A QUANTITATIVE ANALYSIS OF CRIME AND THE LABOUR MARKET

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Abstract

A large number of criminological theories predict a link between crime and the labour market. This thesis takes predictions from those theories and tests them empirically. Using a large range of data and quantitative techniques, this work considers which factors are most associated with crime, while at the same time addressing issues of methodology and interpretation.

The thesis consists of seven Chapters. The first introduces the issues surrounding crime and the labour market, describes the theories which inform the research and discuss the existing empirical work in the area. Sections also describe the data and methodological debates of concern in this field.

The empirical analysis, which forms the body of the thesis, follows from this introduction in five inter-related Chapters. The first two deal with establishing which variables are most associated with crime, which data are most useful and which methodological techniques are most appropriate. They cover cross-sectional analysis, as well as area level longitudinal data at police force area level and Local Authority level over time. The results point to clear methodological advantages of using area level data and find the most robust correlate of crime to be low wages.

The following Chapter uses these findings to frame an analysis of police force area level data in England and Wales. It examines the effect on crime of a substantial pay increase awarded to low wage workers with the introduction of the National Minimum Wage into the UK labour market in April 1999. By comparing crime rates in areas before and after the introduction of the Minimum Wage, it finds that crime fell (in relative terms) in areas where the introduction of the Minimum Wage had the greatest impact.

Having consistently found the labour market, and in particular low wages, to be linked to crime, the final two empirical Chapters address issues of gender and age, two of the most important demographic determinants of crime. The first examines the effect of increasing female labour force participation on crime, and finds that rising female employment is positively associated with crimes done by males. Results indicate that this is because increasing female labour supply forces male wages down. Particularly affected are the wages of the low skilled males who are already low paid and are more likely to be on the margins of crime. The second of these Chapters focuses on youth crime and finds that, although labour market variables matter, other variables such as education, truancy and parental involvement with the police matter more.

The final Chapter draws the material together, offers concluding comments, places the findings within a policy context and offers suggestions for future research.

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Statement of Declaration on Joint Work

This statement confirms that some of the material in Chapters 2 and 4 of this thesis is based upon joint work with me. It also confirms that Kirstine Hansen's contribution to this work formed at least half of the research content.

Stephen Machin

I would like to dedicate this thesis to my family.

My mum Lesley, my dad Bøje, my sister Kia

and my husband Stephen.

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1. Introduction

1.1 Introduction

Understanding why crime occurs and how it varies over time and space is a critical public policy question. Expenditure on the criminal justice system in Britain is now the fourth highest category of public expenditure (following health, education and defence) and many commentators have expressed concerns about how crime tears into the social fabric, producing many undesirable outcomes that may persist through time and that often spill over to other aspects of society.

It should be acknowledged at the outset that examining why crime occurs is no simple task. In the past a wide range of factors were held responsible for crime including the Devil (Williams 2001), retarded evolution (Lombroso 1895), particular body types (Kretschmer 1922), feeble mindedness (Goddard 1921) and hereditary defectiveness (Goring 1913).

While explanations of crime have come a long way since this type of research, identifying the causes of crime remains a complicated task. Although the research in this thesis attempts to explain variations in crime by reference to the labour market in all reality crime is likely to be the outcome of a number of complex and interrelated factors, some to do with biology, some psychological factors, some to do with society, others the law, others to do with factors that no-one has even thought of yet or that we have no way of measuring. Thus, it is likely that factors such as these all contribute to motivation, opportunity, propensity toward and discouragement from crime, the result of which are criminal outcomes.

This introduction to the thesis begins by considering criminological and sociological theories of why people commit crime. The discussion is specifically focused upon informing ways in which crime and the labour market are connected, and on which theories are better suited to offer empirical tests of the importance of any such connection.[1]

1.2 Theoretical Underpinnings

1.2.1 Predictive Power

Theoretical predictions form the basis of much empirical work. They inform the way we as researchers think of issues, formulate research questions and construct empirical models.

> *"because they make statements about the relationship between observable phenomena, a key characteristic of scientific theories is that they can be falsified. The process of attempting to falsify a scientific theory involves systematically observing the relationship described in the theory and then comparing those observations to arguments of the theory itself. This process is called research: That is the assertions of the theory are tested against the observed world facts."*
>
> Vold and Bernard, 1998, p2-3.

In line with the above quote, predictions from criminological theory form the foundations of this research project, against which first order principles concerning the relationship between crime and the labour market can be tested. Although each

[1] As will be seen some theories are more applicable to certain crimes, some to certain groups, some at specific periods in peoples lives. These will be discussed in more detail as they arise throughout the Chapters of this thesis.

empirical Chapter of this thesis discusses the particular theories which inform that specific piece of work, an introduction to the relevant criminological theories which generally offer predictive power in the context of this thesis are given below. However, it should be recognised at the outset that this thesis is an empirical analysis of the relationship between crime and the labour market. It draws heavily on and utilises a quantitative methodological approach. While it is firmly grounded in an appreciation of relevant theoretical issues, it makes no claims to be a theoretical treatise. Instead (and by necessity as this is a quantitative thesis), the focus is placed upon how theories can offer testable predictions of how crime and the labour market may be connected. Thus, the predictive powers of theories discussed below can be viewed as empirically relevant extracts drawn from a number of theories which are able to offer predictive power for framing and designing the empirical work contained in the thesis.[2]

1.2.2 Positivism

As a quantitative study, this work relies more heavily on positivist criminological theory. Although nowadays largely used as a term of criticism, originally positivism in this field referred to work that sought to identify the causes of crime (Vold and Bernard 1998). While thought by some to be too deterministic, a great deal of empirical research within the field of criminology (both qualitative and quantitative) attempts, at least to some extent, to shed light on the causes of crime. This work is no exception. Given the caveat of the likely impossibility of identifying all the wide-ranging, multi-causal factors associated with crime (discussed above),

[2] For a much more detailed discussion of the complexities of criminological theories see Downes and Rock (1998).

this research attempts to explain some of the variation in crime in terms of variations in labour market factors.[3]

The contribution of positivism to this research does not stop here. Although remembered for work that located crime in terms of human biology (Lombroso 1895), the greatest contributions made by positivism are evident in the work of authors such as Guerry (1831) and Quetelet (1842) who used statistics in an attempt to explain crime in terms of social causes. For example, these authors argued that crime is associated with poverty, unemployment, inequality, age and gender. These are factors, which still form the basis of many empirical models of crime today, including those presented in this thesis.

1.2.3 Anomie/Strain

For Durkheim (1933, 1938) the relationship between crime and factors such as inequality and poverty was the result of a breakdown of social norms which accompanied the modernisation of society (Vold and Bernard 1986). Thus, as society became more advanced, economic development increased the availability of material goods and their cultural priority (Downes and Rock 1998) which created insatiable desires. These desires lead to a break down of regulations and rules and an undermining of confidence in the social structure which encouraged crime.

This can be elaborated with reference to Merton's strain theory (1938), an adaptation of Durkheim's anomie theory for the situation in the US. For Merton anomie was not just associated with the specific instance when desires became insatiable but it was endemic in industrial capitalism (Downes and Rock 1998). Thus, he showed how a breakdown of norms could occur in relatively stable economic conditions, which he referred to as 'social structural strain' (Merton 1938).

[3] However, this work does not see labour market factors as the only ones relevant for explaining crime. There are other factors such as those relevant to human biology or psychology or the workings of the criminal justice system which are also likely to be important.

In societies such as the US, and indeed the UK, which encourage economic success individuals are encouraged to achieve certain goals such as securing employment, earning money, providing for one's self and one's family, but also achieving the heights of material success.[4] Because countries such as the US and the UK (at least in theory) are based on the idea of meritocracy individuals are told they all have equal access to these goals. When individuals who have weak labour market positions such as the low paid or unemployed cannot achieve these goals, this causes strain. In other words, there is a mismatch between the culturally accepted goals and the ability of some individuals to achieve them. This is reflected in the winner/loser culture described by James (1995) and in Young's (1999) uneven race track of meritocracy.

Merton (1938) created a typology of the relationship between what he referred to as goals and means:

- **Conformity:** Where individuals have the means to achieve their goals in law abiding ways.
- **Innovation:** Where individuals do not have the means to achieve goals legally, so resort to reach goals in illegal ways.
- **Ritualism:** Goals cannot be reached legally so individuals reappraise their aspirations downwards and become bogged down in routine.
- **Retreatism:** Goals cannot be reached so individuals turn their back on the society which encourage these goals.
- **Rebellion:** Individuals who cannot reach society's goals create new goals and new means.

[4] The importance of achieving these ends is enforced through the media and advertising.

In this way the disjunction between goals and means, which will be most acute for those with weak labour market positions, is associated with various types of crime. Those who innovate may resort to crimes such as property crimes, drug dealing or prostitution to achieve material success. Those who retreat may become homeless, beggars, alcoholics or drug addicts. Those who rebel may adopt new goals which bring them into conflict with the law (such as the anti-capitalist protestors who are involved in violent demonstrations).

1.2.4 Culture and Subculture

Merton's idea of rebellion is closely related to theories of subculture, seen in the work of Cohen (1955), Mays (1954) and Miller (1958). These theories also offer predictions for the relationship between crime and the labour market. For Cohen, young working class boys unable to achieve status elsewhere (either through the status of their parents, or through academic or sporting excellence) often turn to crime in order to gain status and the respect they seek from other youngsters. Usually this involves working class boys joining gangs, which have their own culture and set of ascribed values that are distinct from the dominant middle class culture. In this way, such boys adhere to a 'sub-culture' which rewards certain behaviours such as aggressiveness, fighting and vandalism, as a reaction against their failure to achieve the status in the way prescribed by the dominant middle class values (Cohen 1955).

Cloward and Ohlin (1960) elaborated on these ideas in their theory of differential opportunity structure. They argue that crime results from blocked legitimate opportunities, but that the type of crime may reflect differential access to illegitimate opportunities. Thus, for Cloward and Ohlin (1960) three different types of subculture exist:

- **Criminal:** Where opportunities for property crimes exist, often as a result of the existence of adult criminal networks in the area, youths are involved in utilitarian forms of robbery and theft.
- **Conflict:** Where neither the legitimate nor criminal roles exist, youths turn to fighting.
- **Retreatist:** Youths who are 'double failures', having failed in both the legitimate and criminal spheres, resort to drug-taking and hustling.

Unlike Cohen and Cloward and Ohlin, other subcultural theorists see lower class subculture not as a product of rebellion against middle class values, but as a result of the way the working classes have adapted to life at the bottom of the social structure. Thus, for Mays (1954) and Miller (1958) working class culture rewards attributes such as physical toughness, street sense and excitement. In terms of wider society, this often brings the working classes into conflict with the law.

For Downes (1966) 'delinquency was a fact of life not a way of life' (Downes and Rock 1998). In his study of boys in the East End of London, Downes found that the youths were intermittently involved in a range of delinquent acts ranging from fighting to theft and vandalism. These acts were motivated by a desire for a momentary release from the boredom of their position in society, rather than as an outcome arising from a wider working class culture or an organised rebellion against middle class values.

1.2.5 Drift

Matza and Sykes (1961) and Matza (1964) argued against the idea that delinquents hold different values from non-delinquents. Instead, delinquents are not committed to criminal ways, but simply 'drift' into crime and out of crime, influenced by a variety of factors such as motivation, peer pressure and opportunity. Drift into crime occurs as a result of neutralisation, the justifications given before the act, or excuses made after the act, for delinquent behaviour. Such excuses or rationalisations come under five broad headings:

- **Denial of responsibility:** Crime was the result of an accident, or because of a bad childhood – 'I didn't mean to do it, it just happened'.
- **Denial of Injury:** The crime did not cause injury. No-one was hurt; the victims were insured.
- **Denial of the victim:** The victim was deserving of injury in some way or no victim exists.
- **Condemnation of the condemners:** Those who condemn are themselves venal. Or, the delinquent is victimised in some way - being targeted by corrupt police, for example.
- **Appeal to higher loyalties:** The crime was carried out for a group or gang, loyalties to whom override loyalties to wider society at that particular time.

1.2.6 Differential Association

To some extent, both theories of strain and subcultures depend on learning - that is learning the norms and values associated with culture. The concept of learning norms and behaviours, particularly in relation to crime, is further explored in differential association theory (Sutherland 1924). This theory asserts that criminal values and behaviour such as criminal motivation, attitudes and techniques of crime are learnt through interactions with others. It is likely that those with weaker labour market positions will not only have more time on their hands with which to interact with others, but they are also more likely to come into contact with a greater number of people from whom they can learn criminal values and behaviours. The people with whom individuals associate (peer groups) are central to this idea. For example, those at the bottom of the social structure are likely to live in areas where many people are unemployed or in very low paid menial employment.[5] Therefore they will have greater access to individuals from whom they can learn criminal motivation or drives. Moreover, these areas are likely to have a higher concentration of criminals who can pass on their experiences of committing crime and the criminal justice system.

