/covariance matrix of residuals

0.027	0.008	0.011
	0.046	0.001
		0.015

variance

log CL_B	0.052
log CL_R	0.119
log CL_T	0.028

correlation matrix of residuals

1.00	0.22†	0.52†
	1.00	0.03
		1.00

Table 5.40 Production Functions, 1976

CL (clear up rate)

	BURGLARY	THEFT
log P	0.26* (1.23)	0.24*** (2.29)
log T	- 0.31** (1.55)	- 0.34**** (3.19)
log PC_i	- 0.12 (0.71)	- 0.23*** (1.65)
intercept	4.80 (5.00)	6.27 (6.67)
Test Statistic	1.73 (6,32)	1.91 (6,32)

variance/covariance matrix of residuals

0.036	0.012	0.014
	0.029	0.008
		0.012

variance

log CL_B	0.041
log CL_R	0.069
log CL_T	0.019

correlation matrix of residuals

1.00	0.36†	0.68†
	1.00	0.43†
		1.00

Table 5.41

Production Functions, Pooled 1975/6

CL (conviction rate)

	BURGLARY	THEFT
log P	0.21*** (2.09)	0.15*** (2.25)
log T	- 0.30**** (3.12)	- 0.24**** (3.62)
log PC_i	- 0.33**** (3.09)	- 0.24*** (1.99)
intercept	5.72 (8.91)	5.64 (6.77)
Test Statistic	3.44† (6,73)	4.24† (6,73)

variance/covariance matrix of residuals

0.029	0.003	0.014
	0.052	- 0.000
		0.017

variance

log CL_B	0.041
log CL_R	0.130
log CL_T	0.026

correlation matrix of residuals

1.00	0.07	0.64†
	1.00	- 0.01
		1.00

Table 5.42

Production Functions, Pooled 1975/6

CL (clear up rate)

	BURGLARY	THEFT
log P	0.05 (0.47)	0.10*** (1.92)
log T	- 0.14** (1.40)	- 0.22**** (4.17)
log PC_i	- 0.05 (0.41)	- 0.20*** (2.15)
intercept	4.60 (6.86)	6.24 (9.46)
Test Statistic	2.87† (6,73)	3.29† (6,73)

variance/covariance matrix of residuals

0.033	0.013	0.013
	0.038	0.010
		0.011

variance

log CL_B	0.041
log CL_R	0.130
log CL_T	0.026

correlation matrix of residuals

1.00	0.37†	0.71†
	1.00	0.48†
		1.00

Table 5.43 Modified Estimates of production functions

	BURGLARY Pooled, 1975/6 (clear up rate)	THEFT Pooled, 1975/6 (clear up rate)	BURGLARY Pooled, 1975/6 (conviction rate)	THEFT Pooled, 1975/6 (conviction rate)
log P	0.12* (1.23)	0.09*** (1.65)	0.16** (1.50)	0.06 (0.88)
log T	- 0.13** (1.40)	- 0.19**** (3.29)	- 0.23**** (2.50)	- 0.14*** (2.09)
log PC_i	- 0.26*** (2.17)	- 0.23**** (2.58)	- 0.28**** (2.35)	- 0.70**** (3.74)
log CL_{iA}	0.66**** (3.93)	0.46**** (3.27)		
log U	- 0.05 (0.64)	- 0.07** (1.51)		0.23**** (3.08)
log F_i			- 0.17** (1.51)	- 0.31**** (3.91)
log A			- 0.97**** (2.37)	
log R				0.09**** (2.56)
intercept	3.11 (4.28)	4.71 (5.92)	7.82 (8.78)	9.27 (6.73)
Test Statistic	0.47 (4,73)	1.86 (4,73)	2.01 (4,73)	0.38 (3,73)

Correlations with residuals from other production functions

B	-	0.71	-	0.29
RB	0.36	0.42	0.10	-0.05
TH	0.71	-	0.29	-

Table 5.44

Correlations between the residuals from the crime equations and the residuals from the production functions

(1) 1975, CL (conviction rate)

	Production Functions			
	B	RB	TH	
B	0.56†	0.09	0.42†	
RB	- 0.06	0.48†	- 0.07	Crime Equations
TH	0.07	- 0.06	0.27	

(2) 1975, CL (clear up rate)

	Production Functions			
	B	RB	TH	
B	0.52†	0.44†	0.67†	
RB	0.20	0.73†	0.35†	Crime Equations
TH	- 0.04	0.19	0.24	

(3) 1976, CL (conviction rate)

	Production Functions			
	B	RB	TH	
B	0.35†	0.28	- 0.11	
RB	- 0.06	0.34†	0.04	Crime Equations
TH	- 0.20	0.00	- 0.20	

Table 5.44 (continued)

(4) 1976, CL (clear up rate)

Production Functions

	B	RB	TH	
B	0.58†	0.29	0.52†	
RB	− 0.05	0.18	− 0.09	Crime Equations
TH	0.38†	0.45†	0.25	

(5) Pooled 1975/6, CL (conviction rate)

Production Functions

	B	RB	TH	
B	0.21†	0.15	0.40†	
RB	− 0.28†	0.24†	0.19	Crime Equations
TH	− 0.19	− 0.05	0.62†	

(6) Pooled 1975/6, CL (clear up rate)

Production Functions

	B	RB	TH	
B	0.75†	0.35†	0.57†	
RB	0.04	0.43†	0.04	Crime Equations
TH	0.14	0.10	0.21†	

Table 5.45 Crime Equations, 1975

CL (conviction rate)

	BURGLARY (B)	ROBBERY (RB)	THEFT (TH)
log CL_B	- 0.74* (1.05)	0.19 (0.24)	0.04 (0.12)
log CL_{RB}	0.10 (0.47)	- 0.41* (1.09)	- 0.14* (1.09)
log CL_{TH}	- 0.95 (0.83)	- 1.51** (1.51)	- 0.71** (1.31)
log I_i	- 0.63*** (2.09)	- 0.40*** (1.71)	- 0.17 (0.99)
log S_i	- 0.69** (1.56)	- 0.40* (1.08)	- 0.46** (1.53)
log R	0.16**** (2.70)	0.31**** (3.76)	0.14**** (3.12)
log A	- 0.48 (0.44)	- 0.63 (0.43)	0.59 (0.83)
log U	0.26** (1.28)	0.54*** (2.22)	0.20*** (1.66)
log W	- 0.31 (0.24)	0.68 (0.51)	- 0.45 (0.64)
log CL_{iA}	0.44* (1.05)	0.57* (1.16)	0.37 E-02 (0.95 E-02)
intercept	16.60 (2.28)	6.44 (0.89)	12.44 (2.91)

Table 5.46 Crime Equations, 1975

CL (clear up rate)

	BURGLARY (B)	ROBBERY (RB)	THEFT (TH)
log CL_B	- 1.11* (1.13)	- 1.55 (0.93)	- 1.00* (1.06)
log CL_{RB}	0.09 (0.15)	1.07 (0.95)	- 0.08 (0.16)
log CL_{TH}	0.83 (0.79)	- 0.59 (0.33)	0.91 (0.90)
log I_i	- 0.19 (0.71)	- 0.61**** (2.35)	- 0.03 (0.12)
log S_i	- 0.30* (1.12)	0.05 (0.11)	- 0.38* (1.20)
log R	0.26**** (3.02)	0.51**** (3.03)	0.18**** (2.35)
log A	0.70 (0.76)	0.83 (0.49)	1.03* (1.19)
log U	0.22* (1.17)	0.15 (0.49)	- 0.01 (0.04)
log W	- 0.84 (0.57)	- 1.97 (0.90)	- 1.16* (1.06)
log CL_{iA}	1.21**** (2.57)	2.30**** (2.57)	0.79** (1.30)
intercept	4.87 (0.70)	0.92 (0.11)	8.31 (1.65)

Table 5.47 Crime Equations, 1976

CL (conviction rate)

	BURGLARY (B)	ROBBERY (RB)	THEFT (TH)
log CL_B	0.03 (0.03)	- 1.11** (1.31)	- 0.67 (1.03)
log CL_{RB}	0.20 (0.58)	- 0.90*** (1.85)	- 0.15 (0.68)
log CL_{TH}	- 1.79** (1.64)	1.07 (0.74)	0.12 (0.15)
log I_i	- 0.60*** (1.73)	0.17 (0.57)	- 0.09 (0.59)
log S_i	- 0.35* (1.08)	- 0.11 (0.35)	- 0.19 (0.65)
log R	0.21*** (1.97)	0.22** (1.57)	0.07 (0.92)
log A	- 0.28 (0.25)	0.42 (0.32)	0.33 (0.41)
log U	0.62**** (2.36)	- 0.08 (0.21)	0.15 (0.63)
log W	- 0.53 (0.37)	0.88 (0.58)	0.38 (0.41)
log CL_{iA}	0.51** (1.29)	0.51** (1.61)	0.24 (0.75)
intercept	13.94 (2.07)	- 1.63 (0.26)	7.46 (2.03)

Table 5.48 Crime Equations, 1976

CL (clear up rate)

	BURGLARY (B)	ROBBERY (RB)	THEFT (TH)
log CL_B	0.30 (0.40)	1.48** (1.33)	- 0.32 (0.62)
log CL_{RB}	- 0.38 (0.57)	- 0.59 (0.47)	- 0.09 (0.17)
log CL_{TH}	- 0.02 (0.02)	- 0.86 (0.53)	- 0.29 (0.36)
log I_i	0.26 E-02 (0.88 E-02)	0.18 (0.49)	- 0.04 (0.24)
log S_i	- 0.41* (1.22)	- 0.45** (1.32)	- 0.47 E-02 (0.02)
log R	0.15** (1.41)	0.38*** (2.06)	0.13** (1.60)
log A	0.82 (0.72)	1.83 (0.98)	0.81 (0.99)
log U	0.34** (1.38)	0.32 (0.87)	0.15 (0.74)
log W	0.86 (0.59)	0.58 (0.24)	- 0.28 (0.25)
log CL_{iA}	0.74*** (1.75)	0.16 (0.26)	0.84** (1.47)
intercept	0.64 (0.09)	- 4.20 (0.43)	5.62 (1.27)

Table 5.49 Crime Equations, 1975

CL (conviction rate)

	BURGLARY (B)	ROBBERY (RB)	THEFT (TH)
log CL_i	- 1.48*** (2.06)	- 0.29 (0.59)	- 0.91** (1.58)
log I_B	- 0.90*** (2.03)	0.20 (0.51)	- 0.11 (0.50)
log I_{RB}	0.27* (1.09)	- 0.41** (1.55)	- 0.05 (0.48)
log I_{TH}	0.04 (0.14)	- 0.13 (0.32)	- 0.11 (0.48)
log S_i	- 0.54*** (1.96)	- 0.30 (0.87)	- 0.52** (1.61)
log R	0.12*** (1.70)	0.37**** (3.67)	0.15**** (3.32)
log A	- 0.80 (0.64)	0.69 (0.49)	0.63 (0.72)
log U	0.13 (0.73)	0.36** (1.61)	0.19** (1.46)
log W	- 0.74 (0.69)	0.50 (0.33)	- 0.63 (0.76)
log CL_{iA}	0.42* (1.06)	0.82** (1.32)	- 0.02 (0.04)
intercept	17.47 (2.18)	- 2.28 (0.26)	13.95 (2.29)

Table 5.50 Crime Equations, 1975

CL (clear up rate)

	BURGLARY (B)	ROBBERY (RB)	THEFT (TH)
log CL_i	- 0.91* (1.24)	- 0.67 (0.75)	0.06 (0.10)
log I_B	- 0.32 (0.88)	0.28 (0.64)	0.08 (0.32)
log I_{RB}	- 0.04 (0.24)	- 0.47*** (1.79)	- 0.10 (0.82)
log I_{TH}	- 0.07 (0.22)	- 0.34 (0.69)	- 0.09 (0.35)
log S_i	- 0.37* (1.27)	- 0.17 (0.40)	- 0.21 (0.72)
log R	0.20**** (3.03)	0.38**** (2.72)	0.17**** (3.11)
log A	0.60 (0.56)	0.19 (0.11)	1.43*** (1.81)
log U	0.15 (0.64)	0.14 (0.45)	0.16 (0.96)
log W	- 0.79 (0.59)	- 0.18 (0.10)	- 0.61 (0.67)
log CL_{iA}	1.27**** (2.47)	1.69**** (2.57)	0.43 (0.85)
intercept	8.72 (1.13)	- 1.18 (0.11)	5.36 (0.97)

Table 5.51 Crime Equations, 1976

CL (conviction rate)

	BURGLARY (B)	ROBBERY (RB)	THEFT (TH)
log CL_i	- 1.73* (1.12)	- 0.62** (1.29)	- 0.09 (0.13)
log I_B	- 0.80* (1.15)	- 0.18 (0.59)	0.18 E-02 (0.66 E-02)
log I_{RB}	0.04 (0.13)	0.23 (0.98)	0.13 (0.70)
log I_{TH}	- 0.25 (0.98)	- 0.22 E-02 (0.85 E-02)	- 0.51 E-03 (0.32 E-02)
log S_i	- 0.28 (0.84)	- 0.17 (0.52)	- 0.07 (0.25)
log R	0.11 (0.83)	0.36*** (2.38)	0.14**** (2.90)
log A	- 0.99 (0.56)	1.23 (0.91)	0.95* (1.09)
log U	0.35** (1.63)	0.14 (0.57)	0.32*** (2.01)
log W	- 0.68 (0.49)	- 0.34 (0.20)	- 0.10 (0.12)
log CL_{iA}	0.17 (0.30)	0.48*** (1.72)	0.22 (0.63)
intercept	18.34 (1.25)	0.06 (0.01)	3.50 (0.54)

Table 5.52 Crime Equations, 1976

CL (clear up rate)

	BURGLARY (B)	ROBBERY (RB)	THEFT (TH)
log CL_i	- 1.55 (0.99)	- 0.81 (0.98)	- 0.02 (0.02)
log I_B	- 0.42 (0.79)	- 0.58 (0.94)	0.03 (0.12)
log I_{RB}	0.11 (0.35)	0.33 (0.95)	0.14 (0.90)
log I_{TH}	- 0.15 (0.49)	- 0.10 (0.34)	0.02 (0.13)
log S_i	- 0.17 (0.38)	- 0.34 (1.03)	0.05 (0.16)
log R	0.21**** (2.68)	0.40**** (2.37)	0.15**** (2.87)
log A	0.12 (0.07)	0.95 (0.48)	1.01* (1.26)
log U	0.34* (1.19)	0.10 (0.29)	0.28** (1.28)
log W	- 1.48 (0.67)	- 1.30 (0.84)	- 0.11 (0.12)
log CL_{iA}	1.16** (1.58)	0.53* (1.27)	0.41 (0.76)
intercept	13.54 (1.02)	6.54 (0.90)	2.32 (0.44)

Appendix to Chapter 5

1. Test of the correctness of the over-identifying restrictions of a single equation of a model

The test statistic is given by

$$\frac{T - K_1}{K_2 - G} \times (\lambda - 1)$$

where

$$\lambda = \frac{T\hat{\sigma}^2}{\hat{\alpha}'W\alpha}$$

T is the number of observations,

K_1 is the number of predetermined variables in the model,

K_2 is the number of excluded predetermined variables in any equation,

G is the number of included endogenous variables on the right hand side of any equation,

$T\hat{\sigma}^2$ is the sum of squared residuals of a structural equation,

and $\hat{\alpha}'W\alpha$ is the sum of squared residuals found by regressing $(y_i - \Sigma\, \hat{c}_i\, Y_i)$ on <u>all</u> the predetermined variables of the model

where y_i is the endogenous variable to be explained

$\hat{c}_i$ is 2SLS coefficient estimate attaching to Y_i

and Y_i is a right hand side endogenous variable.

The test statistic has an F-distribution with $(K_2 - G, T - K_1)$ degrees of freedom.

2. Table A.1

Means and Standard deviations of variables

Variable	1975		1976	
	Mean	Standard deviation	Mean	Standard deviation
log PC	8.016	0.275	8.013	0.270
log B	6.745	0.370	6.710	0.357
log RB	2.411	0.603	2.316	0.580
log TH	7.674	0.249	7.686	0.245
log CL (clear up)	3.818	0.127	3.805	0.144
log CL_B " "	3.651	0.177	3.647	0.201
log CL_R " "	3.997	0.230	3.924	0.262
log CL_T " "	3.876	0.120	3.857	0.139
log CL (conviction)	3.148	0.161	3.133	0.171
log CL_B "	2.904	0.202	2.894	0.227
log CL_R "	3.875	0.360	3.967	0.345
log CL_T "	3.224	0.160	3.204	0.168
log CL_A (clear up)	3.822	0.093	3.808	0.111
log CL_{AB} " "	3.663	0.122	3.656	0.159
log CL_{AR} " "	4.020	0.125	3.943	0.183
log CL_{AT} " "	3.876	0.088	3.858	0.104

Table A.1 (continued)

Variable	1975		1976	
	Mean	Standard deviation	Mean	Standard deviation
log CL_A (conviction)	3.157	0.090	3.144	0.119
log CL_{AB} "	2.918	0.134	2.919	0.154
log CL_{AR} "	3.936	0.175	4.019	0.194
log CL_{AT} "	3.224	0.098	3.208	0.115
log I	1.662	0.179	1.757	0.195
log I_B	2.305	0.241	2.396	0.236
log I_R	3.647	0.310	3.754	0.258
log I_T	1.268	0.206	1.338	0.245
log S	5.949	0.145	5.934	0.156
log S_B	6.088	0.178	6.068	0.156
log S_R	7.032	0.174	7.053	0.218
log S_T	5.526	0.150	5.498	0.152
log A	1.977	0.050	2.002	0.050
log U	1.640	0.293	1.729	0.261
log R	5.837	1.012	5.837	1.012
log W	3.611	0.055	3.784	0.051
log P	7.454	0.541	7.495	0.544
log E	4.065	0.051	4.235	0.048
log T	7.287	0.436	7.224	0.465
log M	4.169	0.520	4.176	0.513

5. Table A.2 Correlation Matrices

(i) 1975 Aggregate Data

	log PC	log CL (clear up)	log CL (conviction)	log I	log S	log CL_A (clear up)	log CL_A (conviction)	log A	log U	log R	log W	log P	log T	log E	log M
log PC	1.00	- 0.27	- 0.48	- 0.09	- 0.14	0.30	0.34	0.35	0.22	0.58	0.39	0.43	0.08	0.49	0.42
log CL (clear up)		1.00	0.55	- 0.21	- 0.20	0.23	- 0.02	- 0.19	- 0.01	- 0.41	- 0.25	- 0.36	- 0.52	- 0.32	- 0.46
log CL (conviction)			1.00	- 0.20	- 0.35	0.12	- 0.07	- 0.36	0.22	- 0.34	- 0.19	- 0.22	- 0.29	- 0.37	- 0.34
log I				1.00	0.18	- 0.22	- 0.15	- 0.20	- 0.20	0.18	- 0.30	0.30	0.50	- 0.07	0.34
log S					1.00	- 0.23	- 0.28	0.13	- 0.34	0.11	0.09	- 0.06	0.14	0.11	0.15
log CL_A (clear up)						1.00	0.78	0.14	0.41	- 0.13	0.07	0.03	- 0.27	0.00	- 0.11
log CL_A (conviction)							1.00	0.22	0.52	- 0.05	0.02	0.14	- 0.08	- 0.02	0.00
log A								1.00	- 0.08	0.21	0.29	- 0.06	- 0.11	0.32	0.03
log U									1.00	- 0.17	- 0.07	0.15	- 0.11	- 0.24	- 0.05
log R										1.00	0.60	0.63	0.32	0.68	0.68
log W											1.00	0.15	- 0.16	0.85	0.21
log P												1.00	0.72	0.24	0.96
log T													1.00	0.00	0.78
log E														1.00	0.32
log M															1.00

	log PC	log CL (clear up)	log CL (conviction)	log I	log S	log CL_A (clear up)	log CL_A (conviction)	log A	log U	log R	log W	log P	log T	log E	log M
log PC	1.00	- 0.26	- 0.48	- 0.01	- 0.05	0.26	0.20	0.18	0.35	0.60	0.43	0.52	0.36	0.44	0.44
log CL (clear up)		1.00	0.59	- 0.18	- 0.18	0.35	0.24	- 0.20	0.01	- 0.29	- 0.13	- 0.23	- 0.38	- 0.25	- 0.33
log CL (conviction)			1.00	- 0.37	- 0.43	0.23	0.19	- 0.30	0.21	- 0.32	- 0.09	- 0.26	- 0.41	- 0.25	- 0.36
log I				1.00	0.06	- 0.35	- 0.35	- 0.05	- 0.24	0.24	- 0.27	0.35	0.48	- 0.05	0.42
log S					1.00	- 0.01	- 0.15	0.27	- 0.39	0.19	0.18	- 0.08	0.15	0.21	0.08
log CL_A (clear up)						1.00	0.86	- 0.08	0.43	- 0.09	0.13	0.03	- 0.19	- 0.08	- 0.12
log CL_A (conviction)							1.00	- 0.03	0.48	- 0.16	0.04	0.04	- 0.18	- 0.14	- 0.11
log A								1.00	- 0.09	0.02	0.12	- 0.09	- 0.01	0.22	0.02
log U									1.00	- 0.05	0.15	0.21	- 0.08	0.01	0.01
log R										1.00	0.57	0.65	0.59	0.61	0.66
log W											1.00	0.15	0.02	0.85	0.14
log P												1.00	0.91	0.16	0.96
log T													1.00	0.11	0.97
log E														1.00	0.20
log M															1.00