Differential reinforcement theory (Akers 1964) expands on differential association theory by suggesting that an individual's behaviour will be criminal if the positive images of crime such as the financial rewards and the status criminals receive outweigh the negative images such as the probability of arrest and incarceration. This idea is strongly related to rational choice theory, which will be discussed later. It is probable that those with weaker labour market positions are more likely to have greater access to criminals (for example they are more likely to see drug dealers, pimps and prostitutes in their neighbourhood) than those who have stronger labour market positions and can afford to live in better areas. If they see the local drug dealer driving round in a big car, while they are struggling to support themselves or their families, their positive view of crime is reinforced. If these criminals are arrested, a negative view of crime will be reinforced. But it is often the case that the positive reinforcement images of crime are much more visible.

1.2.7 Ecological theories of Crime

The physical environment in which individuals live is the focus of another set of theories that offer predictions of how the labour market may impact on crime. These are known as ecological theories of crime. They largely stem from the work of the Chicago School and can be seen in the work of authors such as Shaw and McKay (1942). Drawing from Durkheim's theory of anomie, Shaw and McKay argue that

[5] For as Cressey and Sutherland (1992) point out differential association can occur at work too.

crime is related to social disorganisation in areas. Thus, areas with a high proportion of people reliant on welfare, non-employed and low wage workers will have more social disorganisation and thus more crime.

These ideas are related to more recent theories of crime and place including opportunity, routine activities approach, and the theory of broken windows. Firstly, Mayhew et al (1976) argue that the level of crime in areas is directly affected by the criminal opportunities in the area. This refers to the abundance and ease of crime targets. Thus, property crime might be high in areas inhabited by those with weaker labour market positions as these are the people who cannot afford to protect their property. Although more wealthy areas may have goods of higher value, they are also likely to have better security, house and car alarms, gated properties and even private security patrols.

Routine activities theory (Felson 1994) expands on these concepts by noting that crime is related to the day-to-day activities of people in the area. Likened to Durkheim's (1933) work on social solidarity, this theory predicts that crime will be related to social relationships in areas. Where individuals look out for one another and for each other's property and even form neighbourhood watch schemes crime will be lower. Thus, it is clear from these theories that within areas dominated by those with the poorest position in the labour market (such as inner city areas or large council estates), there is likely to be a higher level of anonymity and a lower level of personal surveillance. People are less likely to be concerned about what is happening to others and less likely to get involved in disputes for fear of their own safety.

Moreover, those with weak labour market positions are more likely than other groups to live in social housing or on housing estates, which are often easier targets because of the architectural design of the buildings themselves (Newman 1972), or the design of the street buildings are located on (Hillier and Hanson 1984). The fact that some properties are often less well maintained than other properties also makes them more vulnerable. Wilson and Kelling (1982) show how areas descend into crime if attention is not paid to maintenance. A broken window gives the impression that no-one cares, so more and more windows are broken. If nothing is done about the broken windows, the situation escalates into more and more serious disorder and crime, as criminals (such as drug dealers, pimps and prostitutes) are attracted to the area and the respectable people (who have the means) leave.

1.2.8 Social Control

Rather than focusing on the motivation or opportunity factors that encourage or discourage crime, control theory explains crime in terms of the factors which restrain individuals from breaking the law (Hirshi 1969). Thus, similar to Matza's drift theory, crime does not occur because individuals hold criminal values or beliefs, but because individuals are not bound by conventional social order. According to Hirshi, individuals with strong bonds to society are less likely to commit crime. This depends on:

- **Attachment:** Caring about and being cared for by others
- **Commitment:** How big a stake an individual has in conformity
- **Involvement:** How involved an individual is in conventional activities
- **Belief:** The ability individuals have to neutralise conventional beliefs

In this way, those with weaker labour market positions can be thought of as having weaker social bonds to society than other groups. For example, as employment is one of the main institutions through which individuals develop a stake in conformity those with no jobs, or those in marginalized economic positions will have weaker commitments to society than others, they have less to lose by breaking the law. Moreover, the unemployed or under-employed are also less involved in conventional activities and are likely to have more spare time on their hands. According to social control theory this suggests that such people are more likely to be involved in crime. Finally, it is more likely that those with weak labour market positions will be able to neutralise conventional beliefs and rationalise their criminal behaviour as a result of their position at the bottom of the social structure i.e. 'my need is greater than others'.

1.2.9 Labelling

One of the reasons social control works is because people are concerned about what society thinks about them, about social disapproval. They are scared of the stigma that is associated with being identified as a rule breaker and being labelled a criminal (Becker 1963). Once an individual is labelled as a criminal, not only is the threat of stigmatisation removed, but also an individual may start to identify with the label that is attached to him/her and start acting in a way corresponding to the label. Thus, a person becomes freer to commit crimes without need for motivation or justification as they are just fulfilling the label that society has attached to them.

Many of those with weak labour market positions (such as the unemployed, the low paid, some ethnic minority groups and those living in social housing) are generally perceived by society as more likely to be criminals. Regardless of whether they have committed a crime, such people are often labelled as criminals because of their labour market status, where they live or the way they look. Labelling predicts that such individuals are more likely to have a criminal self-image, which may manifest itself in higher crime rates amongst these groups.

1.2.10 Conflict and Radical Criminology

In the same way that individuals in society see some groups as more criminal, so too does the criminal justice system. This often means that certain groups are more likely to be more heavily policed than others in society. This is demonstrated clearly in the disproportionate number of times police 'stop and search' black people (Home Office 2001c). As a result, such groups are likely to have more confrontational relationships with the law.

The aptly named conflict theory, which largely stems from Marxist criminology, suggests that this conflict is inherent in societies where different interest groups exist within the same culture and where the different groups have incompatible interests. For Vold (1958), as long as the differing groups have similar power, a compromise can be established and society can reach a stable equilibrium. Where the groups have different strengths, the powerful group in society creates and enforces laws to protect its interest, which it forces upon the weaker group in society. Thus, crime is seen as a response from the weaker groups in society to the subjugation of their way of life.

Hence, because the laws are generated by the middle classes for the middle classes (Vold and Bernard 1998) those in the weakest positions are most likely to come into contact with the law and also to have their actions defined as criminal.

Quinney (1978) sets out a typology of crimes that could be produced as a result of these conflicts:

- **Crimes of Domination:** Committed by those in power, such as police brutality, corporate and organised crime.
- **Crimes of Accommodation:** Committed by the subjugated, such as theft, burglary, robbery and violence.

- **Crimes of Resistance**: Also committed by the subjugated, but takes the form of political struggles against the State, such as terrorism.

Closely related to conflict theories are radical theories of crime. A main difference, according to Williams (2001), is that while conflict theories acknowledge a range of potential power groups, the main focus for radical theorists is Capitalism. Thus for 'radicals' like Taylor, Walton and Young (1973), crime is a social construct invented by the powerful to protect their own interests. The replacement of capitalism with a more socialist society, where human diversity would be tolerated would eventually lead to the elimination of crime.

Idealistic in nature, these ideas were later reformed by Young (1975) to take the shape of 'left realism'. This sought to offer a realistic empirical examination of the crime problem. To do so, the left realists turned to victimisation surveys, particularly local surveys such as the Islington Crime Survey, to examine who was at risk of crime and how crime affected lives. In so doing, they discovered that the most vulnerable groups were not only most affected by crime, but had the highest risk of crime. They found that most crime is done by working class people, against working class people (Young 1996).

1.2.11 Rational Choice

Seen in the work of Becker (1968) and Ehrlich (1973), individuals have a choice between crime and work, or more generally, they choose to allocate their time across crime-work space. These decisions are a function of a number of factors, including expected earnings from crime, expected earnings from the labour market, and perceptions of the severity of the punishment if one gets caught.

Thus, this theory predicts that those with the weakest labour market positions are more likely to be involved in crime as they have less to lose and more to gain by doing so. Seen as a simple work/crime decision, this explains why people with no work may decide to partake in crime. But on a more complex level, this can also shed light on how individuals who are employed may decide to commit crimes and the extent to which they allocate their time between work and crime (Fagan and Freeman 1999).

1.2.12 From Theoretical Predictions to Hypothesis Construction

It is quite obvious that a large number of theories predict that shifts in the labour market should be related to crime. Some theories discussed here explain why individuals with weak labour market positions are likely to commit more crime than others in society. Others offer explanations as to why areas that are characterised by factors associated with weak labour market positions (such as high social housing) are likely to have higher crime rates than other areas.

These theories will be discussed further in specific Chapters. But from this discussion, it is evident that a range of different theories predict that those with weak labour market positions are likely to have greater motivation (i.e. strain), greater potential for learning (i.e. differential association), more opportunity (i.e. routine activities) or less control (i.e. social control theory). While for the sake of simplicity and clarity these theories are described here separately it is clear that there is much interaction and overlap among these, often very, different theories, in terms of the predictions they offer empirical work on crime and the labour market. All the theories discussed above predict differences in crime across different labour market situations. It is this relationship which enables the formulation of the key hypothesis of this thesis - namely to what extent are shifts in labour market situations associated with crime.

1.3 Facts: Crime

1.3.1 The Extent of Crime Today

There were 5.5 million crimes recorded by the police in the 2001/2002 (Home Office 2002). This corresponds to a rise of 7% since the previous year. Total crime recorded by the police has fallen in four of the last six years (it rose by 3.8% in 1999/2000).

A massive proportion of total recorded crime in this period were property crimes. Indeed, in 2001/2002 crimes against property accounted for around 82% of the total number of crimes. The largest single crime type within the group of property crime was thefts. Between 2001/2002 there were some 2.3 million thefts recorded by the police. Almost half (46%) of the 2.3 million thefts are made up of thefts of, and from, vehicles. 2001/2002 saw a rise in property crime of 6% on the previous year. However, until this time, property crimes had been falling since the mid 1990s[6] (Home Office 2001a).

During the same period, 812,954 violent offences were recorded by the police. The main offences which made up this group were: common assault (32%), non-life threatening woundings (28%), harassment (14%), robberies (15%) and sex offences (5%). Violent crime rose by 8% compared to the preceding year, the sixth consecutive rise in the last 6 years (Home Office 2001).[7]

1.3.2 Trends in Recorded Crime over Time

Over the longer term the evolution of recorded crime in England and Wales can be seen in Figure 1.1. Although recorded crime declined since its peak of

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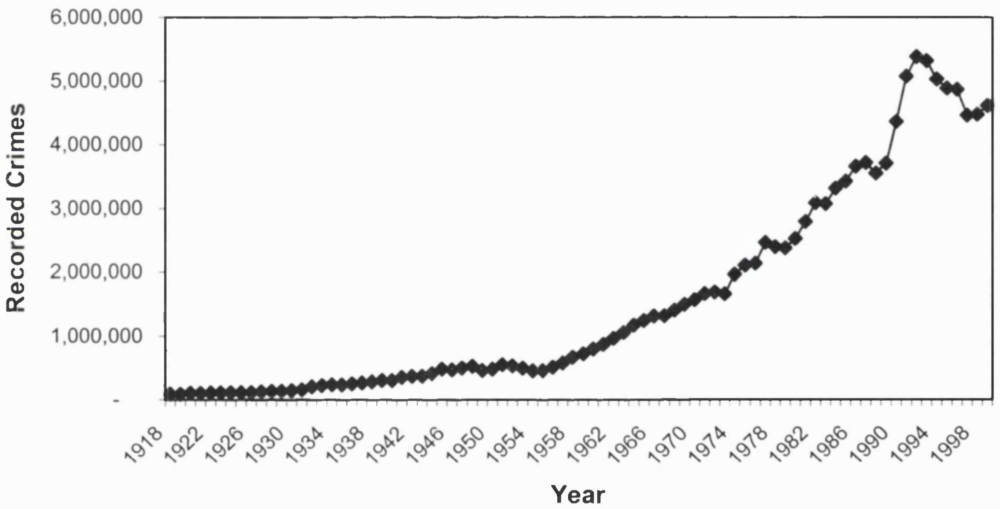
[6] Although changes in recording practises in 1998 means that crime rates after 1999 are not strictly comparable with those before this date.
[7] See above.

5,383,000 crimes in 1992, with 4,615,449 crimes recorded in 1999,[8] recorded crime was some 83% higher than in 1980 and a massive 447% higher than in 1920.

These trends help explain why the government spends around 13 billion pounds a year[9] on the criminal justice system. As noted earlier, this makes the criminal justice system the fourth highest category of public expenditure (following social security, health and education) in Britain.