(iii) 1975, Disaggregated Data (above); 1976, Disaggregated Data (below)

	log B	log RB	log TH	log CL_B (clear up)	log CL_R (clear up)	log CL_T (clear up)	log CL_B (conviction)	log CL_R (conviction)	log CL_T (conviction)	log I_B	log I_R	log I_T	log S_B	log S_R	log S_T
log B	1.00 1.00														
log RB	0.82 0.78	1.00 1.00													
log TH	0.84 0.86	0.81 0.78	1.00 1.00												
log CL_B (clear up)	- 0.17 - 0.08	- 0.26 - 0.23	- 0.21 - 0.19	1.00 1.00											
log CL_R (clear up)	- 0.33 - 0.33	- 0.45 - 0.61	- 0.40 - 0.51	0.55 0.51	1.00 1.00										
log CL_T (clear up)	- 0.15 - 0.16	- 0.36 - 0.42	- 0.26 - 0.31	0.78 0.73	0.66 0.72	1.00 1.00									
log CL_B (conviction)	- 0.47 - 0.47	- 0.60 - 0.55	- 0.56 - 0.54	0.57 0.59	0.40 0.58	0.60 0.59	1.00 1.00								
log CL_R (conviction)	- 0.52 - 0.49	- 0.69 - 0.78	- 0.59 - 0.55	0.23 0.34	0.39 0.65	0.39 0.47	0.61 0.48	1.00 1.00							
log CL_T (conviction)	- 0.19 - 0.25	- 0.33 - 0.31	- 0.43 - 0.41	0.40 0.36	0.24 0.43	0.50 0.56	0.73 0.71	0.40 0.27	1.00 1.00						
log I_B	- 0.40 - 0.28	- 0.26 - 0.16	- 0.19 - 0.05	- 0.12 - 0.33	0.00 - 0.33	- 0.24 - 0.33	- 0.25 - 0.38	0.08 0.12	- 0.19 - 0.41	1.00 1.00					
log I_R	- 0.27 - 0.08	- 0.41 0.08	- 0.19 0.21	0.14 - 0.24	0.19 - 0.14	0.06 - 0.26	- 0.32 - 0.38	0.37 0.05	0.00 - 0.45	0.25 0.50	1.00 1.00				
log I_T	- 0.03 - 0.06	0.03 0.16	0.04 0.13	- 0.06 - 0.23	- 0.23 - 0.36	- 0.32 - 0.27	- 0.20 - 0.33	- 0.04 - 0.17	- 0.15 - 0.23	0.61 0.44	0.23 0.05	1.00 1.00			
log S_B	- 0.24 - 0.16	0.05 0.06	- 0.05 - 0.08	- 0.16 0.01	0.02 - 0.06	- 0.23 - 0.13	- 0.14 - 0.16	- 0.02 - 0.08	- 0.43 - 0.27	0.14 0.11	0.22 0.14	0.10 0.15	1.00 1.00		
log S_R	- 0.31 - 0.07	- 0.22 0.02	- 0.17 0.02	0.04 - 0.0[illegible]	- 0.03 - 0.16	- 0.06 0.08	0.25 - 0.16	0.06 0.08	0.05 - 0.11	0.24 0.3[illegible]	0.19 0.19	0.26 - 0.01	0.19 0.06	1.00 1.00	
log S_T	- 0.19 - 0.05	0.12 0.16	- 0.07 - 0.03	- 0.25 0.04	- 0.17 - 0.01	- 0.29 - 0.14	- 0.14 - 0.29	- 0.05 0.04	- 0.35 - 0.30	0.14 0.08	0.07 0.10	0.13 0.11	0.70 0.55	0.06 0.09	1.00 1.00
log CL_{AB} (clear up)	0.41 0.36	0.20 0.19	0.14 0.09	0.28 0.40	0.11 0.32	0.29 0.33	0.14 0.19	0.01 - 0.04	0.22 0.31	- 0.46 - 0.54	- 0.09 - 0.16	- 0.25 - 0.33	- 0.25 0.05	- 0.18 - 0.12	- 0.32 0.14
log CL_{AR} (clear up)	0.43 0.32	0.25 0.06	0.26 0.08	0.13 0.35	- 0.02 0.29	0.18 0.30	0.02 0.21	- 0.09 - 0.03	0.11 0.31	- 0.44 - 0.52	- 0.01 - 0.32	- 0.27 - 0.22	- 0.15 0.03	- 0.13 - 0.28	- 0.37 - 0.10
log CL_{AT} (clear up)	0.47 0.46	0.18 0.15	0.21 0.18	0.28 0.37	0.11 0.28	0.30 0.36	0.12 0.15	- 0.01 0.02	0.19 0.27	- 0.44 - 0.49	0.00 - 0.17	- 0.18 - 0.31	- 0.28 - 0.11	- 0.20 - 0.13	- 0.37 - 0.04
log CL_{AB} (conviction)	0.41 0.36	0.18 0.13	0.20 0.16	0.15 0.23	- 0.04 0.24	0.12 0.18	0.04 0.10	- 0.08 - 0.11	0.08 0.23	- 0.36 - 0.51	0.01 - 0.22	- 0.11 - 0.20	- 0.30 - 0.09	- 0.11 - 0.27	- 0.37 - 0.13
log CL_{AR} (conviction)	0.29 0.31	0.27 0.08	0.22 0.12	0.13 0.25	- 0.06 0.22	0.09 0.30	0.02 0.07	- 0.37 0.01	0.04 0.11	- 0.35 - 0.41	- 0.08 - 0.23	- 0.22 - 0.31	- 0.13 - 0.14	0.05 - 0.29	- 0.26 - 0.23
log CL_{AT} (conviction)	0.46 0.37	0.19 0.13	0.27 0.15	0.16 0.30	- 0.06 0.25	0.11 0.20	0.00 0.14	- 0.11 - 0.10	0.07 0.22	- 0.32 - 0.51	0.06 - 0.17	- 0.11 - 0.21	- 0.39 - 0.16	- 0.09 - 0.21	- 0.51 - 0.12
log A	0.29 0.07	0.26 0.20	0.37 0.23	- 0.18 - 0.19	- 0.21 - 0.26	- 0.16 - 0.20	- 0.36 - 0.28	- 0.25 - 0.17	- 0.33 - 0.29	- 0.13 0.03	0.06 0.32	- 0.20 0.16	0.09 0.31	- 0.30 0.00	0.13 0.03
log U	0.30 0.43	0.12 0.16	0.16 0.28	- 0.03 0.04	- 0.10 - 0.07	0.05 0.02	0.16 0.08	0.04 - 0.16	0.27 0.29	- 0.33 - 0.31	0.05 - 0.14	- 0.13 - 0.19	- 0.32 - 0.38	0.05 - 0.02	- 0.31 - 0.48
log R	0.58 0.58	0.68 0.76	0.54 0.58	- 0.27 - 0.17	- 0.50 - 0.55	- 0.42 - 0.31	- 0.44 - 0.37	- 0.38 - 0.52	- 0.22 - 0.24	- 0.09 - 0.01	- 0.17 0.08	0.30 0.27	0.08 0.06	- 0.13 0.26	0.31 0.11
log W	0.47 0.46	0.50 0.48	0.33 0.40	- 0.24 - 0.13	- 0.25 - 0.16	- 0.19 - 0.10	- 0.25 - 0.12	- 0.25 - 0.21	- 0.09 - 0.03	- 0.45 - 0.39	- 0.23 - 0.19	- 0.18 - 0.15	0.08 0.07	- 0.24 - 0.01	0.19 0.09
log P	0.51 0.55	0.52 0.52	0.44 0.47	- 0.20 - 0.05	- 0.37 - 0.51	- 0.37 - 0.26	- 0.24 - 0.25	- 0.21 - 0.43	- 0.14 - 0.20	- 0.02 0.06	- 0.02 - 0.09	0.37 0.27	- 0.11 - 0.02	- 0.02 0.20	- 0.03 - 0.15
log T	0.06 0.36	0.20 0.45	0.08 0.33	- 0.32 - 0.17	- 0.33 - 0.56	- 0.59 - 0.42	- 0.26 0.36	- 0.21 - 0.39	- 0.28 - 0.38	0.34 0.30	0.11 0.09	0.47 0.35	0.10 0.18	0.10 0.27	0.21 0.03
log E	0.51 0.42	0.50 0.44	0.44 0.42	- 0.30 - 0.31	- 0.38 - 0.30	- 0.26 - 0.19	- 0.41 - 0.30	- 0.32 - 0.24	- 0.27 - 0.18	- 0.25 - 0.11	- 0.13 0.08	0.01 0.07	0.10 0.07	- 0.19 0.11	0.23 0.13
log M	0.42 0.45	0.51 0.52	0.39 0.40	- 0.29 - 0.15	- 0.41 - 0.56	- 0.49 - 0.37	- 0.31 - 0.34	- 0.21 - 0.42	- 0.27 - 0.31	0.04 0.19	0.00 0.00	0.38 0.34	0.08 0.13	0.00 0.21	0.19 0.00

	log CL_{AB}	log CL_{AR}	log CL_{AT}	log CL_{AB}	log CL_{AR}	log CL_{AT}	log A	log U	log R	log W	log P	log T	log E	log M
	←	(clear up)	→	←	(conviction)	→								
log CL_{AB} (clear up)	1.00 1.00													
log CL_{AR} (clear up)	0.81 0.82	1.00 1.00												
log CL_{AT} (clear up)	0.95 0.91	0.84 0.89	1.00 1.00											
log CL_{AB} (conviction)	0.83 0.80	0.74 0.90	0.86 0.82	1.00 1.00										
log CL_{AR} (conviction)	0.60 0.57	0.67 0.70	0.60 0.70	0.79 0.65	1.00 1.00									
log CL_{AT} (conviction)	0.77 0.83	0.65 0.86	0.79 0.85	0.86 0.94	0.63 0.61	1.00 1.00								
log A	0.14 - 0.11	0.16 - 0.04	0.14 - 0.07	0.13 - 0.03	0.08 - 0.03	0.18 - 0.05	1.00 1.00							
log U	0.35 0.31	0.50 0.48	0.43 0.47	0.56 0.47	0.43 0.44	0.51 0.49	- 0.08 - 0.09	1.00 1.00						
log R	- 0.11 - 0.04	- 0.20 - 0.19	- 0.13 - 0.11	- 0.12 - 0.14	- 0.16 - 0.20	- 0.04 - 0.12	0.21 0.02	- 0.17 - 0.05	1.00 1.00					
log W	0.10 0.12	0.09 0.14	0.06 0.13	0.03 0.06	- 0.37 0.12	- 0.04 0.08	0.29 0.12	- 0.07 0.15	0.60 0.57	1.00 1.00				
log P	- 0.01 0.03	- 0.01 0.02	0.04 0.04	0.06 0.03	- 0.05 0.00	0.15 0.09	- 0.06 - 0.09	0.15 0.21	0.63 0.65	0.15 0.15	1.00 1.00			
log T	- 0.30 - 0.16	- 0.28 - 0.20	- 0.28 - 0.20	- 0.17 - 0.20	- 0.16 - 0.18	- 0.13 - 0.14	- 0.11 - 0.01	- 0.11 - 0.08	0.32 0.59	- 0.16 0.02	0.72 0.91	1.00 1.00		
log E	- 0.01 - 0.10	0.02 - 0.06	0.00 - 0.06	- 0.08 - 0.07	- 0.17 - 0.12	- 0.07 - 0.08	0.32 0.22	- 0.24 0.01	0.68 0.61	0.85 0.85	0.24 0.16	0.00 0.11	1.00 1.00	
log M	- 0.12 - 0.09	- 0.14 - 0.12	- 0.10 - 0.12	- 0.10 - 0.12	- 0.18 - 0.12	0.00 - 0.06	0.03 0.02	- 0.05 0.01	0.68 0.66	0.21 0.14	0.96 0.96	0.78 0.97	0.32 0.20	1.00 1.00

CHAPTER 6: INTERPRETATION OF RESULTS AND CONCLUSIONS.

1. Introduction

In the last chapter we presented a large volume of regression estimates of the model described in Chapter 4. In this chapter we will examine the sizes and significance levels of the estimated coefficients to see what light they can shed upon the validity of the hypotheses outlined in earlier parts of this thesis. In particular, we are concerned to test the importance of deterrence variables and economic factors in influencing rates of property crimes. However, we will also be concerned to examine the other equations of the model to see what can be learned about the determination of the detection rate and the level of police employment.

The probability of obtaining significant coefficient estimates not only depends upon the validity of the underlying model, but also upon the quality of the data used and upon the degree of variation of that data across the sample. In the remainder of this section we will briefly discuss some of the properties of the data set used in this thesis.

Of course, the data are not perfect. All empirical studies must strike a balance between what data is desirable and what is available. For example, it would clearly have been desirable to have had data on the amounts of <u>time</u> that a random cross-section of the population allocated to illegal activity. However, it would be completely impossible to obtain such information. Likewise, it would have been preferable to have had information about individuals' perceptions of the certainty and severity of punishment. Alas, it would be an inordinately expensive exercise to obtain such information and to ensure that it was reliable. Therefore we have been forced to compromise and to use information that is either already published or, as in the case of the deterrence variables, can be fairly readily obtained from unpublished sources. In some cases this has necessitated a slight respecification of the model. For example, the inclusion of (i) a set of recording equations, (ii) some assumptions concerning the formulation of individuals' perceptions about the probability of detection and so on.

We feel relatively confident that the data used are the best that is available, at the present moment. Obviously, that is not meant to imply that they are the best that could ever be available. There are some obvious limitations of the data set and we would not wish to argue otherwise. We must clearly take those limitations into account in reaching any conclusions, particularly where those conclusions relate to possible policies to reduce the rate of recorded property crime.

However, it is not just the lack of compatibility between the available data and the model's data requirements that may cause problems. Other problems may arise as a result of either insufficient variation in the data over the sample or because of high inter-correlations between the exogenous variables in an equation of the model.

The validity of the regression results reported in the previous chapter depends in part upon there being a sufficient degree of variation in the data across the sample. If the observations all lie close to one another then it is difficult to obtain reliable and significant parameter estimates. The amount of variation in the data series can be established, to some extent, by examination of the (means and) standard deviations of the raw data. These are given in Table A.1 of the

Appendix to the previous chapter. Most of the series reported there do show a fair degree of variation, except perhaps for those for the age/sex composition of the population and average male earnings (i.e. log A, log E and log W). Indeed the lack of variation in these variables is possibly sufficient to lead one to expect that the coefficients attaching to these variables would be statistically insignificant. A prediction which, on the evidence of the regression results, is fully justified. One way of getting around lack of variability in the data series is to obtain more data. That is one reason why, in the last chapter, we pooled the data series for the years 1975 and 1976. However, pooling has only a marginal effect upon the statistical significance of the coefficients of the age and earnings variables. Clearly, when interpreting the coefficients attaching to these variables we will need to bear in mind that one reason why they are not statistically significantly different from zero is their virtual constancy across the sample. Fresh data, with greater variation, might yield different conclusions.

A further "data" problem occurs when there are high intercorrelations between the exogenous variables in an equation. This is what econometricians call multi-collinearity. When multi-collinearity is present in an equation it may mean that it is impossible to separate out the different effects of the variables which are highly correlated with one another. A possible solution to multi-collinearity is also to obtain more data. This will lower the estimated variances of the parameters, thus giving the estimators greater precision. Another, rather more dubious solution, is to drop one or more of the variables which are highly correlated with one another. The reason why such a practice is slightly dubious is that exclusion of a relevant variable will bias the estimated coefficient of any variable with which it is strongly correlated, i.e. the coefficient of the retained variable will be picking up effects which strictly speaking are attributable to the excluded variable.

In fact, we practised variable exclusion to a very limited extent in the early phase of model building and estimation. There, we hypothesised that both population density and rateable value per hectare would influence the crime rate. However, the correlation between these two variables was remarkably high ($r > 0.9$). It was decided that the theoretical grounds for including rateable value in the crime equation as a measure of incentives were rather stronger than those for including population density. So, rateable value alone was included. However, we need to bear in mind that the coefficient of log R in the crime supply equations may possibly be measuring the effects of variations in population density, too.

Likewise, in the police production function we included police manpower (P), but not the number of civilians employed in the police service, because of the exceptionally high correlation between these two variables (again $r > 0.9$).

The full correlation matrices are given in Table A.2 of the Appendix to the previous chapter. In looking for high inter-correlations between exogenous variables we chose as a cut off point a value for r (the simple correlation coefficient) in excess of 0.7. The choice is admittedly arbitrary, but 0.7 is a level also chosen by Carr-Hill and Stern (1979) and so is useful for comparison purposes. We did consider, too, correlations in excess of 0.6. In the aggregate data set there are <u>no</u> instances of correlations between two exogenous variables from the <u>same</u> equation being in excess of 0.7 and only one instance of the correlation exceeding 0.6. This is the correlation between log R and log W in 1975 (r = 0.60). In the disaggregated data set there are <u>no</u> instances of correlations between two exogenous variables from the same equation being greater than 0.6 let alone 0.7. The one possible exception is that between log I_B and log I_T (r = 0.61). However, these variables only appear in the same equation when we are testing for substitution amongst types of crimes. This, though, is a subsidiary hypothesis and is not part of the main model.

We can probably feel fairly confident, therefore, that multi-collinearity is not a problem in this particular study.[1] We now, therefore, consider the results for each of the model's equations in turn.

2. The Explanation of the Recorded Crime Rate

We begin by considering the size and significance levels of the coefficients attaching to the deterrence variables, i.e. the detection rate, the imprisonment rate, length of imprisonment and the detection rate in adjacent areas. We then examine the role of the economic factors, i.e. the proxy for illegal gains, unemployment and earnings in legitimate employment.

For ease of reference we reproduce below shortened versions of the results given in the previous chapter. For example, in Table 6.1 we report the coefficient estimates for

---

[1] However, we have not tested for more complex inter-correlations between the exogenous variables in the data set.

the variables log CL, log I, log S and log CL_A in the aggregate equation. Coefficients can be interpreted as elasticities, because all of the model's equations were estimated in double logarithmic format.

Table 6.1 Deterrence elasticities in aggregate study

	1975		1976		Pooled	
	c.u.	con	c.u.	con	c.u.	con
log CL	-0.07	-0.98**	-0.78	-0.67*	-0.37	-0.86***
log I	-0.17	-0.31**	-0.07	-0.26*	-0.10	-0.29***
log S	-0.20	-0.48***	-0.15	-0.19	-0.17	-0.34***
log CL_A	0.73***	0.21	0.90**	0.33**	0.75***	0.32**

Notes: c.u. denotes that the clear-up rate is used to measure the detection rate, whereas
con denotes that the conviction rate is used instead.
Asterisks denote different levels of statistical significance (see previous chapter).

It is noticeable that when the detection rate is measured by the clear-up rate the deterrence variables are rarely significant, with the exception of log CL_A. However, when the detection rate is instead measured by the conviction rate the deterrence variables are invariably significant. This is slightly disturbing and is certainly at variance with the earlier results of Carr-Hill and Stern (1979)[2]. However, we should recall that we are examining a different set of crimes in a different time period from that analysed by Carr-Hill and Stern. Also, we should recall that they found " ... the similarity [between the coefficient estimates using either clear-

2 " The coefficients of p (the detection rate) were similar, whether p clear-up or p convictions were used ... " (Carr-Hill and Stern, 1979, p.232).

up rates or conviction rates] quite surprising in view of the arguments ... that ... one might expect the perceived probability of capture ... to be more sensitive to conviction rates than clear-up rates." (p.232).

Perhaps we should briefly recall some of these arguments at this stage. One argument in favour of using conviction rates is that criminals are more likely to have access to information about court proceedings (which are relatively widely publicised) than they are to confidential (unpublished) police records on crimes cleared up. Second, clear-up rates (even if published) would not necessarily represent an accurate indicator of the probability of being caught, simply because of the way that they are compiled, e.g. by the inclusion of offences taken into consideration. Third, there is a suspicion that clear-up statistics might be massaged by police forces for "political" purposes. Whilst there is no definitive evidence to confirm that suspicion, no such doubt surrounds the use of conviction statistics.

In view of these arguments it is perhaps surprising that Carr-Hill and Stern found basically no difference in the size and significance level of the detection rate elasticity for either measure. Certainly, we have rather more confidence in the conviction rate as a measure of the probability of detection than we have in the clear-up rate, and the estimates of the crime equation seem to confirm that view. This point of view is somewhat strengthened when we consider the determination of the detection rate in the next section.

There is one interesting point of comparison that can be made here with the study by Carr-Hill and Stern. They found that the detection rate elasticity varied around -0.95 in

1961 and around -0.75 in 1966 and 1971 (depending upon which data set was used). They also found that the punishment elasticity (approximately equivalent to log I of our model) was approximately one-third of the size of the detection rate elasticity. These results correspond quite closely with those given in Table 6.1 when conviction rates are used. The detection rate elasticity (using conviction rates) is not statistically significantly different from one, for all three data sets. However, the imprisonment rate elasticity is significantly less than one. This lends support to the old argument that certainty of punishment is a more effective deterrent than its severity.

Interestingly, the variable used to measure spillover effects (log CL_A) invariably has a statistically significant coefficient. However its size seems to depend quite crucially upon whether clear-up rates or conviction rates are being used. This may be explained as follows. Police forces are possibly under pressure to achieve clear-up rates comparable with adjacent areas. Therefore, the gap between their clear-up rate and clear-up rates in neighbouring police force areas is smaller than the gap between the corresponding conviction rates. Accordingly, the coefficient of log CL_A (clear-up) is expected to be larger than that of log CL_A (conviction).

Comparison with Carr-Hill and Stern's study is not possible on this point. They claimed that displacement was unlikely to occur in view of the small monetary amounts involved in most crimes. The results produced here seem to contradict that assertion. It seems that (property) criminals are fairly mobile and that crime can be (and is) displaced from one area to another by variations in the rates of detection across areas.

As we shall see later, the extent of the displacement varies from one type of property crime to another.

One of the main objectives of this research was to break down the aggregate crime index into particular groups of crimes to see whether the rates of different types of crimes were determined in the same way. In Table 6.2, therefore, we reproduce the separate coefficient estimates (for the deterrence variables) for each type of crime. In view of the arguments advanced earlier, the reported elasticities refer only to those obtained when using conviction rates as a measure of the detection rate.

A noticeable feature of the results reported in Table 6.2 (overleaf) is that the deterrence elasticities differ quite substantially in size and significance levels across crimes. For example, burglars generally seem to be much more responsive to changes in the certainty and severity of punishment than either robbers or thieves.[3] It also seems to be the case that whilst burglars and robbers are quite mobile, thieves are less so. This can be seen by the generally insignificant coefficient for log CL_{iA} in the theft equation.

[3] We should perhaps exercise some caution here. Neither of the coefficients for log CL_i for burglary and theft is significantly different from one (in 1975), and the coefficients for log S_i for the same crimes in 1975 are not significantly different from one another. Otherwise our conclusion is valid.

TABLE 6.2 Deterrence elasticities in disaggregated study

	Burglary			Robbery			Theft		
	1975	1976	Pooled	1975	1976	Pooled	1975	1976	Pooled
log CL_i	-1.41**	-1.56**	-0.94	-0.31	-0.66**	-0.19	-0.78**	-0.24	-0.33
log I_i	-0.77***	-0.79*	-0.52**	-0.41***	0.17	-0.24**	-0.19*	-0.02	-0.06
log S_i	-0.40***	-0.30	-0.35***	-0.29	-0.18	-0.26**	-0.49***	0.06	-0.14
log CL_{iA}	0.48*	0.20	0.46**	0.75**	0.51**	0.62***	0.05	0.20	0.26*

In general the theft equation seemed poorly determined. It is possible, as we argued in the last chapter, that this is due to an inappropriate selection of deterrence variables. Imprisonment is a rarely imposed sanction for theft. It is much more common for fines to be used. In Table 6.3 we summarise the deterrence elasticities using average fines rather than the probability and length of imprisonment. Again, only those obtained using conviction rates are reported.

TABLE 6.3 Deterrence elasticities in disaggregated study

	Burglary			Theft		
	1975	1976	Pooled	1975	1976	Pooled
log CL_i	-0.87*	-0.59*	-0.50*	-0.58*	-0.32	-0.39
log F_i	-0.45***	-0.44***	-0.44****	-0.26***	-0.35**	-0.27***
log CL_{iA}	0.76***	0.65****	0.72****	0.27	0.07	0.16

In fact the results in Table 6.3 show that more severe penalties for theft, i.e. larger fines, do exert a deterrent effect. However, the earlier observation that thieves may be less mobile than burglars is strongly reaffirmed. Also, the rate of recorded theft is again generally much less responsive to changes in the detection rate than is burglary.[4] However, this may have as much to do with the recording process as it has with criminal behaviour. We argued in Chapter 4 that the willingness of victims to report crimes may be influenced by the perceived success of the police in catching criminals. This means that a rise in the detection rate will have two effects, (i) a deterrent effect causing the actual crime rate

[4] However, the coefficients for log CL for the two crimes in 1975 are not significantly different from one another.

to fall and (ii) a reporting effect causing the proportion of actual crimes reported to the police to rise. Whether the number of reported crimes will rise or fall depends upon the relative strengths of these two effects (see the Appendix to Chapter 4 where the model's equations are solved formally).

Reporting a crime may be an essential prerequisite before an insurance claim can be settled. It is possible, therefore, that the reporting of crimes may also be related to the extent to which property is insured. This may influence not just the extent of reporting across areas, but possibly across crimes too. If, for example, households tend to insure their household contents against burglary, then the reporting effect of a rise in the detection rate for burglary will be virtually zero. The detection rate elasticity will then be a pure deterrence effect and will be unambiguously negative. However, if individuals rarely insure their valuables for theft outside of the home then reporting may be influenced very strongly by the effectiveness of the police in solving crimes. In that case the detection rate elasticity would be a hybrid of a deterrence effect and a reporting effect. This suggests one possible explanation of why the detection rate elasticities for the theft group are often not significantly different from zero.

However, it would be wrong to place too much emphasis upon that explanation. There are some crimes within the theft group, e.g. motor vehicle theft, for which reporting is supposed to be 100%.[5] One suspects that this is largely because motor vehicle insurance is compulsory. Also, not all households insure their contents against being stolen by burglars.

---

[5] See The British Crime Survey (1983, p. 9.)

It is clear, therefore, that there are counter-examples which possibly disprove the theory. However, there is perhaps a sufficient element of truth for it to be a partial explanation at least.

To conclude. The statistical results reported in this thesis lend some support to the view that increases in the certainty and severity of punishment lead to a reduction in the number of reported property crimes. However the extent of these deterrent effects seems to vary across different types of crimes. Finally, there is some evidence to suggest that some types of criminals (burglars and robbers) are mobile between areas, so that attempts to "get tough" on crime in one area may merely displace some of that crime into other areas.

We now turn to examine the role of the various economic factors in influencing variations in recorded property crime rates.[6] The various elasticities in the aggregate model are given in Table 6.4.

TABLE 6.4 Economic variables in the aggregate model

	1975		1976		Pooled	
	con.	c.u.	con.	c.u.	con.	c.u.
log R	0.14***	0.19***	0.16***	0.15***	0.15***	0.16***
log U	0.26***	0.18*	0.34***	0.20	0.28***	0.20***
log W	-0.37	-0.61	-0.21	-0.21	-0.15	-0.23
log A	0.30	1.16**	0.50	0.84*	0.36	1.07***

Notes: see Table 6.1

6 For completeness we include the age/sex variable (log A) in this discussion.

The most striking feature of the coefficients reported in Table 6.4 is their remarkable degree of stability (with a few minor exceptions) across both time periods and measures of the detection rate.[7] The one exception seems to be log A (the proportion of males aged 15-24 years in the population). This variable is never significant when conviction rates are used, but is always significant when clear-up rates are used. The reasons for this are not altogether obvious. It seems unlikely that this discrepancy has been caused by a high correlation between log CL (conviction rate) and log A, for r is only -0.36 (1975) and -0.30 (1976). Admittedly this correlation is somewhat larger than that between log CL (clear-up rate) and log A, but it does not seem sufficiently high to warrant fears of multi-collinearity. This result must, therefore, remain something of a mystery.[8]

However, conclusions about the importance of the other socio-economic variables seem rather more clear-cut. Rateable value per hectare (log R) is always highly significant. Recall that log R is basically being used as a proxy for illegal gains. However, it is conceivable that the coefficient of log R is picking up other effects. For example, in areas where property values are high householders may tend to report a larger proportion of property crimes, possibly because the

---

[7] This last point may at first seem surprising. However, it should be recalled (see Table A.2 in Appendix to Chapter 5) that the correlations between the economic variables and either measure of the detection rate are remarkably weak. Therefore, use of a poor measure of the detection rate (i.e. the clear-up rate) does not distort the effect of the variables log R, log U, log W and log A upon the crime rate.

[8] Carr-Hill and Stern (1979) found that the sign, size and significance of log A varied greatly across time periods. However, their results usually showed no difference in significance between measures of the detection rate, except for the 1971 "restricted" set (see p.180).

contents of their homes are insured against theft. Generally in areas with high property values there will be more stealable property. This will not only tend to generate more crimes, but also to increase the proportion of crimes reported.

Other investigators have also found rateable value (per hectare) to be a significant correlate with the incidence of property crimes. For example, Baldwin and Bottoms (1976), in a study of patterns of crime in Sheffield, found that the houses most likely to be burgled were those with the highest rateable value. The Home Office Research Study Residential Burglary, which surveyed a sample of over 800 houses in Kent, also found that "... there were significantly more victims living in high rateable value houses ... than there were householders generally ... and that the risk of burglary for houses in the study area tended to increase with increasing rateable value." (Jackson and Winchester, 1982, p.10).[9] Likewise, Carr-Hill and Stern, whose study is much closer to our own than either of the previous two, found a consistently highly significant positive coefficient attaching to log R in their estimated crime equations. Of all their estimates the ones that are closest to ours in spirit are the 2SLS estimates for 1971 given in Table 6.12 (pp.206-7). There, the coefficient of log R is 0.09 (clear-up rates) and 0.17 (conviction rates). These results are remarkably consistent with our own.

It can be argued that rateable value is a rather rough and ready indicator of the stock of stealable property and hence may be a poor proxy for illegal gains. There is clearly some substance to this argument and we would not wish to claim

---

[9] 69% of the victim sample lived in houses with a high rateable value compared with 48% of householders generally.

that rateable value is an exact measure of rewards from successful criminal activity. Certainly, there is evidence to suggest that identical properties may have different assessed rateable values in different parts of the country (see, for example, Hepworth, 1978, p.105). However, of the various measures available it was felt that rateable value per hectare (reflecting not just the approximate amount of property, but also how thinly spread it is) was probably the best. The only other serious contender as a measure of illegal gains, average earnings (E), turns out to be quite strongly correlated with rateable value per hectare (see Table A.2 of Appendix to previous chapter). Experiments with replacing log R by log E in fact produced no substantially different results. We decided to stick with log R for purely practical reasons. Inclusion of log E might lead to some confusion, because its role is possibly ambiguous. It could also be interpreted as a measure of legitimate earnings, whereas log R could not. Further, log E is much more closely correlated with log W than is log R, so that introduction of log E brings with it the threat of multicollinearity and all that that entails.[10]

Turning from measures of illegal gains, there are two variables representing returns in legitimate activity. These are log U (the unemployment rate for all workers) and log W (average earnings of the lowest paid decile of males aged over 21 years). First, consider the coefficient attaching to log U. This is generally statistically significant. Indeed it is often highly significant. Whilst the elasticity of property crimes with respect to the unemployment rate may seem small (it is invariably less than 0.3) this may be slightly

---

10 The simple correlation coefficients between log E and log W in 1975 and 1976 are both 0.85. Between log R and log W they are 0.60 and 0.57 respectively.

misleading, as we shall see later when we come to consider any policy implications of the analysis.

The idea that unemployment may be an (important) determinant of crime rates seems to arouse quite strong responses both for and against.[11] As we saw in Chapter 2, the time allocation model of criminal behaviour produces a (clear and unambiguous) prediction that an increase in the unemployment rate will lead individuals to allocate more time to criminal activity. However, this result seems to emerge from the rather special assumptions that are central to that model, i.e. that leisure time is fixed. In that situation legitimate and illegal activity are directly competitive. A fall in one must lead to an increase in the other. In general the sign of the unemployment rate effect cannot be predicted unambiguously. Whether unemployment and crime are related seems then to be an empirical question.

In Chapter 3 we presented the results of a fairly large number of econometric studies of crime, some of which had included labour market variables like unemployment and participation rates. The evidence reported in that chapter was not altogether decisive about the crime-unemployment link, although in the words of one recent survey "(t)he preponderance of evidence is more favourable to a positive linkage than not ..." (Freeman, 1982, p.13). However, as Freeman rightly concludes " ... if one was anticipating an overwhelmingly strong relation one (would) be severely disappointed." (1982, p.13).[12]

---

[11] Witness, for example, the fairly strong disagreement between the Shadow Home Secretary and the Home Secretary over the causes of the Toxteth riots in 1981 and the rise in reported crime generally. The differences between academics seem almost as strong. Compare, for example, Brenner (1978) with Carr-Hill and Stern (1982).

[12] Freeman (1982) claims that one reason for the conflicting empirical findings on the effect of unemployment is that "... the labour market factors have not received ... careful attention." (p.15)

In view of the supposed link between crime and unemployment (the time allocation model) and the considerable topicality of the subject, it is interesting to see how the unemployment variable turned out. In this regard our results cannot be compared with those of Carr-Hill and Stern, who omitted unemployment from the crime equation. Their reasons for doing this were supposedly two-fold. First, as the [voluntary] unemployment rate in legitimate activity is determined simultaneously with the offence rate in time allocation models, it should not be included as an explanatory variable in the equation for the offence rate. However, as they strongly rejected a time allocation framework this seems to be a rather strange argument to use. Besides, it is not apparent that they are correct in this. In Ehrlich's model (see Chapter 2) u represents the exogenous, unknown risk of involuntary unemployment in legitimate activity. A rise in the expected value of u would lead individuals to revise their time allocations between t_i and t_l. It is not apparent that u is in any sense determined simultaneously with either t_i or t_l. Second, and perhaps more importantly, they rejected the inclusion of unemployment in the crime equation on empirical grounds, i.e. the model worked less well when unemployment was included in that equation than when it was excluded.[13]

Accordingly, none of Carr-Hill and Stern's reported regression estimates for the crime equation includes an unemployment variable. Their results, therefore, seem to be at variance with both the ones reported in this thesis and Wolpin's time series estimates for England and Wales (Wolpin, 1978). It is

---

13 However, it is interesting to note that Carr-Hill and Stern did not test the following alternative hypotheses, (i) that unemployment should appear only in the first equation or (ii) that unemployment should appear in the first and third equations of their model. These seem, on the surface, to be rather more interesting contenders than the hypotheses

interesting to speculate why this might be.

One possible reason may be that in the time periods considered by Carr-Hill and Stern (1961, 1966 and 1971) unemployment was fairly low. Whilst unemployment was rising during this period, even by 1971 it was fairly modest by comparison with recent levels. Also it is conceivable that there was rather less variation across areas in the unemployment series than in later years. After the oil crisis in 1973/4 unemployment levels increased quite dramatically, so that the data for 1975 and 1976 show substantially higher and more variable unemployment levels. Likewise, Wolpin's time series data (covering 1894-1967) encompasses a much greater variation in the unemployment series.

Finally, the low pay variable (log W) proved to be statistically insignificant in the crime equation. This does not necessarily mean that crime and low pay are unrelated, but merely that we have not been able to establish a link between the two using available data. We have already suggested reasons for this and we need only briefly restate them. One possible explanation is that the particular measure used, average earnings of the lowest paid decile of adult male workers, is a poor indicator of legitimate earnings of potential criminals. It is based upon the, perhaps not unreasonable, presumption that it is low paid workers who are on the margin between legitimate and illegal activity. So that changes in their earnings level will tip the balance between whether they do or do not observe the law. This is, of course, a presumption and if it is not valid then the particular measure of W used would not necessarily be significant. If instead one takes the view that " ... we are all criminals, or at least have the potential to be criminals given the right conditions"

(Croft, 1978, p.2), then clearly an alternative indicator would be required. For example, average earnings of <u>all</u> workers (or males). However, such a change is unlikely to dramatically affect the statistical results, because of the extremely high correlations that exist between log W and log E (r = 0.85 in both years). Indeed, inclusion of log E rather than log W in the aggregate crime equation was tried at an early stage without altering the significance of the earnings variable.

If we retain the view that it is 'low' pay that matters, because it is workers on low earnings who are more likely to commit crime, then it is still possible that there are other measures that might be more successful. We did construct several other variables such as the proportion of adult male workers earning (i) less than £30 per week or (ii) less than £50 per week. However, neither of these proved successful. One other measure which seemed to work rather better was what might be described as an index of deprivation. This was the absolute difference in earnings (in £) between the highest paid decile and the lowest paid decile of adult male workers. This variable, which we named "Inequality" seemed to work reasonably well in early trials with the aggregate 1975 model. However, it was fairly strongly correlated with log R and so it was decided not to use this variable further. However, this preliminary finding seems interesting in that it is probably low pay relative to other workers that turns people to crime rather than some absolute standard of low pay. This result confirms one found by Danziger and Wheeler (1975) using both time-series and cross-section data for the USA. They argued that their results contradicted " ... the widely held belief that low incomes per se are an important cause of crime. (I)ncreases in income which result from economic growth with a constant (income) distribution lead to higher crime rates... (It is) a greater degree of inequality (that) leads to higher crime rates." (pp.124-5)

This line of enquiry should probably be continued. However, the measure of income inequality was somewhat imprecise. Also, it was strongly correlated with log R, which on theoretical grounds was felt to have a stronger case for inclusion. It was decided, therefore, not to pursue this investigation at this time.

It remains to consider how the socio-economic variables performed in the disaggregated crime equations. The coefficients are summarised in Table 6.5 below.

TABLE 6.5 Economic variables in the disaggregated model

(i) Imprisonment used to measure severity

		1975		1976		pooled	
		con	c.u.	con	c.u.	con	c.u.
log R	B	0.13^{**}	0.22^{***}	0.09	0.20^{***}	0.15^{**}	0.18^{***}
	RB	0.36^{***}	0.35^{***}	0.35^{***}	0.49^{***}	0.44^{***}	0.42^{***}
	TH	0.16^{***}	0.17^{***}	0.14^{***}	0.14^{***}	0.14^{***}	0.15^{***}
log U	B	0.18^{*}	0.18	0.36^{***}	0.33^{*}	0.28^{***}	0.20
	RB	0.33^{**}	0.10	0.15	0.36^{*}	0.31^{***}	0.27^{**}
	TH	0.20^{**}	0.13	0.33^{***}	0.23^{*}	0.23^{***}	0.20^{***}
log W	B	-0.88	-0.64	-0.23	-1.02	-0.17	-0.35
	RB	0.22	-0.27	0.07	-1.04	-0.86^{***}	-0.52^{*}
	TH	-0.45	-0.67	-0.15	-0.21	-0.20	-0.23
log A	B	-0.55	0.60	-0.94	0.26	-0.09	0.38
	RB	0.78	0.49	1.23	2.18^{**}	1.77^{**}	1.67^{**}
	TH	0.62	1.38^{***}	1.05^{**}	1.12^{**}	0.98^{***}	1.32^{***}

(ii) Fines used to measure severity

		1975		1976		pooled	
		con	c.u.	con	c.u.	con	c.u.
log R	B	0.17***	0.23***	0.17***	0.20***	0.20***	0.20***
	TH	0.14***	0.17***	0.16***	0.16***	0.14***	0.15***
log U	B	0.36***	0.29**	0.41***	0.43**	0.37***	0.34***
	TH	0.23**	0.18**	0.27**	0.19*	0.25***	0.20***
log W	B	0.39	-0.36	0.26	-0.47	-0.05	-0.24
	TH	-0.19	-0.57	-0.49	-0.48	-0.12	-0.17
log A	B	-0.10	0.48	-0.02	0.38	0.26	0.41
	TH	0.73	1.39**	0.99**	1.11**	0.92**	1.29***

Notes: As for Table 6.1, except -
B indicates coefficients in the burglary equation
RB indicates coefficients in the robbery equation
and TH indicates coefficients in the theft equation

The coefficients reported in Table 6.5(i) are those for the economic variables when severity of punishment was measured by the imprisonment rate and average length of imprisonment. Those in Table 6.5(ii) were obtained when the average fine was used to measure punishment severity. The results are broadly similar, whichever measure of severity was used. The one possible exception to this is the coefficient of log U, which tends to be larger and have a higher t-statistic when fines are used.

Of course, these coefficients cannot all be compared with those of Carr-Hill and Stern, because they made little attempt to disaggregate the crime index.[14] Neither, strictly speaking, can they be directly compared with those of Wolpin (1978), for his was a time-series study. However, we shall attempt to draw some perhaps rather superficial comparisons between these earlier results and our own. There simply have not been any previous (simultaneous equation) estimates for disaggregated groups of crimes using cross-section data for England and Wales. Whilst this approach has been fairly common in North America, it was felt that differences in definitions, data sources and police practices were sufficient to also rule out direct comparisons with these studies.

The illegal gains proxy (log R) is highly significant in all of the crime equations and in all time periods. However, its coefficient is rather larger in the robbery equation than in either the burglary or theft equations. In the latter equations the coefficient of log R is very similar, being approximately 0.15, whereas in the robbery equation it is approximately 0.40. Perhaps surprisingly, the illegal gains proxy has its least stable effect in the burglary equation. However, we should perhaps not make too much of this. The limited amount of variation seen in Table 6.5(i) is virtually eliminated altogether from the results shown in Table 6.5(ii). All the coefficients of log R are significantly less than one, but greater than zero, indicating that recorded crimes, and by

---

14 In fact Carr-Hill and Stern analysed breaking and entering offences separately on the grounds that offences of this type were all thought to be reported. Their results, however, " ... would not support the assumption that all breaking and entering offences are recorded" (p.191). The attempt to model breaking and entering offences (roughly comparable with the burglary group in our study) was not altogether successful. Coefficients were erratic in sign and in the run using 1971 data there was not a single statistically significant coefficient in the whole model. Such a result must cast serious doubt upon the value of Carr-Hill and Stern's model and also their findings using the aggregate offence group.

implication actual crimes, are relatively inelastic with respect to changes in illegal gains. This might be regarded as a mildly optimistic conclusion, i.e. as wealth and hence the amount of property increases, property crimes rise at a slower rate, ceteris paribus.

The pattern of performance of the unemployment variable (log U) is similar. However, when imprisonment variables are used its effect is sometimes inconsistent. This slight inconsistency is eliminated when average fines are used. The effect of unemployment seems to vary relatively little across crimes, with an average elasticity of approximately 0.25. Again, property crimes seem to be relatively inelastic with respect to a change in an economic variable. However, this should not be interpreted as saying that increases in unemployment, of the order of magnitude observed between say, 1979 and 1983, have very little effect upon the number of recorded property crimes. For example, an increase in unemployment from say 5% to 10% of the labour force would represent a 100% increase in the unemployment rate, which by our average elasticity would imply a 25% increase in the number of property crimes, ceteris paribus. Given an initial figure of slightly less than 2 million recorded property crimes this would imply an increase of some 500,000 burglaries, robberies and thefts. Now whilst these calculations are very much "back of the envelope" stuff, they serve to indicate that rising unemployment could have a quite dramatic effect upon the number of recorded property crimes and that the orders of magnitude involved are not that remote from what has actually happened in the very recent past.[15] We

---

15 Between 1979 and 1982 unemployment rose from 5.3% to 11.9%. The number of recorded property crimes rose by 611,000.

discuss this further in section 6 of this chapter.

The legitimate earnings variable (log W) is always insignificant, except in the robbery equation when the data series are pooled. Pooling generally increases the t-statistics for this variable, though for the other two crime groups the coefficients remain statistically insignificant. Pooling increases the amount of variation in the data series. It is, therefore, conceivable that with more years data a significant effect of earnings upon burglary and theft rates might have been observed.

Finally, the impact of the age/sex composition variable seems mixed. It is always insignificant in the burglary equation, but is usually significant in the theft equation.[16] It is also significant in the pooled robbery equations. It seems, therefore, that young males are more likely to engage in thefts and possibly robberies than in crimes of burglary. The size of the elasticity varies quite markedly across the three types of crime.

All of the significant coefficients in Table 6.5 have their "expected" signs and indeed only a handful of the statistically insignificant coefficients have the wrong sign. This is a fairly encouraging sign that the modelling is on the right lines. The results also broadly support the economic approach which suggests that alternative employment opportunities do affect the decision to engage in criminal activity.

Comparison with Wolpin's results is complicated, because the Theft Act 1968 redefined certain offences, so that Wolpin's groups larceny, burglary and robbery do not exactly correspond

---

16 The only exception being in 1975 using conviction rates.

with ours. Further, his estimates are single equation, time-series ones, whereas ours are simultaneous equation, cross-section estimates. Unfortunately Wolpin's measures of illegal and legitimate gains perform rather badly, either being insignificant or, where they are significant, having the wrong sign. He found unemployment to be significant only in the burglary equation, although it was close to being significant in the theft equation. However, the age/sex variables (the proportion of males aged 10 to 25 years) was always highly significant.

The two sets of results could hardly be further apart. However, we have rather more faith in our results, because (i) coefficients do not behave erratically (having unexpected signs), (ii) we have used a superior methodology and estimating technique and (iii) we have grave doubts about the reliability of long-run time-series data in this field.

That, for the time being, concludes our discussion of the coefficients of the crime equations. In section 6 we will consider a number of policy issues relating to these estimates. For example, is it possible to trade-off law enforcement expenditures against one another or can we trade-off law enforcement against economic variables in order to reduce crime rates. However, before we can do that we need to examine in rather more detail the determinants of the detection rate. This is done in the next section.

3. The Determination of the Detection Rate

In the last section we found that one important factor influencing the recorded property crime rate was the detection rate and particularly the conviction rate. In discussion of policy it is interesting to ask whether/how improvements in the detection rate can be achieved. As economists we are used to thinking in terms of production functions relating outputs to inputs of resources. In this thesis we have described the equation explaining the detection rate as a production function, relating one aspect of police "output" to inputs of police resources and two workload measures.

Throughout this thesis we have used two measures of the detection rate (the clear-up rate and the conviction rate) almost interchangeably. However, from what we have learnt in the last chapter and have said in the previous section it seems sensible to now treat them separately.

They seem, in fact, to be two quite distinct and not at all closely related entities, whose explanations are quite different. We therefore consider first the determination of the conviction rate.[17] We begin by considering the effect of more police manpower.

(i) Effect of more police manpower

(a) The conviction rate

The results for each offence group and for the group all property offences are given in Table 6.6. The coefficients reported are those obtained when severity of punishment is measured by imprisonment. Parameter estimates obtained when average fines are used are given in the Appendix to this chapter.

---

17. The correlations between clear-up rates and conviction rates are not particularly strong, ranging from r = 0.39 to r = 0.65 and averaging approximately 0.50. See Table A.2 in Appendix to previous chapter.