Figure 1.1 Recorded Crime in England and Wales 1918-1999



Source: Home Office

1.3.3 Problems with Recorded Crime

The figures given above and used in much of this thesis are crimes reported to and recorded by the police. Thus, as is often pointed out such figures exclude any crimes that are either not reported to or recorded by the police. They exclude what is termed 'the dark figure of crime'. The extent to which this is a cause for concern depends on a number of factors: Why do crimes not appear in the official statistics?

[8] The long time trend stops in 1999 because as mentioned above changes in recording practises in 1998 make comparisons after 1999 difficult.
[9] For the year 2000-2001.

Do we need to know every crime in order to study its causes? Can we deal with potential problems methodologically? And, are there any other sources of crime data that are more reliable?

According to Brantingham and Brantingham (1984) and Williams (2001), there are many reasons why individuals may not want to report crimes to the police. These include instances where a crime is so subtle that no one becomes aware of it (e.g. breaking and entering where nothing is touched), instances where an occurrence is not perceived to be a crime (e.g. violence in the course of sport) and events where the victim is willing (e.g. drug offences). While it is true that these do not appear in the official statistics it is doubtful that such offences would ever appear as crimes no matter how they were recorded. Moreover, there is always likely to remain a 'dark figure' of crime regardless of the method used to collect the data (Williams 2001), given that there are some crimes that people will not want to report to the police or tell to an anonymous interviewer.

There is another reason given by Brantingham and Brantingham (1984) and Williams (2001) for failing to report a crime which is that the crime is perceived to be too trivial. Indeed, the British Crime Survey (BCS), indicates that this is one of the main reasons for not reporting a crime to the police (accounting for 70% of all those crimes not reported in the most recent sweep of the BCS) (Home Office 2002). Most serious offences are reported, as are any crimes which are required to be reported under the terms of insurance requirements, such as household theft and vehicle theft (Home Office 2002).[10] This means that many of the crimes analysed in this thesis are well represented in the official statistics.

[10] In the 2001/2002 BCS 94% of all thefts of cars were reported and 84% of all burglaries where something was stolen were reported (Home Office 2002).

Minor offences are also those which are least likely to be recorded by the police. Police forces are bound by law to record crimes, but as Williams (2001) points out there must be *prima facie* evidence that a crime has been committed and it must be of a serious enough nature to warrant police attention. This may result in the less serious crimes going unrecorded by the police.

Given the issues discussed above, there still remain a large number of crimes that do not appear in the official statistics. Brantingham and Brantingham 1984 argue that this does not mean that we are unable to study crime or the causes of it:

> *"Many criminologists...seem to think that the scientific assessment of causal patterns in criminality or criminal events depends on a complete enumeration of all crimes that occur. Such a complete enumeration is no more necessary to criminology than a counting of all the stars is necessary to a viable cosmology."*
>
> Brantingham and Brantingham 1984, p50.

Although there remains a 'dark figure' of unreported and unrecorded crime where this is consistent, an examination of changes in crime as presented in this thesis should not be affected. Thus as Brantingham and Brantingham (1984) note of official statistics:

> *"they consistently index changes in the trends and patterns of crime even though they are an invalid measure of the totality of criminal events."*
>
> Brantingham and Brantingham 1984, p64.

Even in instances when this is not completely accurate (for example if the propensity of different police forces to record crimes is slightly different) the choice of methods used to analyse the data can account for these differences. Such methods will be discussed as and when they are applicable in each Chapter. But as a general introduction, this works because one of the benefits of official statistics is that they allow the analysis of data measured across areas and over time. This allows the researcher to set up area longitudinal data that follows the same units over time and allows the use of methods that control for factors which either differ across area but are constant through time, or are constant across area and differ through time.

For example, if the likelihood of reporting and recording crimes shifts across time (because of a government drive to reduce the 'dark figure' for example), where this affects all police force areas in the same way these time differences can be controlled for. Going back to the previous example, if some police force areas record crime more or less accurately than others, the methods used can control for such differences, as long as these area differences are constant through time.[11]

Potentially more problematic issues are related to changes in definitions that make comparisons across different time periods or different police force areas difficult. There are two issues of this type dealt with in this thesis. The first is related to police force boundary changes that occurred between Gwent and South Wales in April 1996. This is dealt with by amalgamating the two police force areas to provide a consistent area over the period under examination. The second issue is the change in the police accounting rules that occurred in April 1998,[12] that makes it difficult to compare crime rates before and after this date. For the most part, this thesis

[11] This methodology is referred to as accounting for 'fixed effects' and will be discussed in much greater detail in the empirical Chapters where it is applied.
[12] New rules measure one crime per victim. Also the definition of notifiable offences has be widened to include all indictable offences, all triable-either-way offences and associated summary offences (Home Office 1999a).

overcomes this problem by confining the period of examination to years when the accounting rules are constant. However, Chapter 4 also offers a methodological technique to deal with the crime rates over the period in which the accounting rules changed.

Expressed slightly more technically, under-reporting or mis-recording of crime can produce measurement error. This is the difference between the measured observed value y and the true value of a variable y*. So any discrepancy between the true and measured value is given by $e=y-y^*$. The model we want to estimate is:

$$y^* = \alpha + \beta X + \varepsilon$$

But instead we have to estimate:

$$y = \alpha + \beta X + \varepsilon + e$$

So now the error term in the model contains two components, ε the normal error term and e the measurement error. When the measurement error is in the dependent variable (i.e. the crime rate) y replaces y^*. So long as the measurement error in y is not systematically related to any of the independent variables, (for example, in a model of crime where X measures wages if low wage people are less likely to report crime the error term will be correlated with the wages measure on the right hand side of the equation) the estimated model will not be biased.[13]

Even if the above example is correct and low wage people or less likely to report crimes (either because they are not insured or they have a negative view of the law or they are criminals themselves (McDonald 2001)) measurement error need not be too much of a problem. It depends on the size of the measurement error. This in turn depends on the variance of X relative to the variance of the measurement error. When the variance of X is large relative to the variance of the measurement error any

[13] Technically this amounts to $E(X,e) \neq 0$.

inconsistency in the results will be small. The result of measurement error is attenuation bias where the estimate of β will always be closer to 0 than the true β. Thus, the results produced under measurement error will be slightly conservative estimates rather than other way round, which would perhaps be more worrying.

1.3.4 Alternative Sources of Data: Self-Report Studies

There are alternative sources of information on crime, which may or may not be more accurate reflections of the level of crime in society.[14] The main alternative source on the extent of crime comes from self-report studies, where individuals are asked whether they have ever (or within a specific period of time) committed an offence. The Youth Lifestyles Survey is an example of a self-report study and is studied in Chapter 6 (see Chapter 6 for more details of this particular study).

While self-report studies are not affected by bias associated with the selection and processing of individuals by the criminal justice system, they are associated with some methodological problems of their own. Firstly there are hardly any nationally representative self-report studies of crime in the UK.[15] Secondly, these types of studies are usually cross-sections at one point in time.[16] Studies which have been constructed over a period of time, such as the Cambridge Longitudinal Study of Juvenile Delinquency (see Farrington et al 1986), cover only a small sub-sample of a specific group of people.[17]

Thus, while self-report studies provide rich data, the information collected are usually not representative. The small sample sizes mean we have no way of establishing how similar the individuals in a particular study are to the rest of society.

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[14] These are only briefly mentioned here as they are not the main concern of this thesis.
[15] The Youth Lifestyles Surveys are representative of a selection of young people, 16-25 year olds for the 1992/1993 study. The 1998/99 study covers 12-30 year olds. And even these studies exclude young people living in institutions hospitals; prisons or young offender institutions; residential care homes; army barracks; nurses' accommodation, and colleges and public schools. Or the homeless.
[16] Such as the Youth Lifestyle Surveys.
[17] The Cambridge study followed 411 boys from a specific area in South London.

The most extreme example of this is found in case studies of a particular individual or group of individuals or in personal accounts of crime.[18] The cross-sectional aspect of many of these studies[19] also pose problems of representativeness. While results may be representative at that particular time, there is no way of knowing how this compares with previous or later periods.[20] In both cases, it is not possible to infer any conclusions from results drawn from the data outside of those in the study. Usually, it is not even possible to compare the results from study to study. This is not very helpful to any criminologist interested in influencing criminal policy.

Also, there is no way of establishing the validity or reliability of what the respondent tells the interviewer in self-report studies. Respondents may conceal or exaggerate their involvement in crime, or may answer in a way that they think the interviewer wants them to. Moreover, if the information is being asked retrospectively respondents may not remember accurately events that have happened in the past or may say they happened at a specific time which the researcher is asking about when in reality they happened before or after that date (Brantingham and Brantingham, 1984). Technically these induce measurement error as with the official statistics.

1.3.5 Alternative Sources of Data: Victimisation Studies

These are similar to self-report crime studies but instead of asking respondents whether they have committed a crime, they ask whether they have been a victim of crime. There exist a number of local victimisation surveys (such as the Islington Crime Survey (1985, 1990); the Edinburgh Crime Survey (1990); the Manchester Survey of Female Victims (1986); and the Merseyside Crime Survey (1984)), but the largest and most extensive study of this type in the UK is the British Crime Survey

[18] Although this is not to say the rich data these studies produce are not useful for other types of work.
[19] Such as the Youth Lifestyles Surveys.
[20] Also as we will see in later Chapters it is very difficult to establish causality using cross sectional data.

(BCS). This measures crimes against individuals aged 16 and over living in private households in England and Wales (Home Office 2001b).

While some claim these to be the most accurate reflection of the level of crime in society (Williams 2001), like the self-report studies, victimisation studies such as the BCS are associated with their own methodological problems. The first of these is that victimisation surveys tell us about victimisation rather than crime. Thus, they only cover a sub-set of crimes for which there is a victim. Therefore, there is no information on crimes with no victims (such as prostitution); or crimes where the victim may collude with the criminal (such as drug dealing); nor crimes where the victim is no longer around (i.e. murder); or crimes where the victim is a corporation (Williams 2001). In all, only 62% of crimes in the BCS are comparable to the official statistics, while only 53% of officially recorded crime is comparable to the BCS (Home Office 1998b).

Survey victimisation studies are subject to many of the same difficulties as self-report studies for reasons related to representativeness, reliability and validity. In terms of representativeness even the most recent sweep of the BCS, which is by far the largest and most comprehensive to date, notes in its appendix:

> *"As in any sample survey, it is difficult to represent the population adequately. Some respondents are impossible for interviewers to locate at home, and others refused to be interviewed."*
>
> (Home Office 2001b, p89).

If those who did not take part in the survey are in any way different from those who did take part (for example, if they are more or less likely to be victims of crime) the sample will not be representative.[21]

Although the BCS has been carried out over a period of time,[22] the fact that the area information remains anonymous[23] and that area sampling schemes have changed across surveys means that researchers cannot construct area panels to follow over time. The best that can be done is to analyse changes across time in the various cross-sections. Methodologically this is much weaker than using longitudinal data, because the units of comparison are not the same.

Also, there is some evidence that many respondents admit to being victims of fairly minor or trivial offences, which would not necessarily be thought of as criminal offences in the eyes of the law (Conklin 1986). This means that victimisation surveys tend to overestimate the extent of crime (ibid). This factor, combined with issues of validity and reliability discussed above (i.e. respondents lying about crimes or inaccurately remembering time frames etc) make it unlikely that figures from victimisation surveys are any truer a reflection of the level of crime in society than the official statistics.

Moreover, as Williams (2001) points out, the authors of the BCS themselves admit that for crimes that are well reported to the police such as vehicle theft and burglary the official statistics probably offer a truer reflection of crime. While, crimes that are unlikely to be reported to the police such as rape do not appear in the BCS either.

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[21] Like self-reported crime surveys, victimisation surveys tend to under represent crime against particular groups, often the most heavily victimised groups such as young people, the homeless and prostitutes, for example.
[22] 1981, 1983, 1987, 1991, 1993, 1995, 1997, 1999, 2000, 2001/2002.
[23] Although areas codes were initially available for early years of the BCS, these have subsequently been removed.

Thus, it becomes clear that at least in the UK,[24] while there are methodological shortcomings associated with the use of official statistics, this is also true of the alternative measures of crime available. Thus, while the official statistics have some limitations, the issue is to know and acknowledge where the problems lie, try to sort them out or avoid them (as was done with the boundary and accounting rule changes), or to use methodologies which attempt to minimise the problems (by looking at changes over time, for example). Taking all these factors into account, the official statistics provide a rich source of data on crime measured across areas and over time, not found anywhere else in the UK.

1.4 Facts: Labour Markets

The next section describes various aspects of the UK labour market, concentrating on a number of factors that are likely to be salient in studying crime and the labour market.