TABLE 6.6 Effect of police manpower on the conviction rate

	1975	1976	Pooled
Burglary	<u>0.20</u>***	<u>0.34</u>***	<u>0.21</u>***
Robbery	0.56****	0.06	0.38****
Theft/Handling	0.18***	0.41****	<u>0.07</u>
All Offences	0.19***	0.42****	0.19****

Note: Where a coefficient has been underlined it indicates that it is one appearing in a modified estimate of the police production function (see Chapter 5)

All of the coefficients reported in Table 6.6 relate to estimates obtained when severity of punishment was measured by the rate and average length of imprisonment. For brevity we do not report the coefficient estimates obtained when average fines were used to measure sentence severity (in fact they are remarkably similar - see Tables 5.37 - 5.43 inclusive in the previous chapter).

In general more police manpower leads to increases in the detection rate for all types of crime. However, the elasticity varies quite substantially across crimes and across time periods. The variation over time may have been caused by a break in the series for serious traffic accidents (see below). Certainly, estimation of the pooled production functions did cause some problems with the over-identifying restrictions (see the previous chapter). This would certainly merit the exercise of some caution in interpreting the pooled regression estimates.

However, despite these problems the elasticities are all significantly less than one, indicating that the conviction rate is relatively unresponsive to variations in police manpower. They are also, normally, significantly greater than zero. In this respect our results are in marked contrast with those of Carr-Hill and Stern. Their results (1979, pp.174 -80 inclusive) suggest that the effect of more police manpower upon the conviction rate was positive in 1961 and 1966 (pooled Urban and Rural) and negative in 1971. The elasticity also varied greatly in size, from 5.09 in 1961 to 0.39 in 1966.

There seems to be very little by way of convincing argument to suggest why in some years more policemen should increase the conviction rate and in others have completely the opposite effect. Also, it is difficult to explain the rather erratic fluctuations in the size of the elasticity. Why, for example, in 1961 should a one percent increase in the size of the police force lead to a five percent increase in the conviction rate and yet only five years later the same percentage increase in manpower leads to only 0.4 percent increase in the detection rate? Even stranger why, five years further on, should a one percent increase in manpower actually cause the conviction rate to fall by one and a quarter percent?

Now, whilst the elasticities reported in Table 6.6 might be thought to exhibit some inconsistency, they certainly do not reveal the strange and erratic behaviour of the elasticities reported by Carr-Hill and Stern. On the contrary, they are all positive and lie in the range zero to one.

But what of the effect of more police manpower upon the clear-up rate? The parameter estimates are summarised in Table 6.7.

(b) The clear-up rate

Again, reported coefficients are those obtained using imprisonment variables. Estimates found using average fines are reported in the Appendix to this chapter.

TABLE 6.7 Effect of police manpower on the clear-up rate

	1975	1976	Pooled
Burglary	0.11	0.28**	0.11*
Robbery	0.10	0.29**	0.10
Theft/Handling	0.11***	0.26****	0.12***
All offences	0.12***	0.25***	0.12***

Note: see Table 6.6

Following our earlier discussion about the superiority of the conviction rate as a measure of the probability of detection, we would expect the effect of increases in police manpower to be less pronounced upon the clear-up rate than upon the conviction rate. Briefly, the reason for believing this is that police forces have rather more discretion in determining the clear-up rate than they have in determining the conviction rate. They are also likely to feel, at least, that they are under pressure to be seen to be doing at least as well as other police forces. The result is likely to be that the series on clear-up rate statistics will show rather less variation than that for conviction rates.[18] As a consequence,

[18] This, in fact, is borne out by the evidence. From Table A.1 in the Appendix to Chapter 5 we can calculate the coefficients of variation for the two series. These are as follows:

	1975	1976
conviction rate	0.055	0.051
clear-up rate	0.038	0.033

the effect of variations in police manpower will be seen to have a smaller effect upon clear-up rates than upon conviction rates.

This hypothesis seems to be well supported by the evidence. If one compares the results in Tables 6.6 and 6.7 cell by cell, then in all but two cases (robbery in 1976 and theft/handling in the pooled estimate) the ranking of elasticities is as predicted. Further, the number of elasticities that are not significantly different from zero is slightly larger in Table 6.7 than in Table 6.6 and in general significance levels are lower in Table 6.7.

Again, however, those coefficients that are statistically significantly different from zero are always positive and less than one. In that respect the results are remarkably consistent. Further, whilst there again seems to be a break between 1975 and 1976 (see later), the effect of variations in police manpower shows very little difference between crimes. This may say something more about the process by which clear-up rates are generated.

Again, this is in stark contrast with the results presented by Carr-Hill and Stern. As with their results for conviction rates, Carr-Hill and Stern reported erratic parameter estimates for the effect of police manpower upon clear-up rates. The elasticities were as follows, +1.63 (1961, Urban and Rural), -0.61 (1966, Urban and Rural) and -0.47 (1971). The change from a positive to a negative elasticity is not convincingly explained and, indeed, the existence of a negative elasticity seems unlikely. It is noticeable, however, that the reported elasticities are generally smaller for clear-up rates than for conviction rates. This result was not commented upon by Carr-Hill and Stern, at least as far as I am aware.

We feel that the results reported in this section are rather more convincing than those reported by Carr-Hill and Stern and do not require resort to ad hoc arguments such as, "... increased public awareness of the police and crime may have led to more reports of minor events which are difficult to solve or not worthwhile solving." (Carr-Hill and Stern, 1979, p.239).

We now turn to consider the effects of increased workload upon the determination of the detection rate.

(ii) <u>The effect of workload upon the detection rate</u>

The police "production function" contains two workload variables, the crime rate itself and the number of serious traffic accidents. Increases in both are expected, given a fixed amount of police resources, to reduce the detection rate. Again, we shall follow the procedure of discussing their effects first upon the conviction rate and secondly upon the clear-up rate. Also, for brevity, we shall report and discuss only the parameter estimates obtained when imprisonment variables were used to measure the severity of punishment. Parameter estimates obtained using average fines are reported in the Appendix to this chapter. As the results are so similar, irrespective of whichever measure of severity is used, we do not comment separately upon each set of results.

(a) <u>The conviction rate</u>

The results for each offence group and for the group all property offences are shown in Table 6.8.

TABLE 6.8 Effect of workload upon conviction rates

	1975	1976	Pooled	Workload Measure
Burglary	-0.53***	-0.51***	-0.51***	Crime Rate
Robbery	-0.68***	-0.42***	-0.55***	
Theft/Handling	-0.43***	-0.32**	-0.63***	
All offences	-0.45***	-0.36***	-0.35***	
Burglary	-0.19**	-0.33**	-0.19**	Traffic Accidents
Robbery	-0.48***	-0.12	-0.37***	
Theft/Handling	-0.24***	-0.51***	-0.17***	
All offences	-0.25***	-0.52***	-0.27***	

Note: See Table 6.6

With only one exception (effect of traffic accidents upon the conviction rate for robbery in 1976) all coefficients are highly significant and negative. The workload variables have their expected effects, i.e. increases in workload do reduce conviction rates. However, as with police manpower, the effect of workload varies to some extent across crimes and over time. However, all of the parameters lie in the range zero to minus one.

These results should also perhaps be contrasted with the somewhat erratic results of Carr-Hill and Stern. In fact, it is only possible to contrast the effects of an increased crime rate upon the conviction rate, because Carr-Hill and Stern did not include a workload measure based upon traffic accidents. Carr-Hill and Stern found that " ... the behaviour of y [the crime rate] is erratic as between different types of run: in 1961 its coefficient is significant negatively for p clear-up in urban areas and positively for p convictions in the pooled (urban and rural) data; in 1966 it is significant positively for p clear-up in urban areas, negatively for p clear-up in rural areas, and negatively for p convictions in the pooled data; and in 1971 it is significant positively for p convictions." (1979, pp.226-7). Not only that, but the size of the elasticity varies markedly over time. For example, in the runs for the conviction rate it is +6.52 (1961, Urban and Rural pooled), -0.15 (1966, Urban and Rural pooled) and +0.77 (1971).

As a result, Carr-Hill and Stern are forced to conclude somewhat tamely, " ... that if y correctly measures the scale of the detection task confronting the police, then overall a larger or smaller workload does not change the detective efficiency of the police. It is perhaps more likely that the influence of y on p [the detection rate] depends upon recording phenomena in a way which is difficult to disentangle." (p.227)

The results reported in Table 6.8 reveal a much more stable and consistent set of coefficients, all with the "right" signs and highly significant. One possible explanation of this difference is that Carr-Hill and Stern's modelling of the detection rate is deficient, for reasons we have outlined in Chapter 4. Certainly the results reported here seem to be much more satisfactory from a statistical point of view, at least.

However, there is one slight cause for concern, and that is that the coefficients seem to vary slightly between years. This is more noticeable for the effects of police manpower (see the previous section) and for the effects of traffic accidents. One possible explanation of this is a change in the series for traffic accidents in 1976 compared with 1975.

In the earlier year it was possible to obtain a series for the number of serious and fatal road casualties. It was felt that this would represent a reasonable proxy for the number of serious traffic accidents requiring police investigation. However, by 1976 the basis for publishing traffic accident/casualty statistics by county had changed and so it was not possible to produce a strictly comparable series. Instead, a series had to be constructed.[19] The method of construction was clearly somewhat rough and ready, but was felt to be the best available under the circumstances. In fact the mean and standard deviation of the constructed series are remarkably similar to the series for the previous year. However, there must remain some doubt as to the accuracy of the constructed series. It would, therefore, have been useful to have been able to have undertaken a test for structural change between the two years of the sample. However, we have indicated in Chapter 5 that application of the standard Chowtest for the equality of regression coefficients is not strictly valid when 2SLS estimation has been used.

(b) The clear-up rate

The results of the effects of workload upon the clear-up rate are given in Table 6.9. Again, because of the manner in which clear-up statistics are generated, we would presumably expect variations in workload to have a less pronounced effect upon clear-up rates than upon conviction rates. Again, with some minor exceptions, this expectation seems to be confirmed by the results.

---

19 The method of construction was as follows. The proportion of fatal and serious casualties in all casualties was found for Great Britain as a whole. This proportion was then applied to the total number of casualties in each county, so as to obtain an estimate of the number of fatal and serious casualties in each police force area.

<u>TABLE 6.9</u> Effect of workload upon clear-up rates

	1975	1976	Pooled	Workload Measure
Burglary	-0.16*	-0.13	-<u>0.22</u>**	Crime Rate
Robbery	-0.28***	-<u>0.25</u>***	-<u>0.27</u>***	
Theft/Handling	-0.28**	-0.29**	-<u>0.29</u>***	
All offences	-0.29***	-0.24**	-0.22***	
Burglary	-0.22**	-0.33**	-<u>0.13</u>**	Traffic Accidents
Robbery	-0.19**	-<u>0.46</u>**	-<u>0.20</u>**	
Theft/Handling	-0.25***	-0.35***	-<u>0.21</u>***	
All offences	-0.25***	-0.33***	-0.22***	

<u>Note</u>: See Table 6.6

It is also noticeable that the effect of the workload variables is remarkably constant across crimes. (However, once again there seems to be a just discernible break between the two years. This can be seen perhaps more clearly in the coefficients of log T.)

Once again, all but one of the coefficients is negative and highly significant (but less than one in absolute magnitude). The remarkable consistency of this result can again be contrasted with the rather erratic estimates obtained by Carr-Hill and Stern. They found that the crime rate exerted a significant positive effect upon clear-up rates in 1961 (coefficient estimate = +1.59) but insignificant negative effect in 1966 and 1971 (-0.43 and -0.15, respectively).[20]

---

[20] The results reported here refer to Carr-Hill and Stern's estimates for the pooled urban and rural data set in each year. They also refer to estimates of the "full" model. These results are only strictly comparable with the estimates for all offences in Tables 6.6 to 6.9 inclusive.

The remarkable degree of consistency of the parameter estimates, both with prior expectations and across crimes and over time, leave us in relatively little doubt that (i) increases in police manpower do lead to increases in both conviction rates and clear-up rates and (ii) that increases in the workload of the police have adverse effects upon their ability to "produce" conviction rates and clear-up rates. Generally, the responsiveness of conviction rates to changes in inputs and workloads is rather more pronounced.

4. Employment in the Police Service

In Chapter 4 we argued that during much of the post-War period the police service had been seriously undermanned. This led us to conclude that employment in the police service was supply constrained, so that the third equation of the model should be a supply function of police manpower. This argument guided the selection of variables which appear in that equation. We argued, in fact, that the important variables should be (i) the stock of potential recruits living in the area (M), (ii) earnings in other occupations (E) and (iii) the unemployment rate (U).[21]

The arguments of Chapter 4 led us to make some fairly unambiguous predictions about the effects of each of these three variables. Increases in M are expected to make recruitment easier, as are lower levels of E and higher levels of U. The expected signs of the coefficients are, therefore, M (positive), E (negative) and U (positive). As we can see from Table 6.10 these expectations are generally found to be consistent with

---

21 Recall that E is standing for earnings in the police service relative to those in other occupations.

the evidence, except that the coefficient of log E is always statistically insignificantly different from zero.

TABLE 6.10 Employment in the police service and labour market indicators

	1975	1976	Pooled
log M	1.01***	1.02***	1.01***
log E	-0.19	-0.36	-0.05
log U	0.35***	0.40***	0.38***

The performance of the earnings variable is disappointing, but should not be taken to indicate that employment in the police service is completely insensitive to changes in relative earnings.[22] The poor performance of this variable is more likely to be due to its inadequate measurement and also perhaps to a lack of variation in it across the sample. It is more likely to be the former, in view of the fact that pooling of the two data sets leads to no significant improvement in the performance of the earnings variable.

Attempts to improve the measurement of E were, however, largely unsuccessful. Average earnings in the police service are not published on a force by force basis. We decided, therefore, to construct an earnings variable based upon the total salary bill (including rent allowances) and average daily strength in each police force area. However, this variable, expressed as a percentage of E, was no more satisfactory than E itself. In any case there may be doubts about the value of such a measure of relative earnings. For instance, given a national salary structure for the police service it could be argued that potential recruits' expectations about

---

22 The substantial upsurge in recruitment following the Edmund Davies Report [on police pay] in 1977 would testify to the folly of taking such a view.

average earnings in the police service would be relatively constant across areas. They may not necessarily reflect the observed variations caused by differences in rank structure, overtime and so on. Be that as it may, attempts to construct more appropriate pay variables were singularly unsuccessful. This clearly represents an area where more detailed analysis of recruitment and wastage data would be justified, to see for example what kinds of occupations are competing with the police service. Also, more micro-level data may enable the construction of more useful relative earnings indicators.

The other variables perform very satisfactorily, being consistently positive (as predicted) and highly significant. The coefficients are also remarkably constant across time periods. The only variable which is included in this equation and Carr-Hill and Stern's study is U. Like them we are able to conclude that, " ... if there is high unemployment in an area then the problem of recruiting a police force is considerably eased." (Carr-Hill and Stern, 1979, p.231).[23]

We argued in Chapter 5 that other variables could conceivably be included in the manpower equation to reflect either conditions of service or recruitment efforts. In Table 5.9 we reported the results obtained when the crime rate and the detection rate were added to the list of explanatory variables. We found there that these variables were not always significant and sometimes had signs that were contrary to expectation. Further, their inclusion did not drastically alter our conclusions about the impact of the labour market variables. How-

---

[23] In fact their conclusion here seems a little strong. Unemployment was <u>not</u> significant in either 1971 or in 1961 (both rural and pooled urban and rural, the latter when clear-up rates were used). Indeed, only eight of the fourteen estimated coefficients for unemployment were significantly different from zero.

ever, for completeness estimates from the modified police manpower equations are given in Table 6.11.

TABLE 6.11 Service conditions and police employment

	1975		1976		Pooled	
	con	c.u.	con	c.u.	con	c.u.
log PC	0.40***	0.11	0.33**	0.20*	0.20**	0.10*
log CL	0.91***	0.86***	0.72***	0.74***	0.86***	0.91***

Note: See Table 6.1

Again, the coefficient of log PC is contrary to expectation and when clear-up rates are used its significance level is generally low.[24] It is conceivable, therefore, as we argued in Chapter 5, that the manpower equation is not a "pure" supply function, but possibly contains some elements of the demand side, e.g. areas with higher crime rates are allowed to have larger authorised establishments (though, in fact, the Home Office in evidence to the CPRS study Population and The Social Services denied that the crime-rate played any significant role in determining authorised establishments) or are allowed to undertake more vigorous recruitment campaigns in order to reach their establishment figure.

The coefficient of log CL is always positive (as predicted) and highly significant. It is conceivable, therefore, that areas with higher detection rates are able to recruit more easily. Perhaps more importantly, they may suffer less from premature wastage. This might be explained by higher detection rates leading to improved morale and possibly lighter workloads, less overtime and so on. This sets up a kind of vir-

---

24 In fact, given the "incorrect" sign of this coefficient, a one-tail test might be considered inappropriate. If a two-tail test had been used the significance levels would obviously have been much lower and log PC would not have been significant at all when clear-up rates were used.

tuous circle, because as fewer police officers leave the service prematurely detection rates are improved which further lowers voluntary quit rates.

This analysis is obviously somewhat speculative and the unravelling of the link between crime rates, detection rates and police employment requires rather more detailed study than we have so far given it. Indeed, it is a major research topic in its own right. We would need to analyse recruitment and wastage separately, isolating factors lying behind each and possibly engaging in detailed cohort studies. All this would take us far beyond the concerns of this thesis.

Fortunately, mis-specification of the manpower equation (if indeed it has been mis-specified) is not a great problem for us, given that we have estimated the other equations of the model by 2SLS. Any changes in the specification of the third equation, provided the model remains identified, do not change the estimates of the model's other two equations. It is those equations in which we are primarily interested and to which we now return.

5. Alternative Measures of the Probability of Detection

In Chapter 4 we argued that individuals' behaviour was influenced by their <u>perceived</u> probability of detection, which we can label as $\overline{CL}$. So far, we have assumed that $\overline{CL}$ is, in fact, exactly equal to the actual or true probability of detection, which we have previously labelled as CL^*. In this short section we wish to consider an alternative hypothesis about how $\overline{CL}$ may be determined.

Carr-Hill and Stern argued that individuals' perceptions about the probability of detection might be influenced by a number of factors including the "true" probability of detection, the number of policemen per capita and expenditure per police officer. It is, of course, extremely difficult to gain much insight into individuals' thought processes, but we wish briefly to follow one plausible, alternative approach. Instead of assuming perfect knowledge on the part of potential criminals we shall assume that they make a prediction/forecast of the probability of capture based upon evidence of police activity. That is, criminals feel that the chances of being caught increase when the police are much in evidence. More formally, we might argue that,

$$\log \overline{CL}_i = \sigma_{0i} + \sigma_{1i} \log P$$

i.e. that the perceived probability of detection is a function of the number of policemen on average daily strength in the area, so that σ_{1i} is expected to be positive.

The model of Chapter 4 section 3 can then be rewritten as:

$$\log PC_i^* = \alpha_{0i} + \alpha_{1i} \log \overline{CL}_i + \alpha_{2i} \log I_i + \alpha_{3i} \log S_i + \alpha_{4i} \log R + \alpha_{5i} \log A + \alpha_{6i} \log U + \alpha_{7i} \log \overline{CL}_{iA} + \alpha_{8i} \log W + \mu_{1i} \quad (1)$$

$$\log CL_i = \beta_{0i} + \beta_{1i} \log P + \beta_{2i} \log T + \beta_{3i} \log PC_i + \mu_{2i} \quad (2)$$

$$\log P = \gamma_0 + \gamma_1 \log M + \gamma_2 \log E + \gamma_3 \log U + \mu_3 \quad (3)$$

$$\log PC_i - \log PC_i^* = \delta_{0i} + \delta_{1i} \log CL_i + \mu_{4i} \quad (4)$$

$$\log \overline{CL}_i = \sigma_{0i} + \sigma_{1i} \log P + \mu_{5i} \quad (5)$$

Equations (4) and (5) can then be used to eliminate $\log PC_i^*$, $\log \overline{CL}_i$ and $\log \overline{CL}_{iA}$ from equation (1). This gives a modified version of equation (1), which is

$$\log PC_i = \alpha'_{oi} + \delta_{1i} \log CL_i + \alpha'_{1i} \log P + \alpha_{2i} \log I_i + \alpha_{3i} \log S_i$$
$$+ \alpha_{4i} \log R + \alpha_{5i} \log A + \alpha_{6i} \log U + \alpha'_{7i} \log P_A$$
$$+ \alpha_{8i} \log W + \mu'_{1i}. \qquad (1')$$

where
$$\alpha'_{oi} = \alpha_{oi} + \delta_{oi} + \sigma_{oi}(\alpha_{1i} + \alpha_{7i})$$
$$\alpha'_{1i} = \alpha_{1i}\sigma_{1i}$$
$$\alpha'_{7i} = \alpha_{7i}\sigma_{1i}$$
$$\mu'_{1i} = \mu_{1i} + \mu_{4i} + \mu_{5i}(\alpha_{1i} + \alpha_{7i})$$

Results of the estimation of equation (1^1) were singularly unsuccessful. Indeed, estimates of a similar version to equation (1^1)have already been reported in Table 5.7. There we saw that neither P nor P_A (in the crime equation) was statistically significant, and that the sign of δ_{1i} was contrary to expectation. On the whole, the alternative hypothesis about the determination of $\overline{CL}_i$ meets with little success.[25]

The model which assumes perfect knowledge/foresight on the part of the potential criminal seems, on the whole, to work rather better. It may just be that professional criminals have got a very good idea of the chances of "getting away with it". Certainly, their behaviour seems to be rather more consistent with such a view than it is with one which assumes they make rather crude forecasts based upon police manning levels.

6. Reduced Form of the Model

So far, the discussion has centred upon the structural

---

25 In fact the equation estimated and reported in Table 5.7 is slightly different from equation (1^1) above in that log CL_{iA} is also included. However, re-estimation of that equation, with log CL_{iA} excluded, did not alter in any way the significance levels of P and P_A or the unexpected sign of δ_{1i}. The conclusions above, therefore, remain valid.

coefficients of the model. This is quite deliberate, because we have been concerned to find out how the behaviour of criminals and police forces responds to certain other variables in the system. The structural equations of the system are the logical place to seek that information.

However, if we are interested in either using the model for forecasting changes in the endogenous variables or for suggesting possible policy measures, then the structural equations/coefficients are not sufficient.

For example, suppose that we wanted to know what the effect of an increase in the unemployment rate would be upon the crime-rate, ceteris paribus, for either forecasting or policy purposes.[26] Clearly, the unemployment rate affects the crime-rate directly through the supply of offences function. However, unemployment also has indirect effects upon the crime rate. These occur through the second and third equations of the model. An increase in the unemployment rate affects the level of police employment (via the manpower equation), which in turn affects the detection rate (via the police production function). The change in the detection rate then influences the crime rate through the supply of offences function. Of course, the indirect chain does not stop there, for there is yet another interaction set up between the crime rate and the detection rate (via the second equation).