1.4.1 Unemployment

Unemployment in Britain rose rapidly during the 1970s, reaching a peak in 1984. After this unemployment rates fluctuated around a relatively high level (Nickell 1999). The International Labour Organisation (ILO) definition of unemployment currently stands at around 5%. Although this figure is relatively low, it masks many inequalities within unemployment. For instance, for many groups, such as professionals, unemployment is rare, while for other groups such as those with no qualifications unemployment is commonplace (ibid). The young face particularly high rates of unemployment and their position has worsened over the last thirty years. In

[24] The crime data in the US is more extensive.

1975 the unemployment rate for 16 to 24 year olds was around 8%. By 1998 it had risen to 14%.

There are also differences across gender. Females are less likely to be unemployed than males. While unemployment of prime age males (25 to 49) has increased over time (from 4% in 1975 to around 6% in 1998) the unemployment rate of similarly aged females has fallen (from 6% in 1975 to 5% in 1998) (Nickell 1999).

Unemployment rates depend to a large extent on educational qualifications. This feature seems to have become stronger over time. As more and more people are gaining educational qualifications the difference between those with education and those without has widened in terms of unemployment. In 1979 the unemployment rate of those with a degree was 2%, whereas, by 1998 it had only risen slightly to 3%. In comparison, the unemployment rate for those with no qualifications rose massively over this period from 7% in 1979 to 12% in 1998. This rise was primarily the result of rising unemployment rates for uneducated males. Unemployment for males with no educational qualifications rose from 7% to 16% between 1979 and 1998. In comparison the unemployment rate for similarly qualified females rose from only 7% to 8% over this period (Nickell 1999).

1.4.2 Inactivity

The unemployed are not the only group of people not in work. There is another group of people who are out of work but who are not actively looking for a job. This group is known as the inactive. The economically inactive is a large group, which currently constitutes around 8 million people (four times larger than the unemployed) (Gregg and Wadsworth 1999). Like unemployment there are huge differences in labour market inactivity rates across gender, age and education levels. Females traditionally have higher rates of inactivity than males, but while male inactivity has increased in the last thirty years (from 3% in 1975 to 13% in 1998), the female inactivity rate has fallen from 37 to 27% over the same period (ibid).

Like unemployment, inactivity is strongly related to educational attainment. The less education an individual has, the more likely that he/she will become economically inactive. This is true for both males and females. In 1979 the inactivity rate for males with a degree was less than 1%, by 1998 this had risen to 7%. While for those with no qualifications, inactivity rose from 5% to 30% between 1979 and 1998. The rise in inactivity for the least educated females was smaller than for males, going from 41% to 49%. For the most highly educated women inactivity actually fell during this period, from 23% to 13%.

1.4.3 'Workless Households'

Since the 1970s female participation in the labour market has increased considerably. Estimates from the Family Expenditure Survey show that in the UK in 1970 only 38% of all employees between the age of 16 and 64 were female, but by 2000 this figure had risen to almost 50%. However, it is argued that much of the rise in female employment has been amongst women with working partners (Desai et al 1999). Thus, the rise in female employment has not occurred in the same households where male unemployment and inactivity has risen. This has meant that work has become polarised across certain 'work-rich' households, while other 'work-poor' households are left with no access to any earned income. Trends towards this polarisation of work has resulted in a massive rise of 'workless households' (Gregg, Hansen and Wadsworth 1999). In 1975 around 7% of households were workless, by 1998 this had risen to 18%.

Perhaps the most alarming occurrence associated with this phenomenon is the link between workless households and poverty. Indeed, around 75% of workless households live in poverty (defined as having below half the average equivalised household income after housing costs). Poverty among those in workless households is particularly acute amongst those with children. Around 89% of workless households containing children live in poverty (ibid).

1.4.4 Wage Inequality

The gap between the rich and the poor rose during the 1980s, to its highest level last century (Machin 1999). In 1975 the difference between male wages at the top end of the earnings distribution (the 90^{th} percentile) and the bottom end (the 10^{th} percentile), as measured by the 90-10 earnings ratio, was 2.86, (that is the male at the 90^{th} percentile in the earnings distribution was paid 2.86 times more than a male at the 10^{th} percentile of the distribution). By 1996 it had risen to 3.96. The corresponding figures for female wage inequality are 2.91 and 3.54 respectively.

Examining the male wage distribution alone shows that while the gap between those in the middle of the wage distribution (measured by the 50^{th} percentile) and those at the top increased over this period (the 90-50 ratio went from 1.70 in 1975 to 1.93 in 1996), a larger proportion of the overall inequality came from the difference in the gap between those in the middle and those at the bottom end of the distribution. Indeed, the 50-10 ratio increased from 1.69 in 1975 to 2.05 in 1996.

For females, the pattern was the other way round. A greater part of wage inequality came from the difference between those at the top and those in the middle. The 90-50 ratio rose from 1.78 in 1975 to 2.01 in 1996. The 50-10 ratio went from 1.64 to 1.76 in this same period.

Of course, wages are strongly determined by educational qualifications and so to some extent, wage inequality reflects changes in the wage returns to education. Thus, while those with a degree have always been paid more than those with no qualifications, the gap between the two educational groups is now bigger than in the past. Machin (1999) presents evidence to show that in the 1970s the percentage log (weekly wage) difference between a graduate and a person with no educational qualifications was 54%. By the 1990s this difference had risen to 66%.

The main explanation for the rise in wage inequality is skill biased technological change, that is the use of technology that requires a more skilled workforce and reduces, if not removes, the demand for less skilled workers (Machin 1999). Other explanations lie in increased international trade, particularly from less developed countries which reduces the demand for less skilled workers. And the decline of Trade Unions, who in the past compressed wages in their role as 'defenders of the egalitarian pay structures' (Machin 1999, p 199).

The introduction of the National Minimum Wage to the UK labour market in April 1999 made an important contribution to reducing the wage inequality discussed above and improving the financial situation for those workers at the bottom of the wage distribution (at least around the year of introduction). Indeed, Metcalf (1999) estimated that some 2 million workers would see their wages rise by around 30%.

Alleviating the situation for the very low paid is especially important because low pay tends to be persistent (Stewart 1999) and mobility in the wage distribution for those at the bottom is very limited (Dickens 1999). Low paid individuals are more likely to exit into unemployment or inactivity in a 'low pay – no pay' cycle (Stewart 1999) than move up the wage distribution (Dickens 1999).

1.4.5 Hypothesis Testing

It is clear that the last thirty years or so have witnessed many changes in the nature of the labour market. These changes provide an ideal situation in which to test empirically hypotheses concerning possible effects that shifts in the labour market may have on crime. This is explored in some detail in the remaining Chapters of this PhD. Chapters 2 and 3 in particular look at the effect of changes in unemployment, wages and wage inequality on crime, while Chapter 4 looks at the impact of the National Minimum Wage. Chapter 5 examines the effect that increasing female labour force participation may have on crime, while Chapter 6 looks at the importance of education in relation to crimes committed by youths.

1.5 Thesis Aims and Outline

1.5.1 Broad Aims of This Work

There has already been a large amount of work done in the area of this thesis. Yet there remains a general lack of consensus as to which labour market variables are most related to crime; which data are most appropriate to study the question; and, which methodologies are best suited to uncovering causal relationships between crime and the labour market (for discussions see Box 1987, Chiricos 1987 or Freeman 1983, 2000).

In light of the often conflicting evidence that has been presented on these issues, the broad aims of this research are four-fold. Firstly, by taking (often very large) changes in the labour market discussed above and examining their differential impact on crime, this research aims to establish which labour market variables are most associated with crime.

Secondly, by using a number of different data and methodologies, the research attempts to contribute to debates surrounding the strengths and weakness of different data and methods available for their analysis. In particular, much of the work in this area in the UK uses macro level data (see Field 1990, Hale 1998 and Wells 1995 for examples). This research aims to improve upon that by utilising area level data, which allow the use of a wider range of more robust techniques of analysis (for example area fixed effect models that were briefly mentioned above and will be discussed later).

Thirdly, through the dissemination of findings resulting from this research, the aim is to bring the above debates to a wider audience of academics and non-academics, policy makers, and public practitioners where it may have the ability to inform social policy in this area. And fourthly, as well as answering questions in this field this research aims to highlight new questions that social scientists may want to ask and try to answer in the future.

1.5.2 Chapter Outlines

1.5.2.1 Chapter Two – Looking for A Relationship between Crime and the Labour Market: Some Exploratory Research

As noted above, despite the large literature that exists within the field of crime and the labour market, the evidence points to a general lack of consensus as to which labour market variables are most related to crime and what methodologies are most appropriate for examining such a relationship. This Chapter is the first of two which introduce facts, concepts and issues surrounding research in crime and the labour market and which attempt to build up evidence that is utilised in the later Chapters of this thesis.

In an attempt to establish relationships between crime and its correlates in England and Wales in the 1990s, this Chapter looks at a number of key labour market, demographic and deterrence variables and the effect these factors have on different crimes. This Chapter examines two ways in which the crime rate varies: between police force areas and within police force areas. It also uses a number of different methodologies to explore the strengths and weaknesses of each of these approaches.

The results show that the discovery of significant relationships is easier using cross-sectional data, but that these results are possibly misleading, produce difficulties in terms of being able to establish causality and therefore make it hard to draw implications for criminal policy. Examining area level data over time is shown to be much more useful. Although using this data and its associated methodologies makes it more difficult to establish significant relationships, those that are discovered are more robust even to the inclusion of dynamic effects.

By using area-level longitudinal data to exploit cross-area changes to identify the determinants of crime, the results show that the 1990s saw property crimes rising by more in areas where wage inequality rose by more. Crime was also lower in areas where the number of police officers was higher and it was also lower where there was an increase in the proportion found guilty of all crimes.

Explaining violent crime rates proves more difficult, as their relative infrequency makes the results much noisier. Despite this, evidence from this Chapter shows that violent crime is positively related to average wages; it is higher in areas where the average wage is higher over the period under examination and lower in areas where the number of police officers is higher.

The results also show that both property and violent crimes are heavily persistent over time and that failure to account for this persistence may mean that some of the factors that help explain crime are ignored.

1.5.2.2 Chapter Three – Spatial Patterns of Crime: Can Labour Market Variables Explain them?

Residential location is a strong determinant of the level of crime. This theme is the basis of Chapter 3, which provides an introduction to basic facts and details concerning area level crime in England and Wales. Thus, with the aid of mapping technologies, this Chapter carries out an exploration into the spatial distribution of crime across 374 local authorities in England and Wales. Using various statistical and Geographical Information Systems (GIS) mapping techniques, the Chapter focuses on establishing and plotting spatial patterns of crime across different geographical locations. It examines the extent to which the uneven distribution of crime can be explained by the distribution of a range of demographic, labour market and socio-economic determinants of crime.

The findings show that crime is not randomly located but that in general, there exists positive spatial association across areas. Areas of high crime are located near to other high crime areas and low crime areas are located near to other low crime areas. Across the areas of England and Wales there is shown to be clusters of both positive and negative association, although positive spatial associations are more prevalent.

Statistical regression analyses show that some of the spatial association can be explained by the variations in a number of measurable variables. The variables that are found to be statistically significant (and thus able to explain at least some of the spatial association of crime across areas for property crime) are related to the age, sex, educational level, labour market position and the financial situation of individuals living in the area. Property crime is found to be higher in areas where the proportion of males in the area and the proportion of young people aged under 25 are higher and where the proportion of 16-19 year olds in full time education is lower. Property crime is also higher in areas with a higher proportion of lone parents and individuals claiming lone parent income support; in areas where the income at the bottom end of the distribution is lower and the top end higher; and in areas where a higher proportion of the population is unemployed.

Like the previous Chapter, evidence from this Chapter suggests that it is harder to uncover the determinants of violent crime than property crime. Nevertheless, some factors are shown to be significantly related to violent crime. Areas with a higher proportion of males, a higher proportion of non-whites and a higher proportion of people claiming lone parent income support have higher rates of violent crime than other areas.

After controlling for differences in the measurable area characteristics the spatial association of crime across areas that is left is attributable to unmeasured factors. Although on the whole these unmeasured characteristics produce less spatial association, the unmeasured variables do produce some spatial associations. Those that remain are different in nature to the patterns produced by the measurable variables.

The spatial association produced by the measurable characteristics are dominated by positive associations of high crime rates around the large city areas such as London. This is not true of the spatial patterns produced by the unmeasurable determinants of crime. This provides evidence that much of the rural / urban crime differential can be explained by differences across these areas in the measurable characteristics of those areas.

1.5.2.3 Chapter Four – Crime and the Minimum Wage: A Quasi-Natural Experiment

This Chapter looks at the relationship between crime and low wages in a rather different way. If one thinks that differential wage opportunities matter for crime, then presumably the best way of testing for the existence of a crime-wage link is to look at a situation where people on the margins of criminal participation receive a (potentially large) wage increase. Such a situation is clearly offered when a binding minimum wage floor is introduced to a labour market that previously was not regulated by minimum wage legislation. This was the case when a National Minimum Wage (NMW) was introduced in the UK in April 1999. If labour market conditions are related in an important way to crime, or an individual's propensity to commit criminal acts is altered by changing labour market opportunities, then one may well see changes in crime occur in the time period surrounding minimum wage introduction.

The empirical methodology utilised in this Chapter involves comparing what happened to crime rates before and after the Minimum Wage was introduced in the police force areas of England and Wales. Changes in various crime rates before and after minimum wage introduction are related to the initial proportion of low wage workers (i.e. those paid less than the minimum wage prior to its introduction) in those areas. Identification of the minimum wage effect comes from the fact that there are more low wage workers in some areas than in others and therefore, the Minimum Wage should be thought of having more of an effect there than in areas where there are fewer low wage employees.

The results uncover a statistically significant negative relationship, showing relative crime reductions in areas that initially had more low wage workers. This finding remains robust to controlling for other relevant determinants of crime; to benchmarking against earlier time periods; and to using initial period wage measures that look at the types of individual that might be thought of as more likely to be on the margins of crime. Overall, the results are in line with theoretical predictions that crime and low wages are related and that by improving the position of the low paid one does see a reduction in crime.

1.5.2.4 Chapter Five – Rising Crime and Improvements in the Socio-Economic Position of Women: Are they Related?

The previous Chapters show a robust relationship between labour market variables and crime. This Chapter puts this relationship to a different kind of test by utilizing one of the most noticeable changes to have taken place in the labour market in the last thirty or forty years, namely the increased labour force participation of women. If we believe that crime is related to labour market opportunities, the movement of females into the labour market may have an effect on crime. In the past, most theoretical and empirical work in this area has tended to focus on the effect of this movement on female crime, arguing that increases in female labour supply should lead to a shift in the total share of crime committed by women; either generating more or less female crime compared to male crime.

While this is an interesting area of research, females make up only a relatively small fraction of those who engage in crime. Therefore, examining the effect female labour force participation has on female crime is likely to uncover only a very small part of the impact that shifts in female labour supply may have on crime. On the other hand, if increased female labour force participation in any way damages the labour market position of males, and there exists a connection between crime and the male labour market, this will imply a larger effect on the overall crime rate. Thus, this Chapter builds on evidence from earlier Chapters that shows that weak labour market positions are positively related to crime. Using data on overall offences, as well as sex specific convictions data, measured across police force areas between 1975 and 1998, the Chapter examines the effect of increasing female employment on crime by assessing the impact it has on the male labour market and the subsequent effect this has on crime.

The results show that in areas where female employment rose, crime also rose. This result is robust to measuring crime as all notifiable offences for property crimes and male property crime convictions. The results are stronger for male-specific crimes, probably due to the fact that including even a small number of female crimes is likely to bias the coefficient downwards, as female employment and female crime are likely to be negatively related.

Findings suggest that the positive relationship between female labour supply and crime may be produced as a result of female employment reducing male wages. The fact that the results are stronger when female employment is measured as the share of low skilled male occupations suggests that it is the wages of the least skilled males that are most affected. This is supportive of the idea that women substitute for less skilled men, thus increasing pressure on males who are already likely to be on the margins of crime and thereby increasing crime. These results are congruent with the findings from the previous Chapters.

While a positive relationship between female labour supply and crime is uncovered, this does not mean that female employment necessarily produces bad outcomes. The results suggest that the issue may lie with the fact that females entering the labour market are substituting for the low skilled males. It is likely that as females continue to improve their educational qualifications and accumulate labour market experience they will compete for jobs with males further up the employment ladder who are less likely to be on the margins of crime. It is likely that as women substitute for males higher up the employment ladder, the effect of increasing female labour supply on crime will become weaker.

1.5.2.5 Chapter Six – Age Differences in Crime: Are They Explained by Education?

Previous Chapters of this thesis examine the impact of the labour market on crime. As discussed previously, one of the main determinants of an individual's position in the labour market is his/her educational attainment. This is even more pertinent today than in the past, given the large changes that have taken place in both the education system and the labour market in recent years. These include the massive increase in higher educational participation, coupled with a rise in demand for a more skilled workforce and an increase in the wage returns to education.[25] All of which mean that the gap between those with education and those with none is greater today than in the past.

At the same time, education is strongly related to crime. According to a report by HM Chief Inspectorate of Prisons (Home Office 1998c) there were 10570 young people under the age of 22 in the custody of the prison services in England and Wales in 1997. This represented a 5% increase on the previous year. The report points out 'most of the youngsters had been failed by the education system' (Chapter 3, paragraph 3.12). Around two thirds of these youths had no formal qualifications, many had regularly truanted from school and over 50% had been excluded (or left voluntarily) before the age of 16.

With these facts in mind, this final empirical Chapter examines the effect of education on shaping the crime-age profile of two groups of young males: those who have more education (those who stay on after the compulsory school leaving age) and those with less (those who leave school at age 16). As a critical part of childhood years is children's exposure to the education system, the focus of this Chapter is on potentially different crime-age profiles for people with different levels of educational

[25] These were all discussed above in section 1.4 'Facts: Labour Market'.

attainment. And on factors which are likely to be related to crime and age and which may be able to account for observed differences in the two profiles. These factors include: neighbourhood/area, school, individual, family and labour market variables.

The results show that the crime-age profiles for the less educated seem to be different from the profile for the more educated group (those who stayed in education past the compulsory leaving age). Whilst the probability of the more educated group committing offences is reduced to negligible levels by the age of 25, the profile for the less educated group shows little sign of decline from around the age of 22. By age 25 the latter group has a much higher probability of committing all three types of offences than the more educated group.

Once other variables are introduced into the equation, the gap between the two profiles is reduced. In some cases, for particular ages or offences, the gap is completely removed. Overall, the most important sets of variables in accounting for the gap in the profiles for all three crime types are school, family and individual variables. These variables differentially account for more or less of the gap at particular ages. The factors which matter most are: whether individuals live in the parental home (negative for all offences); whether their family had previous contact with the police (positive for all offences); whether the individual had played truant from school (positive for all offences); whether the individual's father was SES V (positive for violent offences), and; whether an individual lived in social housing (positive for violent offences). These are the variables that bring the profiles together in the full model. These are also the variables that act as individual determinants of crime, regardless of age.

This Chapter shows that age, although correlated with crime, is also correlated with other variables such as schooling, individual and family characteristics which are differentially associated with the probability of young people of the same age committing crimes. Once we take into account the fact that the two groups vary in terms of other observable characteristics (such as whether they truanted or were excluded from school, where they live, who they live with and what they do), we see a reduction in the gap between the two groups and the profiles are brought together.

Having discussed the motivation and structure of this thesis the following Chapter begins the empirical analysis of the relationship between crime and the labour market.

2. Looking for A Relationship between Crime and the Labour Market: Some Exploratory Research

2.1 Introduction

Knowledge of what are the most important determinants of criminal behaviour is central to criminology as an academic subject, and to any input the discipline can have into the process of policy design and implementation. As a consequence a number of researchers have adopted a quantitative approach to look at the factors that affect crime. A large number of these have turned to the labour market for explanations of criminal behaviour.

However, data constraints meant that in the early days of this research nationally representative data were only available at the macro level. While work using these aggregated data provides evidence of links between crime and a number of labour market measures, it has been criticised for its failure to look at what is happening beneath the national level. Other types of data available at this time allowed quantitative researchers to carry out cross-sectional analyses examining the relationship between crime and the labour market in a particular area, or between two or more areas in a particular year. While this has also produced a number of findings, its lack of representativeness is a severe limitation.

Improvements in data collection and availability and advances in the methodological techniques for dealing with data now mean that it is possible to look at temporal and spatial differences in crime at the same time. This allows researchers to combine the advantages of both time series and cross-sectional methodologies. Use of area data means that questions can be asked about what is happening at a more micro level, making it possible to discover relationships which may well be obscured in national level data. Moreover, following areas over time makes it possible to control for area characteristics that are otherwise unobserved and may affect the relationship between crime and its correlates. In this way, it may be possible to identify a more accurate relationship between crime and other factors and even to identify causal relations.

This Chapter uses different types of data and a number of different methodologies to address two key areas within the field of crime and the labour market. Firstly, it explores why some areas have higher crime rates than others, paying particular attention to two possible determinants of crime, the nature of the formal labour market and the strength and deterrence capabilities of the criminal justice system. At the same time, this work addresses questions concerning the appropriate use of data and the methodological tools available for dealing with them.

2.2 Existing Empirical Work

Most empirical research on the determinants of crime in the UK has been at the national level. This work typically utilises time series data on crime rates and their determinants. In the UK the leading exponent of this type of work is Field (1990) who, in an examination of crime trends post World War II, found that property crime was negatively related to consumption. When consumption was higher, property crime slowed down or declined, and when consumption was lower, crime rose. When criticised for only looking at short run relationships, Field (1998) extended his data to 1997 and looked at both short and long term relationships. He found a long run positive relationship between the stock of consumer goods and the rise in property crime (burglary and theft). However, he could find no relationship between property crime and unemployment (either in the long or short run)[1], or between property crime and those cautioned, found guilty or imprisoned.

Building on this work, Pyle and Deadman (1994a) used annual data for England and Wales between 1946 and 1991 and found that not only consumption, but also real Gross Domestic Product (GDP) was negatively associated with changes in crime. In fact, real GDP may be a better measure than consumption of the link between crime and the labour market. Unlike Field, they also found a positive relationship between unemployment and crime. Although in a study using Scottish data Deadman and Pyle (1994b) failed to uncover such a relationship between crime and unemployment.

Using the same data as Deadman and Pyle (1994a), Hale (1998) found that personal consumption was the most important correlate of property crime over both the short and long run. While changes in unemployment were related to changes in property crime in the short run, no long run relationship between the two variables could be established.

However, recently macro studies have been criticized for their failure to explain more recent trends in crime (see Dhiri et al, 1999, or Pudney et al, 2000) and for the lack of practical policy implications that can be drawn from their findings. Moreover, it has

[1] Field (1998) found unemployment and property crime to be correlated but that this relationship was wiped out once consumption was included in the equation.

been argued that because of the level of aggregation, the findings from macro studies are less robust than studies using less aggregate data (Chiricos, 1987).

In the United States data quality and collection are clearly more wide-ranging than in the UK and work on the determinants of crime has utilized individual level data (e.g. Witte 1980, Myers 1983, or Thornberry and Christenson 1985). There are, however, very few individual level data sources on crime in the UK and where it does exist, it is either single cross-sections that focus only on young people (like the Home Office's 1992/3 Youth Lifestyles Survey[2] and the 1998/9 Youth Lifestyles Survey[3]), or it covers a very specific (and usually small) cohort of people. An example of the latter is the Cambridge Study in Delinquent Development that has been heavily used by researchers (e.g. by Farrington et al, 1986, or West, 1982), to show that individuals are more likely to commit crimes when they are unemployed than when they are in work. But this survey only covers 411 males born in a particular area of South London in 1953. With the exception of these rather specific data sources there are very few individual level data sources available in the UK and none that are nationally representative.[4]

Whilst there are hardly any individual level sources of crime data in the UK, it is possible to look at the relationship between crime and its hypothesised determinants at the level of police force area. There are 43 police force areas in England and Wales and data have been recorded at this level for some time. The existence of such data means

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[2] This data has been used by Graham and Bowling (1995) and Hansen (2001) (see Chapter 6).

[3] For more details see the report by Flood-Page et al (2000).

[4] Data on convictions does exist in the Offenders Index data but, apart from publicly available data on a few selected cohorts, this is only available for internal Home Office use. Moreover it just contains data on convicted offences with very little data on characteristics of offenders. There is also victimization data in the British Crime Surveys of 1982, 1984, 1988, 1992, 1994, 1996, 1998, 2000 and 2001 (each reports victimizations that have taken place in the previous year). However, as a survey the results are subject to sampling error, the surveys are not nationally representative and cannot be analysed at area level on a consistent basis though time as the areas remain anonymised. Although area codes were available in the past (see Hale et al 1994, Osborn et al 1992, 1996, Osborn and Tseloni 1998, Trickett et al 1995b for examples).

that researchers can carry out empirical work that looks at changes in crime across these police force areas over time. Clearly this adds a cross-sectional dimension that the macro work is unable to consider.

For example, Willis (1983) was one of the first to use police force area level data in his cross-sectional analysis of England and Wales in 1979. He found that a 1% rise in unemployment was associated with a small increase in theft and violence against the person, but was unrelated to sexual crimes. However, this study only used a single cross-section. As will be seen later, this has very serious drawbacks, especially when the main variable of interest, crime, is strongly persistent over time.