The effect of an increase in the unemployment rate is, therefore, somewhat complicated. There is a direct effect which will tend to increase the crime rate. This also sets up

---

26 The choice of unemployment is only illustrative. Similar arguments could be developed for any other exogenous variable.

a chain of amplifying reactions (by lowering the detection rate). However, there is also an indirect effect through improving police recruitment/wastage which will tend to lower the crime-rate and this too sets off its own chain reaction.

The only way in which the total effect of all these direct and indirect influences can be established is by estimating the reduced form of the model. This is done in this section. However, we do not propose to spend a great deal of time interpreting the coefficients of the reduced form. Our main concern is with the analysis of behaviour and not with either forecasting or even with making policy proposals. However, we shall present the reduced form coefficients to illustrate what must be done before the model can be used for framing policy suggestions. It would be misleading, if not dangerous, to jump straight from a knowledge of the structure to [illegible] pronouncements about how to reduce crime (see, for example, the brief discussion of crime and unemployment mentioned earlier).

For illustrative purposes we shall examine only one set of reduced form coefficients (sometimes called multipliers). These are the coefficients derived from the structural equation estimates using the 1975 data set. They are given in Table 6.12 for both measures of the detection rate (i.e. the conviction rate and the clear-up rate).[27]

One immediately obvious feature of the multipliers in Table 6.12 is that they are generally quite small. Invariably

---

27 The reduced form is formally derived from the structural equations in the Appendix to this chapter. The structural model is over-identified and this places restrictions upon the reduced form. For this reason the reduced form parameters have to be derived from the structural coefficients. They cannot be found by estimating the unrestricted reduced form (see Goldberger, 1964, pp.364-371).

TABLE 6.12 Reduced Form, 1975 (i) CL (conviction rate)

	Endogenous Variable	Exogenous Variables										
		Ii	Si	A	U	R	CL_{iA}	W	T	E	M	Inter-cept
Crime Equations	All Offences	-0.55	-0.86	0.54	0.35	0.23	0.38	-0.66	0.44	0.06	-0.33	9.96
	Burglary	-1.56	-0.81	-0.61	0.17	0.26	0.97	1.79	0.77	0.10	-0.55	15.67
	Robbery	-0.52	-0.37	0.99	0.34	0.46	0.95	0.28	0.19	0.04	-0.22	-3.70
	Theft	-0.29	-0.74	0.93	0.23	0.24	0.08	-0.68	0.28	0.04	-0.21	9.46
Production Functions	All Offences	0.25	0.39	-0.24	-0.09	-0.11	-0.17	0.29	-0.45	-0.06	0.34	3.38
	Burglary	0.56	0.29	0.40	0.00	-0.10	-0.35	0.64	-0.55	-0.07	0.39	0.89
	Robbery	0.35	0.25	-0.67	-0.04	-0.31	-0.65	-0.19	-0.61	-0.13	0.72	9.26
	Theft	0.12	0.32	-0.40	-0.03	-0.10	-0.03	0.29	-0.36	-0.05	0.27	3.50

TABLE 6.12 Reduced Form, 1975 (ii) CL (clear-up rate)

	Endogenous Variable	Exogenous Variables										
		Ii	Si	A	U	R	CL_{iA}	W	T	E	M	Intercept
Crime Equations	All Offences	-0.17	-0.20	1.18	0.18	0.19	0.75	-0.62	0.02	0.00	-0.01	5.07
	Burglary	-0.29	-0.42	0.68	0.17	0.25	1.38	-0.73	0.18	0.02	-0.09	3.43
	Robbery	-0.61	-0.23	0.61	0.09	0.43	1.94	-0.33	0.16	0.02	-0.09	-5.00
	Theft	-0.08	-0.23	1.34	0.13	0.16	0.34	-0.65	-0.03	0.00	0.01	6.42
Production Functions	All Offences	0.05	0.06	-0.34	-0.01	-0.06	-0.22	0.18	-0.26	-0.02	0.12	5.95
	Burglary	0.05	0.07	-0.11	-0.12	-0.04	-0.22	0.12	-0.25	-0.02	0.12	5.35
	Robbery	0.17	0.07	-0.17	0.01	-0.12	-0.54	0.09	-0.23	-0.02	0.12	7.01
	Theft	0.02	0.06	-0.37	0.00	-0.05	-0.10	0.18	-0.24	-0.02	0.11	5.59

they are less than one and some are not statistically significantly different from zero e.g. those for W and E in either equation. It is noticeable too that the imprisonment multipliers are generally smaller when the clear-up rate is used than when the conviction rate is used to measure the detection rate. The reasons for this are the same as those advanced for the generally "superior" performance of the conviction rate in the structural equations and need not be restated.

On the whole the reduced form coefficients indicate that both the crime-rate and the detection rate are relatively unresponsive to changes in the exogenous variables. Of course, only a sub-set of the exogenous variables can be considered as potential policy instruments. These are principally the imprisonment variables (log I_i and log S_i), the unemployment rate (log U) and the earnings variables (log W and log E). It is possible that log CL_{iA} (the detection rate in adjacent areas) might be considered a policy instrument from a particular police force area's point of view. However, increasing detection rates in the hope of pushing crime into other localities represents a truly beggar-my-neighbour kind of policy which is not considered further here. It is arguable how far the unemployment and earnings variables can be regarded as policy weapons. The unemployment rate, for example, is presumably chosen (if it is chosen at all) in relation to macroeconomic objectives and not for the effect it might have upon the crime rate. Similar arguments could be made for doubting the usefulness of including the earnings variables in the list of policy instruments. This indicates just how little scope there is for affecting the crime-rate and the detection rate. Further, given the relatively weak multiplier effects indicated in

Table 6.12 the picture looks very pessimistic indeed.

One possible ray of hope is that the imprisonment "multipliers" tend to be somewhat larger than their corresponding structural equation coefficients. The reason for this being the negative feedback from a lower crime rate to a higher detection rate. Even so, the multipliers are not of a size to warrant optimistic claims that small increases either in the proportion of offenders sent to prison or in the average length of imprisonment would have any marked effect upon the rates of property crime.

Whilst the unemployment rate may not be legitimately regarded as a policy weapon to be used to reduce the crime rate, the reduced form multipliers indicate that rising unemployment does seem to be associated with/lead to higher crime rates. It also seems to give rise to lower detection rates, though its effect is rather more marginal on this score. This may be regarded as a somewhat controversial result arising from this study. As we have said earlier, we cannot quite understand why such a result produces such a hostile reaction. However, in view of the somewhat contentious nature of this result, we briefly re-examine the arguments in the final section of this chapter.

As far as the police forces are concerned there seems to be little in the way of encouragement. The only way they have of increasing detection rates is to improve recruitment, but many of the factors affecting this are outside their domain, e.g. the number of males living in the area, the unemployment rate etc. Obviously reductions in workload would have a beneficial effect, but here they are partly into a vicious circle. A high workload leads to a high crime rate, which in turn lowers detection rates and so on ad infinitum. One slightly radical solution might be to off-load to another body some of the burdensome police work unrelated to crime. For example, traffic patrolling might be hived off to a new enforcement authority, just as much of the work on traffic regulation was passed on to traffic wardens in the early 1960s. At the moment traffic patrolling absorbs a substantial minority of police resources (approximately 10-15%). Much of this work could be undertaken by much less expensive inputs of manpower and equipment, thus producing more resources for dealing with crime (see Home Office, 1977).

The ability of the police to produce detections is also dependent upon other parts of the criminal justice system. Harsher penalties (either more use of imprisonment or larger fines) tend to lower crime rates, which has a beneficial effect upon the detection rate. If these results are valid, then present moves towards less severe penalties are likely to have an adverse effect upon police workload and performance.

7. Incapacitation

The generally inverse relationship between the crime rate and the various law enforcement measures has so far been interpreted as indicating a general deterrent effect, i.e. potential offenders are deterred from committing crimes by the punishments imposed upon convicted offenders. An alternative interpretation, which is only briefly explored here due to lack of space, is that at least part of this inverse relationship measures an incapacitation effect, i.e. convicted offenders, when given a custodial sentence, are prevented from committing other offences.

The problem is to decide how much of the negative effect of the law enforcement variables upon crime rates is due to deterrent effects and how much is due to incapacitation effects. Clearly, fines do not incorporate incapacitation effects, so that their effect upon crime should be a pure deterrent effect. Imprisonment, however, does incorporate a possible incapacitating effect in addition to a deterrence effect. One way then of trying to isolate the deterrence and incapacitating effects of punishment is to compare the effects upon the crime rate of increases in imprisonment with increases in the size of fines. However, as a fine is a rather less severe penalty than imprisonment, a comparison of this kind may tend to overstate the incapacitating effects of custodial punishment.

In Table 6.13 we use the regression results of the previous chapter to arrive at tentative estimates of the relative sizes of these two effects of punishment for the two groups burglary and theft and handling of stolen goods. It was not possible to obtain estimates for robbery, because fines were seldom used in such cases. The fine elasticity is assumed to indicate a pure deterrent effect, whilst the imprisonment rate elasticity incorporates both a deterrent effect (assumed to be the same) and an incapacitation effect. The ratio of the two elasticities gives a lower bound to the relative effect of deterrence versus incapacitation.

TABLE 6.13 Incapacitation versus deterrence

	1975			1976			Pooled		
	I	F	F/I	I	F	F/I	I	F	F/I
Burglary	-0.77	-0.45	0.58	-0.79	-0.44	0.56	-0.52	-0.44	0.85
Theft and Handling	-0.19	-0.26	1.37	-0.02	-0.35	17.50	-0.06	-0.27	4.50

Notes: The column headed I indicates the proportionate effect upon the offence rate of a one per cent increase in the probability of imprisonment.

The column headed F indicates the proportionate effect upon the offence rate of a one per cent increase in the average fine.

The column headed F/I is the ratio of those two effects, i.e. deterrence to deterrence plus incapacitation.

The attempt to isolate deterrence and incapacitation effects, summarised in Table 6.13, is not altogether successful. For example, the ratio F/I should lie between 0 and 1. Whilst it does for burglary, it clearly does not for the crime of theft and handling. The reason for this may be that the measured imprisonment elasticities for that crime are unreliable, because imprisonment is a little used sanction against theft.

Obviously this is a somewhat rough and ready kind of exercise and one would not wish to place too much reliance upon the precise results obtained, particularly when some are quite obviously wrong. However, the results for burglary seem to suggest that the incapacitation effect of punishment is rather less important than its deterrent effect. Were such a result to be substantiated by rather more sophisticated analyses than this then it would further justify a move away from the use of imprisonment (and custodial measures generally) towards greater use of fines (and other non-custodial measures).

However, that is rather a large step to take on the basis of these so far rather feeble results. It would perhaps be safer to acknowledge that the effects of punishment upon crime (shown in Chapter 5) incorporate both a deterrent and an incapacitation effect and leave it to others to try to resolve precisely how much is accounted for by deterrence.

8. Conclusions

In this chapter we have undertaken a fairly lengthy analysis of the results of the model estimation. At various points we have suggested possible inferences that might be drawn from those results. In this final section of the thesis we wish to tie all those points together in a brief summary of what we have learned from the whole exercise.

The aims of the thesis were (i) to review the economic analysis of criminal behaviour, (ii) to survey the various econometric studies of crime and (iii) in the light of the first two stages to build and estimate an "economic" model of crime using data for England and Wales. It is the experience of the third stage of that exercise which we now wish to discuss.

The project originated from a feeling that previous attempts to test economic models of crime against data for this country (i.e. Carr-Hill and Stern, 1979 and Wolpin, 1978) were quite seriously flawed. (These weaknesses are discussed at length in Chapter 1.) Whilst the estimates discussed in the last two chapters cannot be regarded as perfect, there are grounds for feeling cautiously optimistic about the final product of the exercise.

The reasons for this optimism should perhaps be explained. First, an exceptionally high proportion of the estimated coefficients have their expected signs. This was certainly not the case with either of the studies undertaken by Carr-Hill and Stern or Wolpin. This is gratifying, because we do not then have to resort to ad hoc theorising in order to explain either the erratic or sometimes totally unexpected performance of a particular coefficient. In a sense, Carr-Hill and Stern are forced into this position to an almost alarming degree. The coefficients also behave consistently across years and on the whole do not change much in size. This result, too, is in marked contrast with those of Carr-Hill and Stern. Further, we have resisted the temptation to drop statistically insignificant variables so as to " ... provide tighter estimates for the coefficients on retained variables" (Carr-Hill and

Stern, 1979, p.162). We can only regard this as a somewhat desperate attempt to improve t-statistics. There can be no justification for such a practice on either theoretical or econometric grounds. It is fairly obvious why Carr-Hill and Stern did this if one examines their estimates for the "full" model using the 1971 data base. These are given on p.215 of their book. There are only two significant coefficients in the crime equation (out of seven) and none whatsoever in the detection rate equation. Dropping several variables from each equation makes a small improvement to the t-statistics, but even then the number of significant coefficients is low. However, more importantly, such a procedure makes a complete mockery of the earlier model-building exercise.

Second, the empirical finding that a significant simultaneous relationship exists between the crime-rate and the detection rate fully justifies the decision to build a simultaneous equation model. Further, it must cast doubt upon Wolpin's single equation results, which do not allow for this possibility.

Third, the finding that some coefficients vary across types of crime lends considerable support to studies which have disaggregated the crime index. It seems intuitively reasonable that the motivation of murderers, sex offenders, burglars and robbers and so on is likely to be different. Doubts must surround the results of any study which lumps all different types of offences into one aggregate. Further, it seems most unlikely that crimes of violence can be explained by an economic approach.[28] There seem, therefore, reasonable grounds for confining economic analyses of crime to crimes against property and within that category attempting to disaggregate into relatively homogeneous groups of crimes. This philosophy underlies the empirical work of this thesis and the results seem to justify the approach.

However, disaggregation also has its associated problems, because we do not know how police time is allocated across crimes. This does not affect the crime equations directly, but affects the police production functions. There is no obvious solution to this problem. Ad hoc solutions such as dividing up police time in proportion to the ratio of crimes of type i to all crimes is unlikely to produce radically different results, because of the virtual constancy of such ratios across police force areas. We cannot know how serious a weakness is caused by the absence of such data. It is really a matter of "feel". If one feels that the absence of detailed manpower allocation is crucial then one should ignore the disaggregated results and concentrate instead upon the aggregate results. However, the arguments in favour of disaggregation are strong, not just in terms of different criminal motivation, but also because the reporting of crime varies by type of crime (Hough and Mayhew, 1983).[29]

On the whole the statistical results offer guarded support for the economic model. In the crime equation, the deterrence variables (detection rates, imprisonment measures and average

28 However, this has not stopped economists from trying. See Pyle (1983, Chapter 4) for a survey of the econometric literature on the deterrent effect of capital punishment, for example.

29 In addition, Burrows and Tarling (1982) have shown that the clear-up rate and methods of clearance vary substantially across crimes.

fines) generally have negative effects upon the crime rate. In the same equation, the illegal gains proxy (rateable value per hectare) and the labour market indicator (the unemployment rate) both have positive effects upon the crime rate. The analysis of the police production function shows that police manpower has a positive effect and that the workload variables (crimes and traffic accidents) have negative effects upon the detection rate, whether measured by clear-up rates or conviction rates. Finally, police manpower was found to be directly related to the unemployment rate and the stock of available manpower.

A number of reservations must, however, remain. First, t-statistics are generally fairly low, so that by rather more conventional significance tests only a relatively small proportion of coefficients would be deemed to be significant. Our results are not unusual in this regard. Indeed, by comparison with Carr-Hill and Stern's earlier study of police force areas in 1971, our results are really quite good. The low t-statistics are caused by a number of factors, including the relatively limited number of observations in the sample, the limited variability in some of the data series and the probable mis-specification of what are essentially a rather complex set of relationships. Attempts to surmount these problems by pooling time-series and cross-section data introduce other problems e.g. structural change, possible serial correlation and so on.

Second, the results concerning the significance of the deterrence variables seem to be sensitive to the choice of measure of the detection rate. We have explored this point at length in earlier chapters and so do not propose to re-open that discussion. However, it seems that the clear-up rate and the conviction rate are two quite different entities. We feel that there are strong reasons for choosing the conviction rate in a study of this kind. However, the difference in the results obtained seems quite substantial, so that it would be wise to exercise caution in trying to draw conclusions about either behaviour or policy.

This leads to a third, perhaps general, point about applied economic research. Data are rarely available in the precise form that one's theoretical model would require. Empirical research in the area of crime is probably more affected by this than many other areas. In particular, we only have data on the amounts of recorded crime and not the actual amount of crime. Whilst we have attempted to surmount this problem through the recording equation of the model, this attempt is bound to be somewhat inexact. It would be safer, therefore, when interpreting coefficients to think of them as representing influences on the rates of recorded crime rather than the "true" rates of crime.

In general, therefore, one should be extremely cautious in trying to draw too many strong conclusions from an exercise of this kind. There remain a number of unanswered questions.[30] Also, at the end of an exercise such as this one feels that one should have done some things differently. For example, whilst we have disaggregated the crime index, some of the individual subgroups (e.g. theft) still encompass a disparate range of crimes. This causes two problems in modelling. First, the explanation of criminal motivation and second, differences in rates of recording across crimes. One way around this would

[30] For example, how much of the effect of imprisonment is due to incapacitation of offenders compared with a general deterrent effect (see previous section).

be to use crimes at an even lower level of disaggregation. The results of The British Crime Survey, for example, indicate that virtually all offences of motor vehicle theft are recorded. Had the results of this Survey been available at the time when this research was being planned, it is probable that we would have concentrated attention upon this single group of crimes. This would have made the research very much easier, not just because recording is not apparently a problem, but also because an index of illegal gains is readily available.

However, we hope that we have been able to push the economic analysis of crime a little further and that some of the inconsistencies of earlier studies have been successfully resolved. Obviously much remains to be done, but approaches of this kind are gradually increasing our understanding of crime and its control.

APPENDIX TO CHAPTER 6

(1) Effects of police manpower upon detection rates

In the main body of the chapter we reported estimates of the effect of police manpower upon conviction rates, when severity of punishment was measured by the imprisonment rate and the average length of imprisonment. However, we also used the average fine as an alternative measure of sentence severity. For completeness, we therefore report the elasticities found in that case. They are so similar to those previously obtained, as might be expected, that they require no further comment.

TABLE A.1 Effect upon the conviction rate

	1975	1976	Pooled
Burglary	0.22***	0.44****	0.16**
Theft/Handling	0.14***	0.38****	0.06
All Offences	0.15***	-	-

Note: See Table 6.6

TABLE A.2 Effect upon the clear-up rate

	1975	1976	Pooled
Burglary	0.12	0.26*	0.12*
Theft/Handling	0.10**	0.24***	0.09
All Offences	0.11**	-	-

Note: See Table 6.6

(2) Effects of workload upon detection rates

We report here the estimates of the coefficients of the workload variables upon (i) the conviction rate and (ii) the clear-up rate when average fines were used. The sizes and significance levels of the coefficients are so similar to those reported in the main body of Chapter (where imprisonment rates were used) that no further comments are necessary.

TABLE A.3 Effect upon the conviction rate

	1975	1976	Pooled	Workload Measure
Burglary	-0.42^{****}	-0.37^{****}	$-\underline{0.28}^{****}$	Crime Rate
Theft/Handling	-0.36^{***}	-0.23^{**}	$-\underline{0.70}^{****}$	
All Offences	-0.41^{****}	-	-	
Burglary	-0.30^{****}	-0.54^{****}	-0.23^{****}	Traffic Accidents
Theft/Handling	-0.21^{****}	-0.50^{****}	-0.14^{***}	
All Offences	-0.22^{****}	-	-	

Note: See Table 6.6

TABLE A.4 Effect upon the clear-up rate

	1975	1976	Pooled	Workload Measure
Burglary	-0.19^{**}	-0.12	$-\underline{0.26}^{***}$	Crime Rate
Theft/Handling	-0.25^{***}	-0.23^{***}	$-\underline{0.23}^{****}$	
All Offences	-0.27^{***}	-	-	
Burglary	-0.22^{***}	-0.31^{**}	$-\underline{0.13}^{**}$	Traffic Accidents
Theft/Handling	-0.24^{****}	-0.34^{****}	-0.19^{****}	
All Offences	-0.24^{****}	-	-	

Note: See Table 6.6

(3) Derivation of the reduced form from the Structural Equations

The partial reduced form of the model, derived previously in Chapter 4, is given by (ignoring the stochastic terms),

(1) $\log PC_i = \alpha'_{0i} + \alpha'_{1i} \log CL_i + \alpha_{2i} \log I_i + \alpha_{3i} \log S_i + \alpha_{4i} \log R + \alpha_{5i} \log A + \alpha_{6i} \log U + \alpha'_{7i} \log CL_{iA} + \alpha_{8i} \log W$

(2) $\log CL_i = \beta_{0i} + \beta_{1i} \log P + \beta_{2i} \log T + \beta_{3i} \log PC_i$

(3) $\log P = \gamma_0 + \gamma_1 \log M + \gamma_2 \log E + \gamma_3 \log U$

if we substitute (3) into (2) we obtain,

(2a) $\log CL_i = (\beta_{0i} + \beta_{1i} \gamma_0) + \beta_{1i} \gamma_1 \log M + \beta_{1i} \gamma_2 \log E + \beta_{1i} \gamma_3 \log U + \beta_{2i} \log T + \beta_{3i} \log PC_i$

Equations (1) and (2a) can now be solved for $\log PC_i$ and $\log CL_i$

This gives,

(4) $\log PC_i = [1 - \alpha'_{1i} \beta_{3i}]^{-1} \Big\{ [\alpha'_{0i} + \alpha'_{1i} (\beta_{0i} + \beta_{1i} \gamma_0)] + \alpha_{2i} \log I_i + \alpha_{3i} \log S_i + \alpha_{4i} \log R + \alpha_{5i} \log A + [\alpha_{6i} + \alpha'_{1i} \beta_{1i} \gamma_3] \log U + \alpha'_{7i} \log CL_{iA} + \alpha_{8i} \log W + \alpha'_{1i} \beta_{2i} \log T + \alpha'_{1i} \beta_{1i} \gamma_3 \log E + \alpha'_{1i} \beta_{1i} \gamma_1 \log M \Big\}$

and

(5) $\log CL_i = [1 - \alpha'_{1i} \beta_{3i}]^{-1} \Big\{ [\beta_{3i} \alpha_{0i} + \beta_{0i} + \beta_{1i} \gamma_0] + \beta_{3i} \alpha_{2i} \log I_i + \beta_{3i} \alpha_{3i} \log S_i + \beta_{3i} \alpha_{4i} \log R + \beta_{3i} \alpha_{5i} \log A + [\beta_{3i} \alpha_{6i} + \beta_{1i} \gamma_3] \log U + \beta_{3i} \alpha'_{7i} \log CL_{iA} + \beta_{3i} \alpha_{8i} \log W + \beta_{2i} \log T + \beta_{1i} \gamma_2 \log E + \beta_{1i} \gamma_1 \log M \Big\}$

STATISTICAL APPENDIX.