More recent work by Wells (1994) who examined changes over time across 41 police force areas[5] between 1975 and 1992, found changes in unemployment to be positively associated with some types of property crime: household burglary and vehicle theft.

Witt, Clarke and Fielding (1998, 1999) aggregated the 43 police force areas in England and Wales to the regional level[6] to look at the relationship between crime, male unemployment and wage inequality. In both studies they find changes in crime[7] to be related positively to changes in male unemployment and wage inequality.[8]

Reilly and Witt (1996) use data from 42 police force areas in England and Wales,[9] between 1980 and 1991, to look at the relationship between crime (burglary, theft and robbery), male claimant count unemployment and household income, while controlling

[5] Surrey was excluded for lack of unemployment data.
[6] The 1998 study considers ten regions (North West, North, Yorkshire and Humberside, East Midlands, West Midlands, East Anglia, London, South East, South West and Wales). The 1999 study considered nine by further aggregating London and the South East.
[7] In the 1998 study the crimes are burglary, theft from a vehicle, other theft, shoplifting and robbery. In 1999 they are property, vehicle, other theft, burglary and handling stolen goods.
[8] No relationship was found for shoplifting crimes in the 1998 study.
[9] There are actually 43 police force areas but the authors aggregate the City and Metropolitan forces.

for other demographic and deterrence variables which may affect their estimated relationships. Their findings show that household income is negatively related to burglary and theft. However, the estimate is driven to insignificance once unemployment is controlled for.

Work on area data by Machin and Meghir (2000) gives a stronger focus to the relationship between crime and the low wage labour market. They look at cross-area changes in crime and changes in the 25th percentile of the area wage distribution, finding a negative correlation between the types of crime they examine (theft and handling, burglary, vehicle crime and total property crime) and low wages, even after controlling for other variables including demographic change and measures of deterrence. They also consider the associations between area crime rates and criminal justice system variables in areas (focusing specifically on conviction rates and sentence lengths) and find that both these criminal justice variables are negatively associated with crime.

It is clear that there has only been a limited amount of work carried out so far in the UK at police force area level. This contrasts with the United States where a larger body of work exists, and where a number of robust findings have emerged. For example, Allan and Steffensmeier (1989) use US state level data between 1977 and 1980 to examine the relationship between property crime arrest rates (robbery, burglary, larceny and auto theft) for juvenile (13 to 17 years old) and young adult (18 to 24) males and employment conditions. They find that unemployment is positively related to juvenile arrests, but that low pay and low hours are associated with high arrest rates for young adults.

Raphael and Winter-Ebmer (2001) focus on the link between crime and unemployment and use annual state level data between 1970 and 1993 to show that unemployment is positively related to both violent and property crimes. They try to account for omitted variable bias by controlling for alcohol consumption and by using prime defence contracts per capita as an instrument for unemployment. When they do this, they find even larger unemployment effects.

Gould, Weinberg and Mustard (2002) look at the link between both unemployment and wages in their analysis of US annual county level data between 1979 and 1995. They find that although unemployment is positively related to crime, the wage of low skilled workers is a more important correlate of crime. Indeed, they report that the falling wages of unskilled men between 1979 and 1995 led to an increase in burglary of nearly 14%, a rise in larceny/theft of around 7%, a 9% increase in aggravated assault and an 18% rise in robbery.

In the US, there have also been a number of area level studies which focus on the relationship between crime and the criminal justice system. For example, Marvell and Moody (1996) use annual state and city level data between 1968 and 1993 to look at the relationship between crime rates and police numbers. They find that increases in crime rates lead to a higher number of police, but the relationship is greater the other way around, a higher number of police reduces crime.

Levitt (1998) considers state level data on youths for the period 1978 to 1993 to look at the relationship between juvenile crime and juvenile punishment. He finds that higher levels of punishment are associated with lower crime rates for both property and violent crimes. Drawing on this work, Levitt and Lochner (2001) use the same data to look at the deterrence effect of differences in juvenile and adult punishment. They find that states where adult punishment is most severe have the largest decline in crime around the age of majority.

This Chapter builds on this research by using data in different ways to find the most robust correlates of crime.

2.3 The Correlates of Crime: Theoretical Considerations

Over the years many variables have been considered as possible determinants or correlates of crime. In this Chapter two groups of variables are examined, the nature of the formal labour market and the strength and deterrence capabilities of the criminal justice system.

There are a number of reasons for focusing on labour market and criminal justice system correlates of crime. Firstly, if we think about the basic economic model of crime (seen in the work of Becker, 1968 or Ehrlich, 1973), an individual's decision to engage in crime is a function of a number of factors including the expected utility from crime, the expected utility from the formal labour market, perceptions of the likelihood of apprehension and the severity of punishment if caught. Thus, the labour market and the criminal justice system account for three out of four factors which enter the simple rational choice economic model of crime.[10]

Secondly, these two factors are potentially important determinants of crime in other frameworks. For example, the labour market position of an individual is of central importance to a number of criminological theories. Strain theory, for example, predicts poor labour market conditions may cause stress or strain and thereby push people towards crime (see Merton 1957). Furthermore, many of the low paid are in jobs where promotion or career advancement is hard (if not impossible). Thus their opportunities to have money

[10] Unfortunately in the UK there is no or little data available at this level which would allow the final factor, expected utility from crime, to be examined. Machin and Meghir (2000) have attempted to proxy for this by using information from the British Crime Survey on the value of goods stolen.

and status may be blocked. Unable to achieve success legally, these individuals may be forced to resort to participate in illegal activities.

Of particular relevance, is social control theory, which predicts a relationship between crime and both labour market position and the ability of legal sanctions to deter. In this framework social control works at two levels: informal social controls are the pressures brought to bear on individuals to abide by societal norms through their ties with society; formal social controls are more coercive attempts by the criminal justice system to deter crime (by threat of detection and incapacitation). Informal controls affect individuals differentially as individuals vary in the extent to which they feel attached to society. As one of the major institutions through which bonds are formed between individuals and society is the labour market, those with weak labour market positions, such as the unemployed or low paid, are likely to feel less attachment to society than others. With weaker bonds to society, these people feel less pressure to conform to societal norms and thus society is less able to deter them from breaking the law. Because they care little about what society thinks of them, even the prospect of stigmatisation, social disapproval or being labelled as a criminal has little power to deter them from breaking the law. Thus, social control theory may predict a positive relationship between crime and unemployment and /or wages.

However, formal social controls exert an additional coercive force that compounds the effects of informal social control discouraging criminal behaviour. Thus, the threat of apprehension and punishment works to persuade individuals, who otherwise may have considered committing a crime, not to do so. If the fear of formal sanctions works in this way we should expect to see a negative relationship between crime and criminal justice variables as the higher the likelihood of detection and the more severe the punishment (or the perceived likelihood and severity), the lower the expected crime rate.

Moreover, there are a number of deterrence theories that predict a relationship between deterrence and crime (for example, Silberman 1976). These are based on similar reasoning to economic rational choice theories, but express scepticism of the assumptions embodied in the economic models and prefer to emphasise the uncertainty and non-rational behaviour of individuals and the inconsistency and discrimination of the criminal justice system.

A third reason why it seems sensible to look at factors related to the labour market or the criminal justice system is that there is disagreement in many quarters as to which set of variables are the more important correlates of crime. Indeed, from a policy perspective it is important to discover whether initiatives to reduce crime would be best targeted at discovering the labour market position of individuals most likely to engage in crime and improving conditions for these individuals (thereby reducing or removing their need to engage in crime); or whether initiatives would be more effective in reducing crime if they were targeted at measures to deter or incapacitate those who do offend.[11]

2.4 Data Description and Descriptive Analysis

There are 43 police force areas in England and Wales, but for the work in this Chapter, two sets of police forces (the City of London and Metropolitan police forces, and the Gwent and South Wales police forces) have been amalgamated together. The reason for joining the City and Metropolitan forces together is because the small number of residents living in the City produces artificially high crime rates. Gwent and South

[11] This is not to deny that there could be other factors which might be important in influencing cross area differences in crime rates but these are not the focus of this Chapter.

Wales have been aggregated as a result of a police force boundary change that occurred in the period under examination so that only the amalgamated area grouping is consistent over the time period studied.[12]

The data have been constructed from a variety of sources at the level of the police force areas of England and Wales for the years between 1992 and 1998. The start date was used on the grounds that 1992 was the first period for which computerized data on measures of the criminal justice system were available.[13] The end date was dictated by changes in the accounting rules that took place in April 1998 which make comparison after this date difficult.[14] The data cover four main areas: crime; features of the criminal justice system; the labour market; and population and demographic characteristics of areas.

2.4.1 Crime Data

The crime data[15] cover notifiable offences at the police force area level, with total recorded crime being broken down into the following categories: violence against the person; sexual offences; robbery; burglary; theft and handling stolen goods; fraud and forgery; criminal damage; drug offences; and other offences.

These are crimes reported to and recorded by the police. As Chapter 1 showed, while official statistics may not identify all crimes, there are still good justifications for using them to study the causes of crime.[16] Increased pressure on the public to report crimes (due to insurance requirements) and on the police to record crimes means that in recent years there has (to some extent) been a convergence of trends in notifiable offences and trends in self-reported victimisations from the British Crime Survey (which

[12] In April 1996.
[13] Also data on the explanatory variables were not available before this date.
[14] Home Office Statistical Bulletin 18. October 1999. Although see Chapter 5 for an attempt.
[15] The crime data was supplied by the Home Office.
[16] Notifiable offences are the only nationally representative data available at the area level.

many believe is a truer reflection of crime (see Brantingham and Brantingham 1984 for discussion)). Moreover, as Chapter 1 discussed, evidence from the British Crime Survey suggests that most of the crimes not reported to or recorded by the police tend to be trivial in nature.[17]

Table 2.1 reports the total number of notified offences in England and Wales between 1992 and 1998 for all crimes and for the crime categories detailed above. It also reports information on crime rates computed as the number of crimes divided by the population. The Table reveals what is by now a well-known pattern. After the very sharp rises that occurred through the 1970s and 1980s[18] total recorded crime peaked in the early 1990s and then began to fall. Crime fell over the 1992 to 1998 period from around 5.6 to 4.4 million crimes or, in terms of rates, from .109 down to .085 crimes per person. But there is some variation by type of crime, while there was little or no change for violent crimes, most non-violent crimes fell over this period. In particular, theft and handling crimes fell rather sharply.

[17] See Appendix A for further discussions concerning the use of official statistics.

[18] In 1970 there were 1,568,000 crimes in England and Wales, by 1980 this had risen to 2,521,000 and by 1990 the figure was 4,364,000.

Table 2.1 Crime in England and Wales, 1992 to 1998 (Numbers of crimes and crimes/population)

	1992	1993	1994	1995	1996	1997	1998	Change 1992-1998
All crime	*5594826* *.109*	*5529219* *.107*	*5255290* *.102*	*5100241* *.098*	*5036553* *.096*	*4598327* *.088*	*4457531* *.085*	***-1137295*** ***-.024***
*All violent**	*284199* *.006*	*294231* *.006*	*311744* *.006*	*310936* *.006*	*344768* *.007*	*347064* *.007*	*330816* *.006*	***226617*** ***.000***
Violence against the person	201777 .004	205102 .004	219741 .004	212588 .004	239342 .005	250827 .005	232736 .004	**210959** **.000**
Sexual	29528 .001	31284 .001	31987 .001	30274 .001	31391 .001	33165 .001	34861 .001	**5333** **.000**
Robbery	52894 .001	57845 .001	60016 .001	68074 .001	74035 .001	63072 .001	63219 .001	**-18033** **.000**
*Non-Violent**	*5285053* *.103*	*5208871* *.101*	*4913306* *.095*	*4759872* *.092*	*4658150* *.090*	*4214620* *.081*	*4085697* *.078*	***-1196247*** ***-.025***
Property+	*4210021* *.082*	*4124449* *.080*	*3822146* *.074*	*3691593* *.071*	*3548529* *.068*	*3180027* *.061*	*3069944* *.059*	***-1140077*** ***-.023***
Burglary	1355274 .026	1369584 .027	1261441 .024	1239484 .024	1164583 .022	1015075 .019	965312 .018	**-389962** **-.008**
Theft	2854747 .056	2754865 .054	2560705 .050	2452109 .047	2383946 .046	2164952 .041	2104632 .040	**-750115** **-.016**
Fraud and forgery	168600 .003	162836 .003	146144 .003	133016 .003	136225 .003	134398 .003	160424 .003	**-8176** **.000**
Criminal damage	892623 .017	906746 .018	927447 .018	913991 .018	951274 .018	877042 .017	833314 .016	**-59309** **-.001**
Drugs	13809 .0003	14840 .0003	17569 .0003	21272 .0004	22122 .0004	23153 .0004	22015 .0004	**8206** **-.0001**

* Excluding 'Other' crimes as they are a mixture of violent and non-violent offences.
\+ Property crimes = theft + burglary

2.4.2 Criminal Justice System Data

Although this thesis is mainly interested in the relationship between crime and the labour market, it is also important to look at the effect of deterrence (for reasons already discussed). Not only is the effect of deterrence on crime of interest, but also, if deterrence is related to crime, failing to include it in the model will mean that the model will be under-specified and could suffer from omitted variable bias (see Appendix B for further discussion of bias). This will result in biased estimates of the coefficients on all the independent variables, including the labour market ones.[19]

For these reasons, for each crime category there is also information on a number of features of the severity of the criminal justice system.[20] These include the total number of people found guilty, the number placed in immediate custody, the average sentence length and the number of police officers.