TABLE A-1

Crime rates and criminal justice variables for each police force area in England and Wales in 1975

Police Force Area	PCR	BURG	ROB	THSG	CUR	CURB	CURR
AVON AND SOMERSET	2776.4	661.7	9.0	2105.7	37.5	28.5	45.4
BEDFORDSHIRE	3455.1	945.9	21.2	2488.0	42.6	32.8	43.3
CAMBRIDGESHIRE	3857.7	818.2	8.3	3031.2	49.7	44.2	45.7
CHESHIRE	2440.3	782.1	7.5	1650.7	47.9	39.0	61.8
CLEVELAND	3898.5	1343.5	9.7	2545.3	54.7	45.4	58.2
CUMBRIA	2812.2	681.1	5.5	2125.6	53.1	44.8	57.7
DERBYSHIRE	2921.4	987.0	13.5	1920.9	41.8	33.6	56.7
DEVON AND CORNWALL	2377.4	531.8	7.2	1838.3	43.6	39.6	39.2
DORSET	3342.1	804.3	8.6	2529.2	39.5	31.6	53.1
DURHAM	3074.9	1054.0	7.7	2013.2	50.3	43.1	66.0
DYFED-POWYS	1842.9	500.6	3.1	1339.2	54.6	48.2	100.0
ESSEX	2842.4	722.2	11.9	2108.2	41.3	35.6	44.4
GLOUCESTERSHIRE	2435.4	657.1	9.0	1769.3	46.0	41.5	54.5
GREATER MANCHESTER	4473.8	1423.3	20.2	3030.3	45.9	39.8	55.4
GWENT	3263.8	869.3	13.9	2380.6	51.8	44.1	55.7
HAMPSHIRE	3241.6	844.4	12.7	2384.5	41.0	35.1	44.4
HERTFORDSHIRE	3120.6	648.9	11.5	2460.2	43.6	36.1	58.7
HUMBERSIDE	3840.6	1216.7	16.3	2607.6	40.1	30.9	54.3
KENT	2559.7	728.7	9.5	1821.5	35.4	25.2	43.1
LANCASHIRE	2759.1	926.5	6.9	1825.7	52.7	49.3	68.1
LEICESTERSHIRE	2437.4	632.8	9.0	1795.6	51.6	52.1	58.7
LINCOLNSHIRE	2221.8	578.4	7.5	1635.9	52.4	43.7	71.8
MERSEYSIDE	6089.9	2163.4	67.6	3858.9	37.6	28.8	27.1
NORFOLK	2381.4	635.5	8.3	1737.6	45.3	35.0	65.5
NORTHANTS	3040.9	952.4	13.0	1988.8	45.5	39.2	47.7
NORTHUMBRIA	4898.8	1711.4	20.8	3166.6	47.6	37.8	57.7
NORTH WALES	3036.3	949.1	11.7	2075.5	45.9	37.2	62.9
NORTH YORKSHIRE	2461.1	658.1	4.0	1798.2	48.9	42.4	57.7
NOTTINGHAMSHIRE	5460.0	1618.5	56.2	3785.3	50.9	51.9	80.8
SOUTH WALES	4146.1	1398.2	21.0	2726.9	37.0	30.8	39.1
SOUTH YORKSHIRE	3158.1	1006.9	12.8	2138.4	51.4	43.0	64.9
STAFFORDSHIRE	2262.1	677.8	10.6	1574.2	50.5	40.8	58.1
SUFFOLK	2229.7	536.0	9.3	1684.4	50.5	43.7	69.8
SURREY	2514.4	687.2	8.9	1818.3	41.2	33.3	53.8
SUSSEX	2737.6	632.4	8.9	2096.3	52.0	42.6	63.2
THAMES VALLEY	2858.3	799.3	13.0	2046.0	39.4	31.6	57.5
WARWICKSHIRE	2076.1	572.5	7.2	1496.4	46.5	44.4	44.1
WEST MERCIA	1995.7	459.9	5.4	1530.4	50.3	46.3	60.8
WEST MIDLANDS	3903.6	1195.1	24.6	2683.9	34.2	34.1	39.4
WEST YORKSHIRE	4679.3	1655.9	26.1	2997.3	47.9	45.6	43.6
WILTSHIRE	3160.1	773.1	7.8	2379.2	41.6	30.3	60.0

TABLE A-1 (continued)

Crime rates and criminal justice variables for each police force area in England and Wales in 1975

Police Force Area	CURT	CON	CONB	CONR	CONT	CURA	CURBA
AVON AND SOMERSET	40.3	22.7	17.0	53.8	24.4	44.8	37.4
BEDFORDSHIRE	46.4	23.0	16.4	57.7	25.2	44.8	37.8
CAMBRIDGESHIRE	51.2	17.1	15.9	58.7	17.3	46.7	39.8
CHESHIRE	52.1	27.5	22.0	76.5	29.9	45.4	37.8
CLEVELAND	59.6	29.8	20.7	56.4	34.5	49.5	42.8
CUMBRIA	55.8	27.0	25.2	53.9	27.5	50.0	43.2
DERBYSHIRE	46.0	20.1	13.9	46.7	23.2	49.3	44.6
DEVON AND CORNWALL	44.7	30.9	25.4	57.7	32.4	38.5	30.1
DORSET	42.0	19.5	13.5	36.7	21.4	41.0	33.4
DURHAM	54.0	23.1	19.6	55.3	24.8	51.3	42.6
DYFED-POWYS	57.0	24.2	24.2	92.3	24.1	46.3	39.6
ESSEX	43.2	23.0	17.7	49.4	24.7	40.2	32.9
GLOUCESTERSHIRE	47.6	26.1	14.1	52.3	28.5	44.5	37.5
GREATER MANCHESTER	48.8	25.6	19.8	53.9	28.1	45.8	39.3
GWENT	54.6	28.7	24.8	60.7	29.9	45.0	39.1
HAMPSHIRE	43.1	20.2	16.3	40.4	21.5	42.8	33.9
HERTFORDSHIRE	45.5	19.6	18.3	39.1	19.8	38.8	31.9
HUMBERSIDE	44.4	23.6	17.4	55.1	26.4	50.5	45.3
KENT	39.4	19.0	14.5	52.6	20.6	38.8	31.7
LANCASHIRE	54.3	32.4	26.9	78.7	34.9	46.8	40.3
LEICESTERSHIRE	51.4	23.7	19.6	80.0	24.8	48.4	42.5
LINCOLNSHIRE	55.4	28.7	22.7	64.1	30.7	47.3	42.2
MERSEYSIDE	42.7	18.0	11.9	18.0	21.4	49.0	42.7
NORFOLK	49.0	22.3	18.4	70.9	23.6	51.0	43.8
NORTHANTS	48.4	25.7	20.3	29.2	28.3	47.2	41.5
NORTHUMBRIA	52.8	20.0	16.5	44.0	21.8	51.5	44.0
NORTH WALES	49.8	23.3	19.0	42.9	25.1	51.0	44.5
NORTH YORKSHIRE	51.2	25.9	20.2	42.3	28.0	50.0	43.2
NOTTINGHAMSHIRE	50.1	18.5	13.3	15.4	20.8	47.4	40.7
SOUTH WALES	40.2	22.2	16.1	35.0	25.3	53.5	46.2
SOUTH YORKSHIRE	55.2	25.5	18.9	64.3	28.4	46.0	40.9
STAFFORDSHIRE	54.6	27.0	21.9	54.3	28.9	45.5	41.6
SUFFOLK	52.6	27.9	21.2	39.6	30.0	44.3	38.3
SURREY	44.1	18.8	14.7	43.1	20.2	37.6	29.9
SUSSEX	54.8	22.5	17.5	43.0	24.0	39.0	31.2
THAMES VALLEY	42.3	19.8	14.6	43.0	21.7	41.2	34.2
WARWICKSHIRE	47.3	24.9	20.4	32.4	26.5	45.0	39.9
WEST MERCIA	51.4	26.8	24.7	80.4	27.3	47.4	41.2
WEST MIDLANDS	34.1	19.5	15.9	36.8	21.0	49.3	43.8
WEST YORKSHIRE	49.2	20.2	15.6	37.4	22.6	48.2	41.6
WILTSHIRE	45.3	22.2	16.2	47.5	24.4	40.6	33.7

TABLE A-1 (continued)

Crime rates and criminal justice variables for
each police force area in England and Wales in 1975

Police Force Area	CURRA	CURTA	CONA	CONBA	CONRA	CONTA	IMP
AVON AND SOMERSET	52.5	46.8	25.5	18.8	51.0	27.2	6.0
BEDFORDSHIRE	52.4	46.9	20.5	17.3	42.5	21.8	5.4
CAMBRIDGESHIRE	57.5	49.0	24.2	19.3	53.8	25.9	5.7
CHESHIRE	53.5	48.9	23.5	18.5	49.4	25.7	5.9
CLEVELAND	61.9	52.6	24.5	19.9	48.8	26.4	5.4
CUMBRIA	62.4	53.1	25.4	20.8	55.1	27.4	4.1
DERBYSHIRE	58.4	51.1	24.1	18.9	51.8	26.3	4.7
DEVON AND CORNWALL	49.3	41.2	21.1	15.3	45.3	22.9	6.2
DORSET	47.3	43.4	24.0	18.7	49.9	25.6	7.3
DURHAM	57.8	54.9	25.7	20.7	49.2	28.0	4.2
DYFED-POWYS	54.6	49.0	25.3	21.2	54.8	26.9	5.8
ESSEX	48.6	42.4	20.9	15.9	41.7	21.0	4.9
GLOUCESTERSHIRE	53.9	46.9	24.2	19.6	53.0	25.6	5.3
GREATER MANCHESTER	51.5	48.9	23.6	18.1	51.5	26.4	5.3
GWENT	60.0	47.3	24.4	19.2	62.8	25.9	3.2
HAMPSHIRE	57.5	45.7	20.6	15.3	42.7	22.3	6.0
HERTFORDSHIRE	43.3	41.2	20.7	14.9	45.5	21.2	5.7
HUMBERSIDE	68.8	53.0	24.7	18.8	46.5	27.0	4.8
KENT	46.8	41.3	21.4	14.9	38.6	21.5	5.7
LANCASHIRE	48.3	49.5	23.3	18.5	41.1	25.5	6.4
LEICESTERSHIRE	57.8	50.4	23.1	18.3	43.0	25.1	6.4
LINCOLNSHIRE	58.8	49.1	21.8	17.5	51.6	23.5	4.6
MERSEYSIDE	61.8	51.7	28.5	22.9	69.7	31.0	4.8
NORFOLK	62.4	53.1	24.6	19.9	54.1	26.0	7.3
NORTHANTS	53.5	49.0	22.9	18.3	56.0	24.4	4.8
NORTHUMBRIA	61.9	54.9	25.1	22.4	54.6	26.2	4.3
NORTH WALES	74.2	53.5	26.2	23.6	83.1	27.1	4.0
NORTH YORKSHIRE	59.0	53.2	26.0	20.6	57.3	28.4	5.2
NOTTINGHAMSHIRE	61.3	50.5	24.3	18.5	62.0	26.7	5.0
SOUTH WALES	77.9	55.8	26.5	24.5	76.5	27.0	6.0
SOUTH YORKSHIRE	58.6	48.2	21.7	16.1	39.4	24.2	4.6
STAFFORDSHIRE	53.6	47.1	23.8	19.4	58.8	25.5	4.4
SUFFOLK	51.9	47.8	20.8	17.3	59.7	21.9	5.3
SURREY	46.8	40.5	20.4	14.5	39.5	21.0	5.4
SUSSEX	47.1	42.2	19.3	15.2	45.4	20.8	6.4
THAMES VALLEY	48.0	43.4	22.6	16.3	40.0	23.5	6.3
WARWICKSHIRE	54.2	47.0	23.6	18.1	52.8	25.5	4.8
WEST MERCIA	59.6	49.6	25.2	20.3	56.0	26.7	5.3
WEST MIDLANDS	54.3	51.1	26.2	22.3	55.7	27.6	5.7
WEST YORKSHIRE	60.6	51.1	25.9	19.9	57.2	28.5	7.0
WILTSHIRE	51.0	43.1	21.7	15.1	45.2	23.5	3.8

TABLE A-1 (continued).

Crime rates and criminal justice variables for each police force area in England and Wales in 1975

Police Force Area	IMPB	IMPR	IMPT	SENT	SENTB	SENTR	SENTT
AVON AND SOMERSET	13.0	42.2	4.1	334	395	1133	215
BEDFORDSHIRE	9.1	23.3	4.1	402	436	949	321
CAMBRIDGESHIRE	11.5	55.6	3.8	447	520	1368	267
CHESHIRE	10.8	44.2	3.7	439	423	1626	293
CLEVELAND	9.9	58.1	3.6	306	347	989	202
CUMBRIA	7.9	28.6	2.9	341	428	1460	214
DERBYSHIRE	9.6	23.2	2.9	372	442	1159	211
DEVON AND CORNWALL	12.8	55.4	4.4	345	393	1557	207
DORSET	16.7	38.9	5.3	375	527	1276	240
DURHAM	6.1	53.9	2.9	345	420	685	227
DYFED-POWYS	10.2	66.7	3.6	378	392	1275	216
ESSEX	11.1	44.3	3.0	479	515	1227	320
GLOUCESTERSHIRE	15.5	21.7	3.6	258	300	803	194
GREATER MANCHESTER	7.9	32.5	4.0	354	393	1232	238
GWENT	5.5	37.8	2.1	384	435	898	235
HAMPSHIRE	11.0	41.3	4.3	396	492	957	276
HERTFORDSHIRE	12.4	61.1	3.6	479	543	1268	306
HUMBERSIDE	8.7	34.2	3.2	368	405	1137	231
KENT	11.5	38.9	3.7	427	496	1103	270
LANCASHIRE	10.4	48.7	4.5	319	337	1289	213
LEICESTERSHIRE	12.5	45.0	4.1	442	478	1212	275
LINCOLNSHIRE	10.1	32.0	2.9	379	463	1183	220
MERSEYSIDE	8.0	28.0	3.4	373	394	1233	254
NORFOLK	15.3	66.7	4.2	522	588	1139	309
NORTHANTS	9.6	26.3	3.1	372	400	1020	304
NORTHUMBRIA	7.6	22.2	2.7	346	399	845	233
NORTH WALES	6.8	33.3	2.7	358	387	1357	214
NORTH YORKSHIRE	11.5	54.6	3.4	317	287	1033	214
NOTTINGHAMSHIRE	10.0	35.3	3.4	387	477	1118	229
SOUTH WALES	8.8	54.2	4.6	389	472	1163	238
SOUTH YORKSHIRE	7.7	34.3	3.3	375	444	994	235
STAFFORDSHIRE	8.3	31.6	2.8	385	412	959	278
SUFFOLK	10.5	33.3	3.9	467	642	1251	311
SURREY	10.2	35.7	3.7	488	618	1094	330
SUSSEX	13.3	26.5	4.8	326	374	1247	257
THAMES VALLEY	12.1	44.2	4.3	424	489	1092	289
WARWICKSHIRE	8.0	27.3	3.8	343	432	1460	241
WEST MERCIA	10.3	58.5	3.3	482	634	1186	302
WEST MIDLANDS	8.6	34.7	4.3	409	453	1066	294
WEST YORKSHIRE	11.8	37.0	4.7	364	427	990	234
WILTSHIRE	10.3	36.8	2.2	384	433	1093	254

TABLE A-1 (continued)

Crime rates and criminal justice variables for each police force area in England and Wales in 1975

Police Force Area	POL	CIV	VEH	AVF	AVFB	AVFT
AVON AND SOMERSET	2738	956	582	31.5	33.4	31.2
BEDFORDSHIRE	824	338	172	32.7	33.5	32.7
CAMBRIDGESHIRE	1008	418	228	21.8	22.4	20.6
CHESHIRE	1699	552	417	26.5	25.4	26.7
CLEVELAND	1331	395	209	21.4	22.4	21.3
CUMBRIA	1028	288	256	17.5	18.3	17.4
DERBYSHIRE	1517	820	292	24.4	20.5	25.2
DEVON AND CORNWALL	2643	961	530	24.0	25.5	23.8
DORSET	1066	375	197	29.0	35.3	28.2
DURHAM	1328	619	288	56.9	20.3	66.2
DYFED-POWYS	903	264	173	25.5	30.4	24.9
ESSEX	2281	884	539	32.4	55.7	28.8
GLOUCESTERSHIRE	1001	312	236	29.3	31.7	28.9
GREATER MANCHESTER	5760	2129	1039	23.0	25.8	22.5
GWENT	937	254	160	16.9	18.8	16.6
HAMPSHIRE	2765	970	813	26.8	26.0	26.9
HERTFORDSHIRE	1363	611	352	28.3	25.1	28.8
HUMBERSIDE	1731	673	312	19.9	20.2	19.8
KENT	2395	1270	704	27.9	26.0	28.2
LANCASHIRE	2983	1165	561	28.8	31.0	28.4
LEICESTERSHIRE	1601	547	340	29.7	32.2	29.3
LINCOLNSHIRE	1147	400	257	20.3	18.1	20.6
MERSEYSIDE	3977	1129	590	28.5	27.1	28.7
NORFOLK	1176	338	264	25.0	26.2	24.8
NORTHANTS	867	356	197	24.1	25.2	23.9
NORTHUMBRIA	3183	1033	520	23.2	22.9	23.3
NORTH WALES	1208	413	265	16.7	20.6	15.9
NORTH YORKSHIRE	1284	469	292	21.4	26.5	20.6
NOTTINGHAMSHIRE	2087	805	425	21.3	21.9	21.2
SOUTH WALES	2917	1151	519	21.5	20.5	21.6
SOUTH YORKSHIRE	2411	888	405	18.7	19.2	18.6
STAFFORDSHIRE	1992	728	470	23.9	24.6	23.7
SUFFOLK	1009	417	222	29.5	20.5	30.8
SURREY	1331	455	258	29.3	27.4	29.7
SUSSEX	2740	978	674	29.9	24.9	30.5
THAMES VALLEY	2844	1200	707	29.2	27.7	29.5
WARWICKSHIRE	831	294	237	23.0	19.7	23.6
WEST MERCIA	1561	666	443	24.5	25.4	24.4
WEST MIDLANDS	5462	2228	1017	30.6	29.5	30.8
WEST YORKSHIRE	4495	1618	813	25.6	25.2	25.7
WILTSHIRE	936	378	251	25.3	23.4	25.7

Notes for Table A-1

1. PCR is the number of all recorded property crimes, i.e. crimes of burglary, robbery and theft and handling stolen goods, per 100,000 population.

2. BURG is the number of recorded crimes of burglary per 100,000 population.

3. ROB is the number of recorded crimes of robbery per 100,000 population.

4. THSG is the number of recorded crimes of theft and handling stolen goods per 100,000 population.

5. CUR is the clear up rate for all recorded property crimes.

6. CURB is the clear up rate for recorded crimes of burglary.

7. CURR is the clear up rate for recorded crimes of robbery.

8. CURT is the clear up rate for recorded crimes of theft and handling stolen goods.

9. CON is the conviction rate for all recorded property crimes i.e. the ratio of those found guilty to the number of recorded crimes.

10. CONB is the conviction rate for recorded crimes of burglary.

1. CONR is the conviction rate for recorded crimes of robbery.

12. CONT is the conviction rate for recorded crimes of theft and handling stolen goods.

13. CURA is average clear up rate for all recorded property crimes in adjacent (i.e. contiguous) police force areas.

14. CURBA is the average clear up rate for recorded crimes of burglary in contiguous police force areas.

15. CURRA is the average clear up rate for recorded crimes of robbery in contiguous police force areas.

16. CURTA is the average clear up rate for recorded crimes of theft and handling stolen goods in contiguous police force areas.

17. CONA is the average conviction rate for all recorded property crimes in contiguous police force areas.

18. CONBA is the average conviction rate for recorded crimes of burglary in contiguous police force areas.

19. CONRA is the average conviction rate for recorded crimes of robbery in contiguous police force areas.

20. CONTA is the average conviction rate for recorded crimes of theft and handling stolen goods in contiguous police force areas.

21. IMP is the percentage of those found guilty of all property crimes (including those cautioned) who were sentenced to immediate imprisonment.

22. IMPB is the percentage of those found guilty of burglary (including those cautioned) who were sentenced to immediate imprisonment.

23. IMPR is the percentage of those found guilty of robbery (including those cautioned) who were sentenced to immediate imprisonment.

24. IMPT is the percentage of those found guilty of theft and handling stolen goods (including those cautioned) who were sentenced to immediate imprisonment.

25. SENT is the average length of imprisonment (in days) imposed by the courts upon those sentenced to immediate imprisonment for all property crimes.

26. SENTB is the average length of imprisonment (in days) imposed by the courts upon those sentenced to immediate imprisonment for burglary.

27. SENTR is the average length of imprisonment (in days) imposed by the courts upon those sentenced to immediate imprisonment for robbery.

28. SENTT is the average length of imprisonment (in days) imposed by the courts upon those sentenced to immediate imprisonment for theft and handling of stolen goods.

29. POL is the number of policemen on average daily strength in each police force area.

30. CIV is the number of full-time equivalent civilians employed by each police force area.

31. VEH is the number of police vehicles including motorcycles and vans.

32. AVF is the average fine (in £) imposed upon those convicted of property offences.

33 AVFB is the average fine (in £) imposed upon those convicted of burglary offences.

34. AVFT is the average fine (in £) imposed upon those convicted of theft and handling offences.

Sources

1. PCR, BURG, ROB and THSG.

   a. numbers of recorded crimes obtained from Criminal Statistics 1975 Table VI London: HMSO (Cmnd 6566)

   b. population figures obtained from Police Force and Regional Crime Squad Statistics 1975-6 Actuals London: CIPFA Statistical Information Service

2. CUR, CURB, CURR and CURT.

   Obtained from unpublished statistics made available by the Home Office.

3. CON, CONB, CONR and CONT.

   Numbers found guilty at Crown Courts and Magistrates' Courts, numbers cautioned, and numbers of recorded crimes obtained from Criminal Statistics 1975 Tables IX, XI, VII and VI respectively London: HMSO (Cmnd 6566)

4. CURA, CURBA, CURRA and CURTA

   Calculated from 2. above.

5. CONA, CONBA, CONRA and CONTA

   Calculated from 3. above.

6. IMP, IMPB, IMPR and IMPT

   Calculated from unpublished statistics made available by the Home Office.

7. SENT, SENTB, SENTR and SENTT

   Calculated from unpublished statistics made available by the Home Office.

8. POL and CIV

   Obtained from Police Force and Regional Crime Squad Statistics 1975-6 Actuals London: CIPFA Statistical Information Service

9. VEH

   Annual Reports of Chief Constables of Police Force Areas plus private communications to the author.

10. AVF, AVFB and AVFT

    Calculated from unpublished statistics made available by the Home Office.

TABLE A-2

Socio-economic and demographic variables for each police force area in England and Wales in 1975

Police Force Area	POP	AGE	NEWC	WIND	MALE	POPDEN	UNEMP
AVON AND SOMERSET	1321.3	7.2	12.9	4.1	144.3	2.8	4.9
BEDFORDSHIRE	489.5	7.3	33.4	11.0	55.4	4.0	4.3
CAMBRIDGESHIRE	551.1	7.8	14.7	2.2	67.4	1.6	3.6
CHESHIRE	910.9	6.9	5.0	0.7	97.7	3.9	5.1
CLEVELAND	565.4	7.8	7.7	0.3	64.0	9.7	6.4
CUMBRIA	473.8	7.1	3.7	0.3	49.9	0.7	5.5
DERBYSHIRE	887.4	6.9	11.3	3.1	94.3	3.4	4.1
DEVON AND CORNWALL	1338.5	6.6	10.1	0.7	134.0	1.3	8.6
DORSET	572.9	7.1	10.7	0.8	60.4	2.2	7.0
DURHAM	607.6	7.2	3.3	0.3	66.3	2.5	6.7
DYFED-POWYS	422.5	7.2	3.5	0.3	45.4	0.4	7.6
ESSEX	1341.6	7.0	10.3	1.3	155.1	3.7	5.1
GLOUCESTERSHIRE	487.6	7.4	13.7	4.0	53.3	1.8	4.8
GREATER MANCHESTER	2702.8	7.2	17.2	3.9	297.2	21.0	4.9
GWENT	440.1	7.2	5.2	1.0	47.3	3.2	6.9
HAMPSHIRE	1560.4	7.7	18.1	1.7	180.9	3.8	4.8
HERTFORDSHIRE	800.7	7.6	16.7	3.4	107.8	5.4	2.7
HUMBERSIDE	848.2	7.3	5.0	0.4	92.7	2.4	6.7
KENT	1445.4	7.0	15.9	1.3	154.3	3.9	4.8
LANCASHIRE	1369.2	6.6	14.1	0.9	138.4	4.5	5.9
LEICESTERSHIRE	836.5	7.5	35.2	4.1	97.0	3.3	4.5
LINCOLNSHIRE	521.3	7.2	7.8	0.6	57.4	0.9	5.4
MERSEYSIDE	1588.4	8.0	5.8	1.0	183.7	24.5	10.0
NORFOLK	659.3	6.9	6.8	0.7	70.5	1.2	5.5
NORTHANTS	500.1	7.1	13.0	4.8	55.7	2.1	3.6
NORTHUMBRIA	1475.6	7.5	4.6	0.3	164.5	2.6	7.5
NORTH WALES	599.0	7.2	3.9	0.3	64.4	1.0	9.8
NORTH YORKSHIRE	646.1	7.5	8.0	0.7	71.4	0.8	4.2
NOTTINGHAMSHIRE	982.7	7.2	14.9	6.5	107.6	4.5	4.5
SOUTH WALES	1306.6	7.2	6.0	1.1	140.5	5.8	6.3
SOUTH YORKSHIRE	1317.5	7.2	9.1	3.1	144.0	8.4	5.1
STAFFORDSHIRE	988.4	7.2	7.0	1.6	111.7	3.6	4.0
SUFFOLK	570.0	7.4	10.8	3.2	64.2	1.5	4.5
SURREY	727.6	7.4	17.4	2.0	110.7	4.9	2.7
SUSSEX	1280.4	6.2	14.4	1.3	119.6	3.4	4.0
THAMES VALLEY	1699.2	7.8	25.5	6.0	202.3	3.0	3.6
WARWICKSHIRE	471.8	7.1	18.0	2.8	52.9	2.4	4.7
WEST MERCIA	940.4	7.1	8.2	1.3	103.2	1.3	5.0
WEST MIDLANDS	2777.5	7.4	48.6	15.0	314.3	30.9	5.8
WEST YORKSHIRE	2082.6	7.2	27.3	5.1	226.9	10.2	4.7
WILTSHIRE	511.6	7.7	17.0	2.4	59.8	1.5	4.8

TABLE A-2 (continued)

Socio-economic and demographic variables for each police force area in England and Wales in 1975

Police Force Area	POOR	EARN	RVH	TA
AVON AND SOMERSET	37.1	59.6	314.5	2238
BEDFORDSHIRE	40.2	60.1	564.5	832
CAMBRIDGESHIRE	34.1	59.1	195.9	1033
CHESHIRE	38.9	61.7	499.0	1044
CLEVELAND	40.4	64.8	1188.9	710
CUMBRIA	37.2	57.9	61.8	862
DERBYSHIRE	38.4	59.9	345.0	1244
DEVON AND CORNWALL	33.2	52.7	135.5	2553
DORSET	35.4	55.8	276.9	1158
DURHAM	38.7	59.7	211.2	823
DYFED-POWYS	33.5	51.8	32.3	1626
ESSEX	38.7	61.1	573.9	2904
GLOUCESTERSHIRE	35.6	56.3	213.5	1366
GREATER MANCHESTER	37.2	58.5	2356.1	2846
GWENT	38.8	59.1	301.7	518
HAMPSHIRE	37.0	60.5	459.3	2837
HERTFORDSHIRE	40.3	62.2	1019.4	1403
HUMBERSIDE	36.2	59.1	251.6	1198
KENT	37.8	61.0	437.3	2818
LANCASHIRE	35.4	56.3	423.0	1716
LEICESTERSHIRE	37.2	57.6	377.6	967
LINCOLNSHIRE	34.3	53.6	85.5	985
MERSEYSIDE	38.3	60.8	2887.3	1582
NORFOLK	34.3	55.1	140.3	1454
NORTHANTS	36.3	59.1	250.1	1615
NORTHUMBRIA	38.0	59.5	256.2	1507
NORTH WALES	38.1	56.5	87.7	1023
NORTH YORKSHIRE	33.3	54.0	75.0	1485
NOTTINGHAMSHIRE	37.8	60.4	493.1	1672
SOUTH WALES	39.3	61.2	509.0	2033
SOUTH YORKSHIRE	39.9	60.7	793.2	1109
STAFFORDSHIRE	37.7	57.2	397.7	1458
SUFFOLK	35.7	54.6	173.1	1179
SURREY	37.5	61.4	1061.5	1584
SUSSEX	34.4	56.5	454.1	1702
THAMES VALLEY	38.5	61.2	437.3	2722
WARWICKSHIRE	38.9	60.2	297.4	1096
WEST MERCIA	34.7	54.6	147.2	2077
WEST MIDLANDS	38.7	59.5	4271.1	3307
WEST YORKSHIRE	36.5	57.6	928.0	2411
WILTSHIRE	36.0	54.4	147.3	1011

Notes for Table A-2

1.	POP	is the population of the police force area in thousands.
2.	AGE	is the percentage of the population that is both male and aged 15-24 years.
3.	NEWC	is the number of residents per 1000 population born in the new commonwealth.
4.	WIND	is the number of residents per 1000 population born in the West Indies.
5.	MALE	is the number of males aged 15-29 years living in the police force area.
6.	POPDEN	is population density measured by persons per hectare.
7.	UNEMP	is the unemployment rate for all workers in the police force area.
8.	POOR	is the average weekly earnings level below which the earnings of 10% of males aged over 21 years fall.
9.	EARN	is the average weekly earnings level for males aged over 21 years in the police force area.
10.	RVH	is total rateable value (industrial and domestic) per hectare in the police force area.
11.	TA	is the number of fatal and serious casualties in road traffic accidents in the police force area per year.

Sources

1. POP and POPDEN

   Police Force and Regional Crime Squad Statistics, 1975-6 Actuals
   London: CIPFA Statistical Information Service.

2. AGE and MALE

   OPCS Population Projections. Area 1975-1991. England Series PP3 No. 2 and OPCS Population Projections 1975-2015 Series PP2 No. 1 both London: HMSO

3. NEWC and WIND

   OPCS Census 1971 County Tables (for 1974 county areas)

4. UNEMP, POOR and EARN

   British Labour Statistics 1975 London: HMSO

5. RVH

   Rates and Rateable Values in England and Wales 1975-6 London: HMSO

6. TA

   Road Accidents G.B. 1975 London: HMSO

TABLE A-3

Crime rates and criminal justice variables for each police force area in England and Wales in 1976

Police Force Area	PCR	BURG	ROB	THSG	CUR	CURB	CURR
AVON AND SOMERSET	2824.8	652.6	9.5	2162.6	37.6	30.1	36.5
BEDFORDSHIRE	3459.2	928.4	20.9	2509.9	40.2	31.1	45.6
CAMBRIDGESHIRE	3465.0	717.4	10.7	2736.9	45.2	37.9	40.0
CHESHIRE	2444.8	756.9	7.0	1680.9	51.3	43.6	57.8
CLEVELAND	4177.7	1166.6	11.4	2999.6	50.9	39.4	50.8
CUMBRIA	2894.4	787.4	3.6	2103.5	46.6	36.9	64.7
DERBYSHIRE	3198.6	1012.7	13.6	2172.3	40.2	32.9	58.7
DEVON AND CORNWALL	2332.2	520.4	7.6	1804.2	40.0	36.1	40.8
DORSET	3325.5	775.3	9.2	2541.0	38.4	29.6	43.4
DURHAM	3043.3	928.9	6.9	2107.5	46.0	36.0	61.9
DYFED-POWYS	1889.5	500.5	2.1	1387.0	56.7	56.9	88.9
ESSEX	2921.2	680.4	11.2	2229.5	32.9	31.2	27.0
GLOUCESTERSHIRE	2328.0	600.8	7.1	1720.0	43.5	35.5	62.9
GREATER MANCHESTER	4461.4	1362.0	17.3	3082.1	45.9	38.1	46.3
GWENT	2790.7	702.9	10.2	2077.6	51.6	40.9	66.7
HAMPSHIRE	3190.1	831.8	13.1	2345.3	39.2	31.9	36.6
HERTFORDSHIRE	3179.2	670.8	9.8	2498.6	47.2	41.5	62.8
HUMBERSIDE	3732.7	1135.8	14.5	2582.5	42.4	32.5	48.8
KENT	2659.4	727.4	7.9	1924.1	34.9	26.8	38.6
LANCASHIRE	2661.1	847.1	6.1	1807.9	53.7	51.0	67.9
LEICESTERSHIRE	2530.1	614.8	8.7	1906.7	56.8	59.4	60.3
LINCOLNSHIRE	2300.3	550.3	4.6	1745.5	55.3	50.0	62.5
MERSEYSIDE	6099.5	2117.1	53.5	3928.9	42.1	42.2	25.5
NORFOLK	2349.9	620.1	7.2	1722.6	42.6	33.7	50.0
NORTHANTS	3082.0	861.0	18.2	2202.8	46.1	41.3	51.1
NORTHUMBRIA	4680.5	1658.7	15.6	3006.2	48.7	41.6	49.8
NORTH WALES	2978.2	932.5	8.2	2037.6	48.8	40.8	85.7
NORTH YORKSHIRE	2540.1	630.2	6.6	1903.4	50.4	40.0	51.2
NOTTINGHAMSHIRE	5377.7	1534.8	18.6	3824.2	47.7	49.6	50.6
SOUTH WALES	4128.5	1372.0	18.5	2737.9	38.0	29.1	45.6
SOUTH YORKSHIRE	3009.9	950.0	12.5	2047.4	49.3	41.1	50.9
STAFFORDSHIRE	2347.8	684.2	9.9	1653.7	49.7	43.1	50.5
SUFFOLK	2206.9	522.3	8.0	1676.6	50.2	37.6	67.4
SURREY	2600.8	730.5	9.3	1861.0	40.3	28.4	48.5
SUSSEX	2718.4	612.9	6.6	2098.8	51.8	41.2	44.7
THAMES VALLEY	2946.9	755.9	11.0	2180.0	39.5	31.0	41.3
WARWICKSHIRE	1975.2	531.0	9.1	1435.0	47.8	48.7	51.2
WEST MERCIA	2002.3	505.6	4.8	1491.9	52.9	51.4	73.9
WEST MIDLANDS	3982.5	1183.3	30.7	2768.5	35.1	33.3	38.0
WEST YORKSHIRE	4548.4	1555.8	25.0	2967.6	49.2	51.0	49.8
WILTSHIRE	3101.4	780.6	9.0	2311.8	34.6	29.7	47.8

TABLE A-3 (continued)

Crime rates and criminal justice variables for each police force area in England and Wales in 1976

Police Force Area	CURT	CON	CONB	CONR	CONT	CURA	CURBA
AVON AND SOMERSET	39.9	22.6	17.7	40.5	24.0	41.6	34.4
BEDFORDSHIRE	43.6	22.2	16.0	47.6	24.3	44.5	37.9
CAMBRIDGESHIRE	47.1	18.1	14.3	50.0	19.0	46.4	40.7
CHESHIRE	54.8	28.6	20.0	62.5	32.3	46.6	41.4
CLEVELAND	55.4	27.0	19.7	69.2	29.7	48.2	38.0
CUMBRIA	50.2	25.1	21.8	135.3	26.1	49.7	42.2
DERBYSHIRE	43.5	18.5	12.7	40.5	21.1	49.7	46.8
DEVON AND CORNWALL	41.2	28.9	22.1	43.7	30.8	38.0	29.9
DORSET	41.1	19.0	13.2	45.3	20.6	37.9	32.0
DURHAM	50.3	24.3	20.6	73.8	25.8	49.2	39.5
DYFED-POWYS	56.6	25.6	26.0	88.9	25.4	47.8	40.6
ESSEX	33.5	21.6	18.0	46.7	22.6	39.4	31.5
GLOUCESTERSHIRE	46.3	25.6	21.6	57.1	26.8	44.0	38.6
GREATER MANCHESTER	49.4	25.5	19.7	47.6	23.0	47.3	44.1
GWENT	55.1	33.9	31.4	33.3	34.7	45.7	40.6
HAMPSHIRE	41.8	16.2	15.4	40.0	16.4	40.9	32.0
HERTFORDSHIRE	48.7	19.7	18.6	65.4	19.8	35.5	29.0
HUMBERSIDE	46.7	24.7	18.4	48.0	27.3	50.7	45.2
KENT	37.9	18.9	14.5	64.9	20.3	36.1	28.6
LANCASHIRE	54.9	24.6	25.6	75.0	23.9	46.8	41.6
LEICESTERSHIRE	56.0	25.0	22.9	76.7	25.4	47.4	43.4
LINCOLNSHIRE	57.1	30.3	26.7	79.2	31.2	46.8	42.4
MERSEYSIDE	42.3	17.6	11.4	19.7	20.9	50.3	44.2
NORFOLK	45.7	21.4	15.1	64.6	23.5	50.2	41.8
NORTHANTS	47.9	23.2	18.9	35.9	24.8	47.5	43.0
NORTHUMBRIA	52.6	20.7	14.9	56.3	23.7	46.3	36.5
NORTH WALES	52.3	22.2	17.4	61.2	24.3	53.6	50.6
NORTH YORKSHIRE	53.8	25.3	19.7	41.9	27.1	48.3	41.1
NOTTINGHAMSHIRE	47.0	18.5	14.3	44.5	20.0	48.8	43.2
SOUTH WALES	42.3	21.9	14.5	31.5	25.6	54.2	48.9
SOUTH YORKSHIRE	53.1	28.6	18.5	52.1	33.2	46.0	41.2
STAFFORDSHIRE	52.5	26.7	21.5	50.5	28.7	47.4	44.9
SUFFOLK	54.0	26.4	17.2	71.7	29.0	40.2	34.3
SURREY	44.9	18.6	13.2	52.9	20.6	37.0	28.9
SUSSEX	54.9	22.8	17.9	47.1	24.1	38.1	29.0
THAMES VALLEY	42.4	18.5	13.1	41.8	20.2	39.8	33.5
WARWICKSHIRE	47.5	26.4	22.0	67.4	27.7	45.5	41.0
WEST MERCIA	53.4	27.6	23.2	95.7	28.9	48.1	42.9
WEST MIDLANDS	35.8	19.8	16.2	34.6	21.1	50.1	47.7
WEST YORKSHIRE	48.2	21.9	18.7	44.6	23.4	47.9	40.6
WILTSHIRE	36.1	20.3	15.0	52.2	22.0	39.6	31.6

TABLE A-3 (continued)

Crime rates and criminal justice variables for each police force area in England and Wales in 1976

Police Force Area	CURRA	CURTA	CONA	CONBA	CONRA	CONTA	IMP
AVON AND SOMERSET	52.3	44.0	25.5	20.7	46.3	27.0	5.6
BEDFORDSHIRE	48.8	46.5	19.9	16.3	48.3	21.0	6.1
CAMBRIDGESHIRE	53.3	48.3	23.7	19.2	61.0	25.1	6.0
CHESHIRE	56.8	48.9	23.0	17.7	52.5	25.3	6.2
CLEVELAND	56.6	52.1	24.8	20.2	57.9	26.5	6.5
CUMBRIA	57.7	52.9	23.7	20.2	61.8	25.1	5.4
DERBYSHIRE	52.2	51.1	25.2	19.7	55.7	27.3	5.2
DEVON AND CORNWALL	40.0	40.5	20.8	15.5	42.9	22.3	6.9
DORSET	40.4	39.8	22.0	17.6	44.1	23.3	7.6
DURHAM	54.1	53.0	24.5	19.0	75.7	26.7	4.2
DYFED-POWYS	68.0	50.8	26.4	21.6	55.4	28.4	5.0
ESSEX	45.8	41.9	19.7	14.9	54.4	21.1	6.4
GLOUCESTERSHIRE	52.9	45.7	24.9	20.4	55.2	26.3	6.0
GREATER MANCHESTER	51.9	48.7	22.2	17.7	48.5	24.3	6.0
GWENT	61.6	47.7	24.7	20.6	62.7	26.1	3.3
HAMPSHIRE	45.1	43.9	19.8	14.5	47.9	21.5	8.3
HERTFORDSHIRE	34.9	37.7	19.1	14.2	41.2	20.7	5.8
HUMBERSIDE	53.8	52.8	25.7	19.8	54.4	27.9	5.0
KENT	35.2	38.8	19.6	14.7	41.7	21.1	6.4
LANCASHIRE	47.5	48.8	23.1	18.3	57.8	25.1	9.3
LEICESTERSHIRE	52.1	48.9	24.6	18.6	52.6	24.6	6.4
LINCOLNSHIRE	50.1	48.4	23.6	17.3	53.3	23.3	4.4
MERSEYSIDE	57.3	53.0	26.2	21.8	61.7	28.1	5.0
NORFOLK	56.6	52.7	24.9	19.4	67.0	26.4	6.5
NORTHANTS	50.2	49.0	23.4	19.2	60.5	24.6	4.5
NORTHUMBRIA	63.3	50.3	24.7	21.2	104.6	26.0	4.8
NORTH WALES	73.5	54.9	27.3	23.1	82.4	28.9	5.2
NORTH YORKSHIRE	56.4	51.3	25.2	20.5	71.1	27.1	5.8
NOTTINGHAMSHIRE	56.2	51.3	25.4	19.8	59.3	27.6	5.9
SOUTH WALES	77.8	55.9	29.8	28.7	61.1	30.1	5.4
SOUTH YORKSHIRE	51.8	47.8	21.8	16.8	43.9	23.8	4.7
STAFFORDSHIRE	56.7	48.5	24.3	19.5	65.8	26.1	4.8
SUFFOLK	39.0	42.1	20.4	15.8	53.8	21.7	6.2
SURREY	36.3	39.8	18.3	14.1	42.8	19.6	6.6
SUSSEX	41.2	41.5	17.9	14.3	52.6	19.1	7.4
THAMES VALLEY	47.4	42.1	20.8	16.7	48.7	22.2	6.6
WARWICKSHIRE	54.6	47.2	23.1	18.8	54.1	24.6	5.2
WEST MERCIA	62.7	50.1	26.1	22.0	56.9	27.1	6.5
WEST MIDLANDS	58.5	51.1	26.9	22.2	71.2	28.4	6.8
WEST YORKSHIRE	55.0	50.9	24.5	19.2	51.4	26.7	7.1
WILTSHIRE	44.1	42.3	20.4	16.2	44.9	21.6	4.9

TABLE A-3 (continued)

Crime rates and criminal justice variables for each police force area in England and Wales in 1976

Police Force Area	IMPB	IMPR	IMPT	SENT	SENTB	SENTR	SENTT
AVON AND SOMERSET	12.1	43.1	3.8	320	400	1039	203
BEDFORDSHIRE	13.4	49.0	3.6	452	407	1340	298
CAMBRIDGESHIRE	15.3	53.3	3.7	461	547	1201	282
CHESHIRE	11.9	50.0	4.2	396	451	1198	275
CLEVELAND	12.1	53.3	4.6	328	357	1525	184
CUMBRIA	10.1	52.2	3.5	378	432	910	261
DERBYSHIRE	9.8	44.9	3.5	464	472	1408	310
DEVON AND CORNWALL	15.5	44.4	4.9	288	371	1102	188
DORSET	16.1	79.2	5.4	324	359	997	225
DURHAM	8.0	45.2	2.5	294	289	1003	178
DYFED-POWYS	8.7	25.0	3.5	350	410	1138	267
ESSEX	14.3	38.3	4.1	409	469	1429	260
GLOUCESTERSHIRE	8.5	30.0	5.1	287	354	1429	196
GREATER MANCHESTER	9.3	42.5	4.6	342	408	1172	226
GWENT	5.4	26.7	2.6	336	524	771	208
HAMPSHIRE	13.2	54.9	6.0	428	544	1090	260
HERTFORDSHIRE	10.8	49.0	4.0	394	423	853	302
HUMBERSIDE	9.7	39.0	3.3	360	345	1257	266
KENT	14.2	44.6	3.9	435	432	1674	250
LANCASHIRE	12.2	52.4	1.8	330	350	1609	217
LEICESTERSHIRE	10.6	48.2	4.5	515	587	1615	305
LINCOLNSHIRE	10.1	36.8	2.6	406	493	1408	220
MERSEYSIDE	7.9	49.4	3.6	424	420	1438	251
NORFOLK	14.7	41.9	4.2	407	471	1028	283
NORTHANTS	8.1	45.5	2.9	383	406	861	275
NORTHUMBRIA	8.3	27.9	3.4	311	360	979	199
NORTH WALES	10.7	60.0	2.8	432	506	1003	218
NORTH YORKSHIRE	12.4	44.4	4.0	279	350	863	191
NOTTINGHAMSHIRE	11.4	46.9	3.8	412	450	1149	283
SOUTH WALES	9.2	29.0	4.2	354	456	977	254
SOUTH YORKSHIRE	9.3	27.9	3.3	360	400	1307	253
STAFFORDSHIRE	8.9	38.0	3.2	415	455	1329	265
SUFFOLK	11.2	36.4	4.9	391	444	1130	305
SURREY	14.7	58.3	3.9	509	517	1837	249
SUSSEX	16.3	27.5	5.3	298	385	1190	211
THAMES VALLEY	12.8	51.9	4.7	427	595	1027	253
WARWICKSHIRE	8.9	31.0	3.7	360	442	666	262
WEST MERCIA	12.5	50.0	4.4	403	465	1206	258
WEST MIDLANDS	10.6	37.8	5.0	403	471	1080	263
WEST YORKSHIRE	11.0	42.0	4.9	375	429	1069	227
WILTSHIRE	11.8	58.3	2.8	431	464	1221	246