Table 2.2A shows that for almost all crime categories, convictions have risen. For all crimes, the conviction rate rose by about 1/3, going from 7 percent to just over 10 percent. At the same time (as Table 2.2B shows), the total number given immediate custody as a proportion of those found guilty of each crime increased. This is true for most crimes. The total number imprisoned went up from 12 percent of all convictions to 19 percent, corresponding to a rise of over 50 percent between 1992 and 1998.

Table 2.2A Disposals on Principal Offence Basis (Total found Guilty as a Proportion of Each Notifiable Offence)

	1992	1993	1994	1995	1996	1997	1998	Change 1992-1998
Total crime	*.074*	*.070*	*.075*	*.075*	*.078*	*.091*	*.101*	*.027*
*All violent**	*.353*	*.311*	*.301*	*.301*	*.285*	*.308*	*.352*	*-.001*
- Violence against the person	.443	.397	.380	.389	.363	.382	.453	**.011**
- Sexual	.198	.160	.170	.192	.178	.163	.153	**-.039**
- Robbery	.096	.088	.082	.076	.080	.089	.088	**-.008**
*Non-Violent**	*.055*	*.052*	*.056*	*.055*	*.058*	*.067*	*.074*	*.019*
Property+	*.049*	*.047*	*.049*	*.047*	*.050*	*.058*	*.063*	*.013*
- Burglary	.033	.029	.030	.029	.028	.031	.032	**-.001**
- Theft	.057	.056	.058	.057	.062	.071	.077	**.019**
- Fraud and Forgery	.154	.147	.178	.178	.161	.163	.152	**-.003**
- Criminal damage	.039	.034	.035	.035	.035	.040	.045	**-.006**
- Drugs#	1.643	1.476	1.583	1.485	1.540	1.757	2.218	**.575**

*Excludes 'other' crimes. +Property crimes = theft + burglary. # Value >1 because of differences in the accounting rules of drugs crimes. For notifiable offences the crime is counted, for disposals each person involved in that crime is counted.

[19] Unless in the special case that they are completely independent of the omitted deterrence measures.
[20] Provided by the Home Office.

Table 2.2B Disposals on Principal Offence Basis (Total given Immediate Custody as a Proportion of those found Guilty of Each Crime)

	1992	1993	1994	1995	1996	1997	1998	Change 1992-1998
Total crime	*.123*	*.128*	*.145*	*.170*	*.179*	*.186*	*.191*	***.068***
All violent*	*.142*	*.159*	*.168*	*.187*	*.200*	*.197*	*.196*	***.054***
- Violence against the person	.098	.111	.125	.141	.150	.152	.153	**.055**
- Sexual	.334	.398	.366	.416	.446	.465	.504	**.170**
- Robbery	.706	.695	.686	.668	.711	.717	.715	**.381**
*Non-Violent**	*.111*	*.113*	*.130*	*.157*	*.163*	*.173*	*.175*	***.064***
Property+	*.119*	*.120*	*.147*	*.178*	*.179*	*.194*	*.200*	***.081***
- Burglary	.273	.295	.343	.382	.419	.452	.473	**.200**
- Theft	.077	.075	.098	.126	.126	.140	.148	**.071**
- Fraud and Forgery	.096	.102	.103	.141	.155	.165	.171	**.075**
- Criminal damage	.042	.035	.039	.045	.047	.048	.048	**.006**
- Drugs	.162	.165	.145	.167	.197	.191	.173	**.011**

* Excludes 'other' crimes. + Property crimes = theft + burglary

Whilst the conviction rates have risen, average sentence lengths seem to have fallen a little. This can be seen in Table 2.3. This is true for most crime categories except sexual crimes and burglaries, where sentence lengths have risen.

Table 2.3. Average sentence lengths (months)

	1992	1993	1994	1995	1996	1997	1998	Change 1992-1998
Total crime	*14.7*	*14.7*	*14.1*	*13.9*	*14.9*	*14.8*	*13.6*	***-1.1***
- Violence against the person	14.3	13.8	13.8	13.3	14.1	12.9	11.8	**-2.5**
- Sexual	36.4	36.1	36.3	36.8	37.1	37.9	38.7	**2.3**
- Robbery	39.0	38.8	39.8	38.2	38.1	39.1	35.3	**-3.7**
- Burglary	11.5	11.1	11.4	12.0	13.8	15.8	15.5	**4.0**
- Theft	6.1	6.4	6.1	6.0	5.7	5.7	4.9	**-1.2**
- Fraud and Forgery	12.3	11.3	11.0	9.8	10.5	9.7	9.3	**-3.0**
- Criminal damage	11.3	14.3	14.7	13.6	12.9	13.4	10.6	**-0.7**
- Drugs	28.1	28.1	27.7	28.1	28.1	28.9	27.0	**-1.1**

The final criminal justice related variable is the number of police officers. This is described in Table 2.4. The consistently defined data on the number of police officers run from 1993 onwards (no numbers were provided by the Metropolitan Police in 1992) and shows a fall of around 1000 police offices over this period.

Table 2.4 Number of Police Officers

	1992	1993	1994	1995	1996	1997	1998	Change
Number of police officers	97778*	124663	123743	124811	124792	124802	123780	**-883 (93-98)**

* Excludes numbers in the Metropolitan Police which are not available for 1992.

2.4.3 Labour Market Data

While there has been a fair amount of work done in the area of crime and the labour market, there is no agreed consensus as to which labour market variable has the greatest effect on crime. Various research studies find that unemployment (Land, McCall and Cohen 1990), low wages (Gould et al 2002), inequality (Fowles and Merva 1996), at least to some extent, are related to crime.

The labour market information used in this Chapter comes from two main sources, the New Earnings Survey (NES) and the Labour Force Survey (LFS). The former is an employer based survey (covering about 1 percent of the workforce in each year). It reports in April of each year which enables these data to be matched to the 43 police force areas, mainly at county level.[21] The same is true of the Labour Force Survey's anonymised area level data.[22] From the NES average hourly wages are

[21] The match is geographically exact for almost all police force areas. A problem occurs where the Metropolitan Police offers services to some (mostly) small areas of counties on the border of London. This affects the borders of Essex, Hertfordshire and Surrey and means that one should be careful to look at changes over time in modeling work (where this feature of the Metropolitan Police stays constant over time, for the sample period we have here).
[22] Individual level data contains county level identifiers, but only from 1995 onwards.

calculated, as well as the 10th, 25th, 50th, 75th and 90th percentiles of the hourly wage distribution. From the LFS unemployment rates have been calculated for each police force area. Table 2.5 shows hourly wages at different percentiles of the wage distribution, and shows evidence of rising inequality as the higher percentiles grow at a faster rate between 1992 and 1998 than the lower percentiles. From the Table we can see that the unemployment rate has fallen from 10 to 6 percent over this period.

Table 2.5 Earnings (£ per hour) and ILO Unemployment

	1992	1993	1994	1995	1996	1997	1998	Change 1992-1998
Mean	7.19	7.50	7.71	8.00	8.29	8.67	8.88	**1.69**
10th percentile	3.37	3.47	3.52	3.57	3.71	3.86	3.93	**0.56**
25th percentile	4.33	4.47	4.55	4.62	4.79	5.00	5.04	**0.71**
50th percentile	5.94	6.17	6.29	6.49	6.73	7.01	7.13	**1.19**
75th percentile	8.60	8.95	9.20	9.60	9.94	10.38	10.63	**2.03**
90th percentile	12.35	12.80	13.11	13.91	14.38	14.95	15.36	**3.01**
ILO Unemployment	.104	.105	.095	.087	.080	.072	.063	**-.041**

Source: Earnings from New Earnings Survey, ILO unemployment from Labour Force Survey.

2.4.4 Population and Demographic Data

Areas vary greatly in the size of the population and the population make-up. These differences can also affect the level of crime in areas. Usually areas with a higher population also have more crime. This makes sense in that the larger the population, the greater the pool of potential perpetrators and victims of crime and the greater the stock of goods to steal. Of course, some people are more likely to be involved in crime than others, so it is also important to control for the demographic make-up of the population in the area. For example, evidence suggests that blacks (Freeman 2000), and those with no educational qualifications (Lochner 1999) are more likely to commit crime than others.

Population numbers, which match police force areas, have been supplied by the Home Office. Demographic data have been assembled from the LFS.[23] These include the number of ethnic minorities and the number of 16 to 19 year olds in full time education. Table 2.6 shows that the demographics (population shares of ethnic minorities), unsurprisingly, stay fairly constant through this time period. Finally, the percentage of 16 to 19 year olds in education has increased from 49 to 57 percent between 1992 and 1998, reflecting the growing participation of students in post compulsory education.

Table 2.6 Unemployment and Demographics from the Labour Force Survey

	1992	1993	1994	1995	1996	1997	1998	Change 1992-1998
Share non-white	.052	.052	.053	.053	.055	.058	.061	**.009**
Share of 16-19 year olds in education	.494	.530	.558	.569	.579	.586	.568	**.074**

2.5 Methodology

Studies of data that vary across time and space have a great number of methodological advantages. Firstly, from an exploratory point of view, the data can be aggregated in a number of ways to show the strengths and weaknesses of the different data and methodologies available for dealing with them. This Chapter will focus on two ways of looking at the data. The first will look at all the time periods combined and examine the differences *between* police force areas. In doing this, the data effectively become cross-sectional data (but using cross-sectional data averaged over a number of years means that results are likely to be more accurate and robust than data that use a single period cross-section, as they ameliorate measurement error (see Appendix B)). The model that makes this possible is:

[23] The data used are anonymised county level data from the LFS. Individual level data is available at county level but only between 1995 and 1999.

$$\overline{C}_a = \beta\overline{X}_a + \overline{\varepsilon}_a$$

where $\overline{C}$ is the mean crime rate between 1992 and 1998, $\overline{X}$ is a mean measure of the explanatory variables over the same time period and $\overline{\varepsilon}$ is the mean error term reflecting the fact that explanatory variables are unlikely to fully explain the variation in crime. The subscript 'a' denotes police force area.

Between area differences allows the identification of high crime areas and low crime areas and can inform us which variables are related to high and low crime. However, with area level data measured over time, it is also possible to control for differences in crime across the police force areas and create an even arena where crime and its correlates can be examined. This is done by holding constant factors that may differ across high and low crime areas, some of which we would otherwise be unable to observe. These are referred to as 'area fixed effects'. Moreover, factors which vary over time (but are constant across areas (such as macro-economic shocks which hit the economy as a whole) can also be controlled for by including time dummies in the model, in the same way as the area fixed effects. The model in this case becomes:

$$C_{at} = \alpha + \beta X_{at} + F_a + T_t + \varepsilon_{at}$$

Where F is the area fixed effects and T are time dummies. The subscripts 'a' and 't' denote that the regressions are run on data following areas over time.

Thus, from a methodological point of view, spatial data measured over time has a number of advantages and provides the opportunity to use various techniques to analyse different aspects of the relationship between crime and its correlates, an analysis to which this Chapter now turns.

2.6 Splitting Crime into its Constituent Parts

It is possible to decompose the variance of changes over time in crime rates into two groups. The first group is the variation in crime occurring between areas, in other words the amount of variance in the crime rates that can be attributed to differences in the characteristics of different police force areas. The second is the variance within areas. The following Table shows these variance decompositions for the three crime rates.

	All Crimes	Property Crimes	Violent Crimes
Percent of Variation in Crime Between/Within Areas	87/13	81/19	87/13

Between 1992 and 1998 most of the variation in crime occurred between areas, 87 percent of the variation in all/violent crimes occurred between areas and 81 percent of the variation in property crimes. This leaves 13 percent of variation in crime occurring within areas for all crime and violent crime and 19 percent for property crime. Both types of variation will now be discussed in turn in an attempt to establish a relationship between crime and its determinants.