TABLE A-3

Crime rates and criminal justice variables for each police force area in England and Wales in 1976

Police Force Area	POL	CIV	VEH	AVF	AVFB	AVFT
AVON AND SOMERSET	2862.5	875	581	36.6	33.8	36.9
BEDFORDSHIRE	870	326	172	33.5	33.8	33.4
CAMBRIDGESHIRE	1061.5	387	228	25.6	27.1	25.5
CHESHIRE	1775	495	419	28.9	26.8	29.2
CLEVELAND	1372	380	209	23.4	24.9	23.2
CUMBRIA	1043	302	257	20.3	21.1	20.2
DERBYSHIRE	1575	760	295	28.1	29.6	27.9
DEVON AND CORNWALL	2645.5	934	530	28.1	31.4	27.7
DORSET	1111.5	339	198	33.7	32.4	33.8
DURHAM	1369	602	288	20.4	23.5	19.7
DYFED-POWYS	923	233	183	30.9	39.2	29.7
ESSEX	2373.5	816	558	31.4	31.1	31.4
GLOUCESTERSHIRE	1068	301	240	30.7	29.1	31.0
GREATER MANCHESTER	6187	1898	991	25.9	27.7	25.7
GWENT	983	230	160	20.6	19.5	20.8
HAMPSHIRE	2874.5	925	837	30.4	31.2	30.3
HERTFORDSHIRE	1460.5	569	377	30.8	27.8	31.4
HUMBERSIDE	1790	655	330	20.8	23.3	20.4
KENT	2544.5	1131	707	33.1	32.9	33.0
LANCASHIRE	3102.5	1120	561	30.7	34.0	30.1
LEICESTERSHIRE	1672.5	522	340	35.4	34.5	35.5
LINCOLNSHIRE	1162	368	260	22.8	24.6	22.6
MERSEYSIDE	4369	1106	590	27.8	28.2	27.8
NORFOLK	1223.5	344	264	31.5	27.7	31.9
NORTHANTS	913.5	329	205	29.5	31.0	29.3
NORTHUMBRIA	3250.5	939	534	27.0	26.7	27.0
NORTH WALES	1233	399	268	22.0	26.9	21.2
NORTH YORKSHIRE	1330.5	413	303	23.7	25.8	23.4
NOTTINGHAMSHIRE	2152.5	755	425	24.0	23.7	25.0
SOUTH WALES	3000.5	1025	522	24.6	26.0	24.4
SOUTH YORKSHIRE	2572.5	832	436	21.9	24.9	21.5
STAFFORDSHIRE	2054	727	470	26.1	31.3	25.3
SUFFOLK	1043	401	224	32.9	29.4	33.3
SURREY	1459	412	260	33.7	28.0	34.4
SUSSEX	2787.5	883	675	33.0	27.6	33.7
THAMES VALLEY	2902.5	1137	719	34.9	35.4	34.9
WARWICKSHIRE	862.5	270	236	26.9	29.4	26.4
WEST MERCIA	1635.5	615	443	26.3	26.1	26.3
WEST MIDLANDS	5771.5	1658	1017	35.2	35.4	35.1
WEST YORKSHIRE	4735	1456	856	28.3	30.6	27.9
WILTSHIRE	965	341	249	31.9	32.3	32.0

Notes for Table A-3

See Notes for Table A-1

Sources

As for Table A-1, except

1. PCR, BURG, ROB and THSG

   (a) Criminal Statistics 1976 Table 29
   London: HMSO (Cmnd 6909)

   (b) Police Force and Regional Crime Squad Actual Statistics 1976/77
   London: CIPFA Statistical Information Service

2. CON, CONB, CONR and CONT

   Numbers found guilty at Crown Courts and Magistrates' Courts, numbers cautioned and numbers of recorded crimes obtained from Criminal Statistics 1976 Tables 7, 3(a), 31(a) and 29 respectively.
   London: HMSO (Cmnd 6909)

3. POL and CIV

   Police Force and Regional Crime Squad Actual Statistics 1976/77
   London: CIPFA Statistical Information Service

TABLE A-4

Socio-economic and demographic variables for
each police force area in England and Wales in 1976

Police Force Area	POP	AGE	NEWC	WIND	MALE	POPDEN	UNEMP
AVON AND SOMERSET	1324.6	7.4			146.1	2.8	5.5
BEDFORDSHIRE	491.7	7.5			56.0	4.0	5.1
CAMBRIDGESHIRE	560.3	8.2			70.8	1.7	4.5
CHESHIRE	916.4	7.1			98.6	3.9	5.8
CLEVELAND	567.9	7.9			64.8	9.7	8.1
CUMBRIA	473.6	7.2			50.5	0.7	5.9
DERBYSHIRE	887.6	7.0			94.0	3.4	4.7
DEVON AND CORNWALL	1349.2	7.3			145.0	1.3	8.5
DORSET	575.8	7.1			61.3	2.2	6.2
DURHAM	610.4	7.3			66.8	2.5	7.7
DYFED-POWYS	424.6	7.2			46.0	0.4	6.6
ESSEX	1355.0	7.2			155.7	3.8	6.0
GLOUCESTERSHIRE	491.5	7.5			54.3	1.9	5.3
GREATER MANCHESTER	2684.1	7.3			295.9	20.9	5.8
GWENT	439.6	7.2			47.8	3.2	7.4
HAMPSHIRE	1567.4	8.2			190.3	3.8	5.2
HERTFORDSHIRE	796.9	7.5			105.1	5.4	3.1
HUMBERSIDE	848.6	7.4			92.3	2.4	6.9
KENT	1448.1	7.3			157.9	3.9	5.4
LANCASHIRE	1375.5	6.8			139.9	4.5	6.1
LEICESTERSHIRE	837.9	7.5			96.6	3.3	4.7
LINCOLNSHIRE	524.5	7.5			59.1	0.9	5.6
MERSEYSIDE	1578.0	7.9			178.8	24.3	10.8
NORFOLK	662.5	7.1			72.0	1.2	5.6
NORTHANTS	505.9	7.3			56.9	2.1	4.5
NORTHUMBRIA	1470.2	7.5			162.9	2.6	8.8
NORTH WALES	601.1	7.2			65.2	1.0	8.8
NORTH YORKSHIRE	653.0	8.0			75.6	0.8	4.9
NOTTINGHAMSHIRE	977.5	7.3			107.3	4.5	5.1
SOUTH WALES	1301.5	7.2			141.6	5.8	7.0
SOUTH YORKSHIRE	1318.3	7.2			142.4	8.4	6.3
STAFFORDSHIRE	997.6	7.3			111.1	3.7	4.1
SUFFOLK	577.6	7.6			66.2	1.5	5.0
SURREY	732.5	7.6			111.4	5.0	3.2
SUSSEX	1279.0	6.5			123.8	3.4	4.6
THAMES VALLEY	1715.2	8.3			211.6	3.0	3.8
WARWICKSHIRE	471.0	7.3			52.7	2.4	4.4
WEST MERCIA	953.2	7.4			106.8	1.3	5.2
WEST MIDLANDS	2743.3	7.4			306.9	30.5	6.1
WEST YORKSHIRE	2072.5	7.2			226.2	10.2	5.3
WILTSHIRE	512.8	8.1			62.6	1.5	5.4

TABLE A-4 (continued)

Socio-economic and demographic variables for each police force area in England and Wales in 1976

Police Force Area	POOR	EARN	RVH	TA	
AVON AND SOMERSET	44.7	70.4		1870	
BEDFORDSHIRE	46.0	74.6		822	
CAMBRIDGESHIRE	42.6	69.8		915	
CHESHIRE	46.2	73.6		1283	
CLEVELAND	49.4	78.1		763	
CUMBRIA	43.7	68.1		796	
DERBYSHIRE	45.5	70.0		1366	
DEVON AND CORNWALL	39.7	62.9		2156	
DORSET	41.1	66.6		924	
DURHAM	46.4	68.9		751	
DYFED-POWYS	40.6	66.3		715	
ESSEX	46.4	72.4		2497	
GLOUCESTERSHIRE	42.8	67.6		815	
GREATER MANCHESTER	43.4	69.8		3259	
GWENT	47.3	71.9		582	
HAMPSHIRE	45.6	71.6		2440	
HERTFORDSHIRE	47.6	75.1		1472	
HUMBERSIDE	43.2	69.5		1297	
KENT	43.3	70.7		2198	
LANCASHIRE	43.2	66.8		1821	
LEICESTERSHIRE	43.1	66.1		1297	
LINCOLNSHIRE	41.6	62.9		996	
MERSEYSIDE	46.3	72.5		2166	
NORFOLK	41.0	64.6		1104	
NORTHANTS	43.9	67.2		938	
NORTHUMBRIA	45.4	70.5		1716	
NORTH WALES	45.0	67.9		1098	
NORTH YORKSHIRE	39.8	64.7		1159	
NOTTINGHAMSHIRE	44.3	68.0		1600	
SOUTH WALES	44.7	71.1		1611	
SOUTH YORKSHIRE	47.2	72.4		1520	
STAFFORDSHIRE	44.3	67.3		1659	
SUFFOLK	42.9	65.5		822	
SURREY	43.1	72.4		1982	
SUSSEX	41.1	65.9		1877	
THAMES VALLEY	44.7	72.0		2724	
WARWICKSHIRE	44.7	69.1		726	
WEST MERCIA	41.4	66.1		1589	
WEST MIDLANDS	46.5	70.0		3417	
WEST YORKSHIRE	42.9	67.3		2805	
WILTSHIRE	42.9	66.3		973	

Notes for Table A-4

See Notes for Table A-2

For NEWC, WIND and RVH see Table A-2.

Sources

As for Table A-2, except,

1. POP and POPDEN

   Police Force and Regional Crime Squad Actual Statistics 1976/7
   London: CIPFA Statistical Information Service.

2. AGE and MALE

   Interpolated from OPCS Population Projections. Area. 1977-1991
   and Population Projections. Area. 1975-1991
   Series PP3 Nos 2 and 3.

3. UNEMP, POOR and EARN

   British Labour Statistics 1976 London: HMSO

4. TA

   Road Accidents G.B. 1976
   In 1976 Road Accidents G.B. did not provide statistics by county of numbers (i) killed and seriously injured and (ii) slightly injured. Area estimates of the numbers killed and seriously injured were made using the area's total number of road casualties and the percentage of casualties (nationally) that were either killed or seriously injured.

BIBLIOGRAPHY

Allingham M.G. and Sandmo A. (1972), "Income Tax Evasion: A Theoretical Analysis", Journal of Public Economics, vol.1, pp.323-338.

Avio K.L. (1975), "Recidivism in the Economic Model of Crime". Economic Inquiry, vol.13, pp.450-6.

Avio K.L. and Clark C.S. (1976), Property Crime in Canada. An Econometric Study. Toronto, University Press.

Avio K.L. and Clark C.S. (1978), "The Supply of Property Offences in Ontario: Evidence on the Deterrent Effect of Punishment", Canadian Journal of Economics, vol.11 no.1, pp.1-19.

Baldry J.C. (1974), "Positive Economic Analysis of Criminal Behaviour" in A.J. Culyer (ed) Economic Policies and Social Goals. London, Martin Robertson, pp.171-98.

Baldry J.C. (1976), Some Theoretical and Empirical Aspects of the Economic Analysis of Criminal Behaviour. Unpublished Ph.D. thesis, University of York.

Baldwin J. and Bottoms A.E. (1976), The Urban Criminal: A Study in Sheffield. London, Tavistock Publications.

Beccaria-Bonesana C. (1767), An Essay on Crimes and Punishments translated from Italian with a commentary by Voltaire (London, Alman).

Becker G.S. (1968), "Crime and Punishment: An Economic Approach". Journal of Political Economy, vol,76 no.2, pp.169-217.

Bentham J. (1896), Theory of Legislation. London, Kegan Paul.

Block M.K. and Heineke J.M. (1975), "A Labor Theoretic Analysis of Criminal Choice". _American Economic Review_, vol.65 no.3, pp.314-325.

Block M.K. and Lind R. (1975), "An Economic Analysis of Crimes Punishable by Imprisonment". _Journal of Legal Studies_,vol.4 no.2, pp.479-92.

Blumstein A.,Cohen J. and Nagin D. (ed) (1978), _Deterrence and Incapacitation: Estimating the Effects of Criminal Sanctions on Crime Rates_. Washington D.C.,National Academy of Sciences.

Blumstein A. and Nagin D. (1977), "The Deterrent Effect of Legal Sanctions on Draft Evasion", _Stanford Law Review_,vol.29,pp.241-270.

Bonger W.A. (1916), _Criminality and Economic Conditions_. Boston, Little,Brown and Co. (out of print). Reissued by Agathan Press, New York.

Bottomley and Coleman (1980), "Police Effectiveness and the Public: the Limitations of Official Crime Rates" in R.V.G. Clarke and J. Hough (eds) _The Effectiveness of Policing_. Farnborough, Gower, pp.70-97.

Brenner H. (1976), _Economic Crises and Crime_, part 1. United Nations, Social Defence Research Institute.

Brown W.W. and Reynolds M.O. (1973), "Crime and 'Punishment': Risk Implications". _Journal of Economic Theory_,vol.6,no.5,pp.508-14.

Burrows H.P. and Veljanovski C. (eds) (1981), _The Economic Approach to Law_. London, Butterworths.

Burrows J. (1982), "How crimes come to police notice". HORPU _Research Bulletin_,no.13,pp.12-15.

Burrows J. and Tarling R. (1982), _Clearing Up Crime_. HORPU Report no.73. London, HMSO.

Carr-Hill R.A. and Stern N.H. (1973), "An Econometric Model of the Supply and Control of Recorded Offences in England and Wales". Journal of Public Economics, vol.2, no.4, pp.289-318.

Carr-Hill R.A. and Stern N.H. (1977), "Theory and Estimation in Models of Crime and its Social Control and their Relations to Concepts of Social Output". In M.S.Feldstein and R.P.Inman (eds) The Economics of Public Services. London, MacMillan, pp.116-147.

Carr-Hill R.A. and Stern N.H. (1979), Crime, The Police and Criminal Statistics. London, Academic Press.

Carr-Hill R.A. and Stern N.H. (1982), "Crime, Unemployment and the Police". SSRC Programme on Taxation, Incentives and the Distribution of Income. Research Note no.2.

Cloninger D.O. (1975), "The Deterrent Effect of Law Enforcement: An Evaluation of Recent Findings and some New Evidence". American Journal of Economics and Sociology, vol.24, no.3, pp.323-35.

Croft J. (1978), Research in Criminal Justice. HORPU Report no.44. London, HMSO.

Danziger S. and Wheeler D. (1975), "The Economics of Crime: Punishment or Income Redistribution?" Review of Social Economy, vol.33, no.2, pp.113-31.

Ehrlich I. (1973), "Participation in Illegitimate Activities: A Theoretical and Empirical Investigation". Journal of Political Economy, vol.81, no.3, pp.521-564.

Ehrlich I. (1975a), "The Deterrent Effect of Capital Punishment: A Question of Life and Death". American Economic Review, vol.65, no.3, pp.397-417.

Ehrlich I. (1979), "The Economic Approach To Crime. A Preliminary Assessment" in S.L. Messinger and E. Bittner (eds) Criminology Review Year Book,vol.1,pp,25-60.

Ehrlich I. (1981), "On the Usefulness of Controlling Individuals: An Economic Analysis of Rehabilitation, Incapacitation, and Deterrence". American Economic Review,vol.71,no.3,pp.307-322.

Engels F. (1892), The Condition of The Working Class in England in 1844. London, George Allen and Unwin.

Estimates Committee (1966-7), Police. 1st Report of The Estimates Committee. London, HMSO, HC 145.

Expenditure Committee (1974), Police Recruitment and Wastage. 7th Report from the Expenditure Committee. London, HMSO, HC 310.

Ferri E. (1893), La Sociologie Criminelle. Paris, Felix Alcan.

Fisher F.M. and Nagin D. (1978), "On The Feasibility of Identifying the Crime Function in a Simultaneous Model of Crime Rates and Sanction Levels" in Blumstein,Cohen and Nagin (1978),pp.361-399.

Fleisher B.M. (1963), "The Effect of Unemployment on Juvenile Delinquency". Journal of Political Economy,vol.71,no.6,pp.543-555.

Fleisher B.M. (1966a), "The Effect of Income on Delinquency". American Economic Review,vol.56,no.1, pp.118-137.

Fleisher B.M. (1966b), The Economics of Delinquency. Chicago, Quadrangle.

Fleisher B.M. (1970). "The Effect of Income on Delinquency: Reply". American Economic Review,vol.60, no.1,p.257.

Forst B.E. (1976), "Participation in Illegitimate Activities: Further Empirical Findings". Policy Analysis, vol.2,no.3,pp.477-92.

Freeman R.B. (1982), "Crime and the Labour Market". NBER Working Paper No.1031.

Furlong W.J. and Mehay S.L. (1981), "Urban Law Enforcement in Canada: an Empirical Analysis". Canadian Journal of Economics, vol.XIV, no.1, pp.44-57.

Gibbs J.P. (1968), "Crime, Punishment and Deterrence". South Western Social Science Quarterly, vol.48, no.4, pp.515-30.

Goldberger A.S. (1964) Econometric Theory. New York, Wiley.

Green H.A.J. (1964), Aggregation in Economic Analysis: An Introductory Survey. Princeton, University Press.

Grunfeld and Griliches (1960), "Is Aggregation Necessarily Bad?" Review of Economics and Statistics, vol, 42, no.1, pp.1-13.

Heineke J.M. (1975), "A Note on Modeling the Criminal Choice Problem". Journal of Economic Theory, vol.10, no.1, pp.113-6.

Heineke J.M. (ed) (1978a), Economic Models of Criminal Behavior, Amsterdam, North-Holland.

Heineke J.M. (1978b), "Economic Models of Criminal Behavior: An Overview". In Heineke (1978a), pp.1-33.

Heineke J.M. (1978c), "Substitution among Crimes and the Question of Deterrence ...". In Heineke (1978a) pp.153-209.

Hepworth N.P. (1978), The Finance of Local Government 4th Edition. London, Allen and Unwin.

Hilton B. (1979), "The Police Production Function and the 'Dark Figure': Notes on an Empiricist Exploration". Bramshill Journal, vol.1, no.1, pp.49-58.

Holtmann A.G. and Yap L. (1978), "Does Punishment Pay?". Public Finance, vol.33, nos.1/2, pp.90-7.

Home Office (1967), Police Manpower, Equipment and Efficiency. London, HMSO.

Home Office (1973-4), Police Programme Accounts, 1973-4. London, Home Office.

Home Office (1977), A Review of Criminal Justice Policy 1976. London, HMSO.

Hough M. and Mayhew P. (1983), The British Crime Survey. HORPU Report No. 76. London, HMSO.

Kolm S.C. (1973), "A Note on Optimum Tax Evasion". Journal of Public Economics, vol.2, pp.265-70.

Landes W.M. (1978), "An Economic Study of US Aircraft Hijacking 1961-76". Journal of Law and Economics, vol.21, no.1, pp.1-31.

Mannheim H. (ed) (1960), Pioneers in Criminology. London, Stevens.

Manski C.F. (1978), "Prospects for Inference on Deterrence Through Empirical Analysis of Individual Criminal Behavior". In J.M. Heineke (1978a) pp.83-121.

Mathieson D. and Passell P. (1976), "Homicide and Robbery in New York City: An Economic Model". Journal of Legal Studies, vol.6, pp.83-98.

Mathur V.K. (1978), "Economics of Crime: An Investigation of the Deterrent Hypothesis for Urban Areas". Review of Economics and Statistics, vol.60, no.3, pp.459-66.

Mehay S.L. (1977), "Interjurisdictional Spillovers of Urban Police Services". Southern Economic Journal, vol.43, no.3, pp.1352-9.

More T. (1551), Utopia, Translated by R. Robinson. Cambridge.

Nagin D. (1978), "General Deterrence: A Review of the Empirical Evidence". In Blumstein, Cohen and Nagin (eds) (1978).

Palmer J. (1977), "Economic Analysis of the Deterrent Effect of Punishment: A Review". Journal of Research in Crime and Delinquency, vol.14 part 1, pp.4-21.

Phillips L. and Votey H.L. (1975), "Crime Control in California". Journal of Legal Studies, vol.5, pp.327-49.

Pogue T.F. (1975), "Effect of Police Expenditures on Crime Rates: Some Evidence". Public Finance Quarterly, vol.5 no.1, pp.14-44.

Pyle D.J. (1983), The Economics of Crime and Law Enforcement. London, MacMillan.

Radzinowicz L. and King J. (1977), The Growth of Crime. The International Experience. London, Hamish Hamilton.

Shaw M. and Williamson W. (1972), "Public Attitudes to the Police". The Criminologist, vol.7, no.26, p.18.

Singh B. (1973), "Making Honesty the Best Policy". Journal of Public Economics, vol.2 no 3, pp.257-63.

Sjoquist D.L. (1973), "Property Crime and Economic Behavior: Some Empirical Results". American Economic Review, vol.63 no 3, pp.439-446.

Smith A. (1759), The Theory of Moral Sentiments. London, A. Millar.

Smith A. (1763), Lectures on Justice, Police, Revenue and Arms. Edited by Edwin Cannan, Oxford 1896.

Smith A. (1776), An Inquiry into the Nature and Causes of the Wealth of Nations. Edited by Edwin Cannan, Oxford 1896.

Stewart M.B. and Wallis K.F. (1981), Introductory Econometrics. 2nd Edition. Oxford, Basil Blackwell.

Tarling R. (1979) Sentencing Practice in Magistrates' Courts. HORPU Report No.56. London, HMSO.

Taylor J.B. (1978), "Econometric Models of Criminal Behaviour: A Review". In J.M. Heineke (1978a), pp.35-81.

Thaler R. (1977), "An Econometric Analysis of Property Crime: Interaction between Police and Criminals". Journal of Public Economics, vol.8 no.1, pp.37-52.

Tittle C. (1969), "Crime Rates and Legal Sanctions". Social Problems, vol.16, pp.408-28.

Vandaele W. (1978), "Participation in Illegitimate Activities: Ehrlich Revisited". In Blumstein, Cohen and Nagin (eds) (1978).

Willis K.G. (1983), "Spatial Variations in Crime in England and Wales: Testing an Economic Model. Regional Studies, vol.17 no.4, pp.261-72.

Winchester S. and Jackson H. (1982), Residential Burglary. HORPU Report No.74. London, HMSO.

Witte A.D. (1980), "Estimating the Economic Model of Crime with Individual Data". Quarterly Journal of Economics, vol.94, pp.57-84.

Wolpin K.I. (1978a), "An Economic Analysis of Crime and Punishment in England and Wales 1894-1967". Journal of Political Economy, vol.86 no.5, pp.815-40.

Wolpin K.I. (1978b), "Capital Punishment and Homicide in England: A Summary of Results". American Economic Review, vol.68 no.2, pp.422-7.