2.6.1 Between Area Variation in Crime

Between area variation is an important aspect of crime. Indeed, there exist large differences in crime across different areas of England and Wales. According to the 2001 British Crime Survey, crime is much higher in inner city areas than any other areas, while rural areas have much lower crime rates than elsewhere (Home Office, 2001b). Police force statistics reveal similar geographical patterns; the metropolitan forces (City, Greater Manchester, Merseyside, Metropolitan, Northumbria, South Yorkshire, West Midlands, West Yorkshire) tend to have higher crime rates than other forces. In the year April 2000 to March 2001 Greater Manchester had the highest crime rate with over 1,400 crimes per 1000 of the population. Crime tends to be lowest in the more rural forces such as Dyfed-Powys which had only 476 crimes per 1000 of the population during the same period (Home Office 2001a).

As early as the 1920s and 1930s, the Chicago School established that crime varied across area and identified some areas as high crime areas and others as low crime areas. They also noted that these patterns persist long after the initial cause of the high or low crime incidence in the area no longer exist. This is because people do not change their behaviour immediately to a given stimuli, but react slowly over much longer periods. If an area is formally associated with high crime, it will take quite some time for people to notice a change and it will take even more time for confidence in the area to grow to the point where residents and business may feel safe there. We can think of this as the permanent component of crime. Even though crime rates fluctuate, crime is, on average, higher in some areas than others. For example, here are the crime rates (expressed per 1000 of the population) in two imaginary areas, Area A and Area B over a four year period:

Year	Area A	Area B
Year 1	23.3	6.1
Year 2	23.0	5.3
Year 3	22.9	4.5
Year 4	22.8	4.1

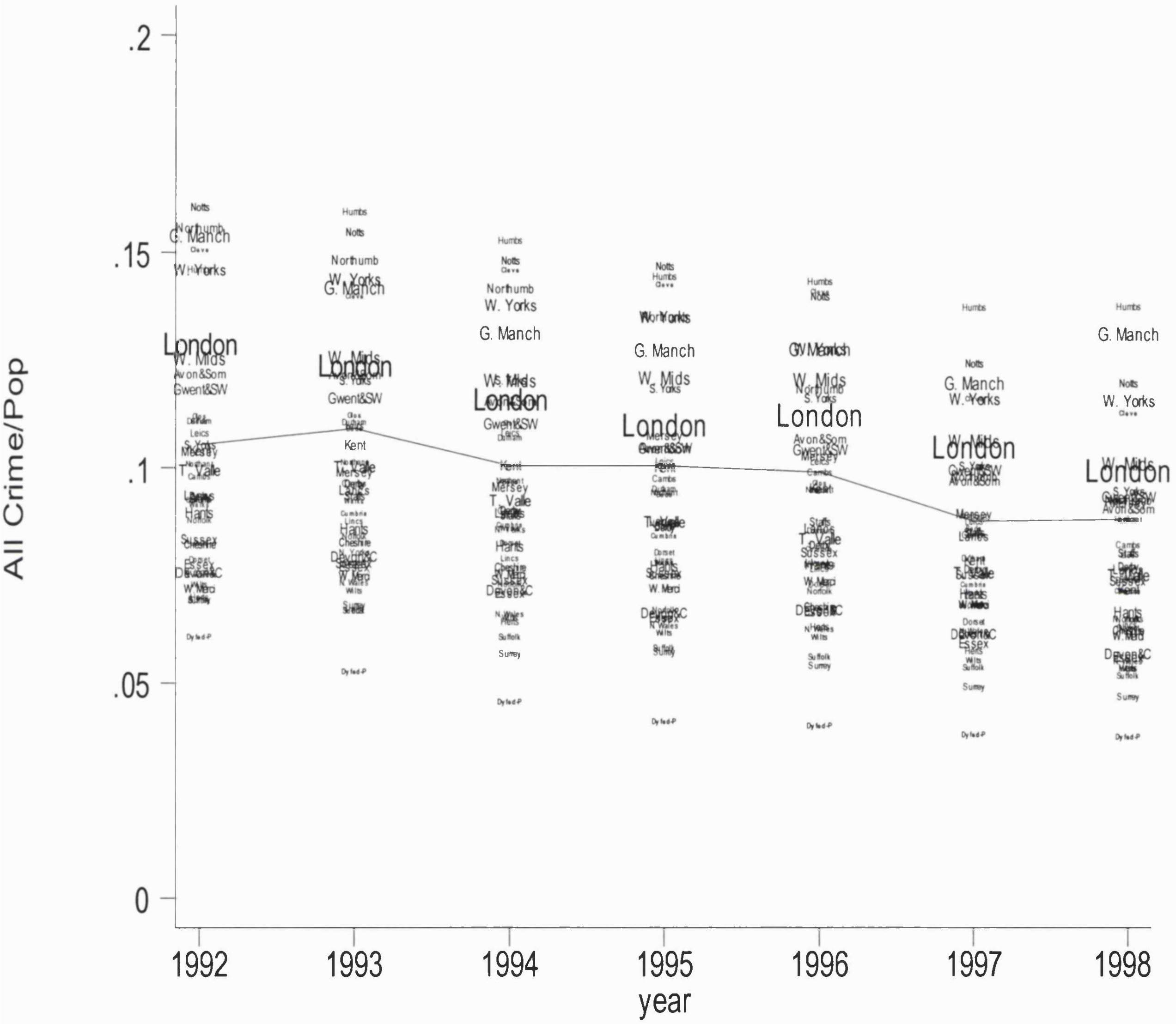
We can see from this example that on average Area A is a high crime area (23 crimes per 1000 of the population) and Area B is a low crime area (5 crimes per 1000 of the population) and that despite movement over time about these mean crime rates (there is in fact more movement in Area B) Area A remains a high crime area and Area B remains a low crime area.

That some areas are essentially high crime areas and others are low crime areas (and remain so over time) can be seen clearly in Figures 2.1 to 2.3. These show crime rates for all crimes (Figure 2.1), property crimes (Figure 2.2) and violent crimes (Figure 2.3) between 1992 and 1998, with the crime rates expressed as the number of crimes per person. In each case, lines are fitted through the median crime rate in each time period.

This persistence can also be seen by calculating the correlation between crime in the start year (1992) and end year (1998) of the sample. The closer the correlation coefficient is to 1 the more the crime rates in the two periods are similar (1 indicates a perfect positive linear relationship between the two variables, -1 would indicate a perfect negative linear relationship). From the table below we can see that the coefficients are high (very high for the aggregate crime measure and for property crime, slightly lower for violent crime) indicating the crime rates in 1992 and 1998 are highly correlated.

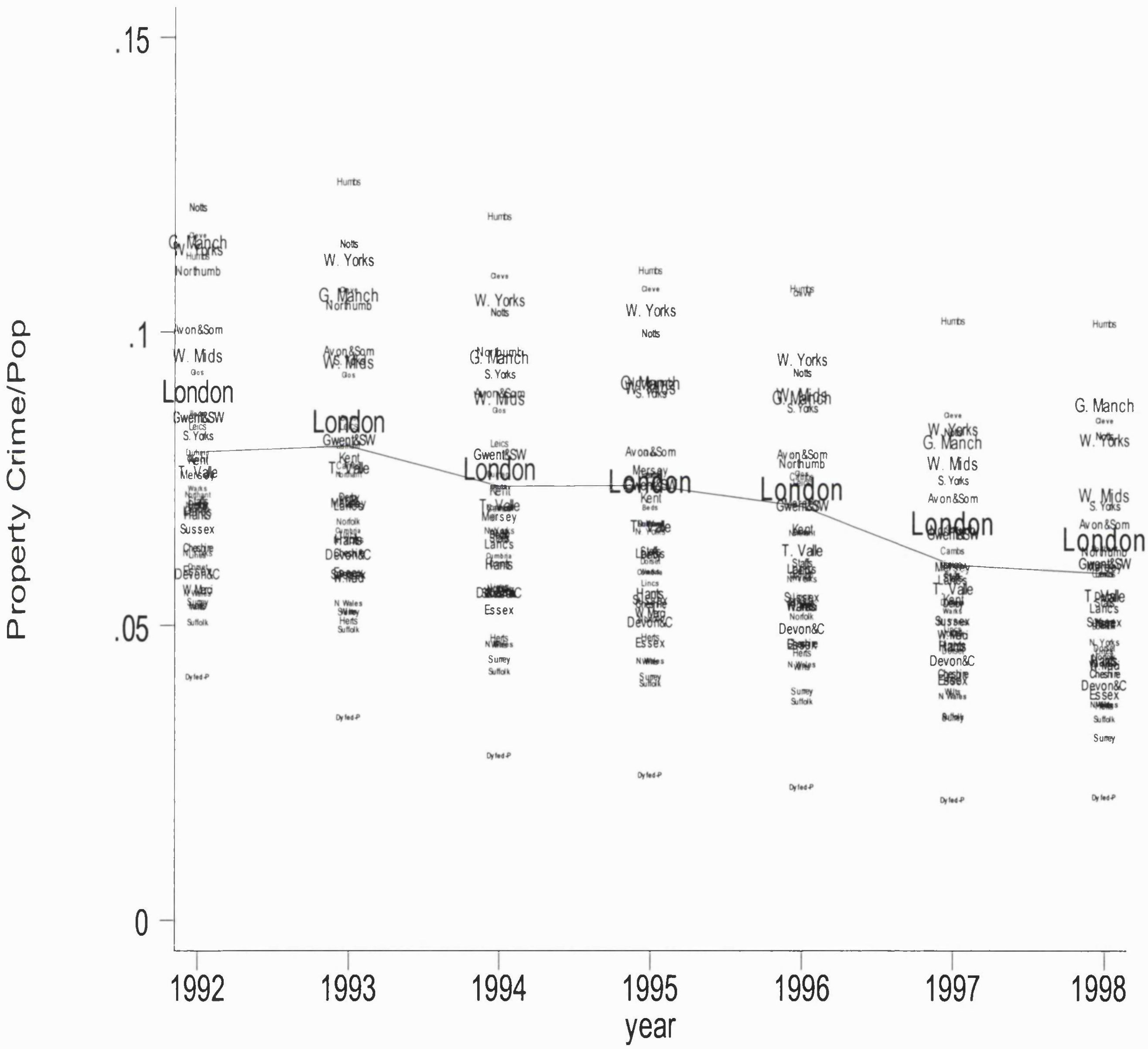
	All Crimes	Property Crimes	Violent Crimes
Correlation Coefficient For 1992 and 1998 Crime Rates	.93	.93	.81

Figure 2.1 Area Crime Rates 1992-98 (All Crimes / Population)



Notes:
Line fit through median crime rate.
Area names proportional in size to area population

Figure 2.2 Area Property Crime Rates 1992-98 (Theft + Burglary/ Population)



Notes:
Line fit through median crime rate.
Area names proportional in size to area population

Figure 2.3 Area Violent Crime Rates 1992-98 (Murder+Sex+Robbery/ Pop)

Notes:
Line fit through median crime rate.
Area names proportional in size to area population

In the same way that crime is unevenly distributed across areas, it is likely that so too are the determinants of crime. By carrying out a regression of the mean crime rates across areas on the mean of the independent variables we will be able to see which variables are associated with high crime areas and which are associated with low crime areas.[24] There are three sets of independent variables considered: the first are demographic variables and include the proportion of non-whites in the area and the proportion of 16 to 19 year olds in full time education. The second set of variables are labour market variables and include the area unemployment rate and a measure of wage inequality (75th percentile-25th percentile). The final set of explanatory variables are deterrence measures, these include the proportion found guilty, the proportion incarcerated, the number of police officers and the average sentence length.[25]

Table 2.7 shows police force area models of crime averaged over the years 1992 to 1998,[26] carried out separately for property and violent crimes. For property crimes all the demographic and labour market variables are statistically significant as are two of the four deterrence measures. As might be expected, high crime areas are also those with a higher proportion of non-whites and a lower proportion of 16 to 19 year olds in full time education. They are also areas with a higher proportion of people unemployed and where wage inequality is greater. Higher property crime areas are also those with a lower number of police officers and where average sentence lengths are shorter.

For violent crime high crime areas are also areas with a higher proportion of non-whites and a higher proportion of unemployed. Unlike property crime, areas of high violent crime are also areas with a higher proportion of 16-19 year olds in full time

[24] The model used can be seen in the methodology section (2.5).
[25] The log of variables is used as it allows the examination of elasticities, in other words it makes it possible to say how much the dependent variable will be affected by a 1% rise in the independent variables in percentage terms.
[26] So the data effectively become a cross-section.

education, perhaps suggesting a higher incidence of fighting or other forms of violence amongst students.[27] Alternatively this may be a spurious relationship reflecting the fact that violent crime is less frequent, and therefore, more noisy than property crime.[28] Violent crime is also higher in areas where average sentence lengths are shorter and rather surprisingly where more people are found guilty. It appears rather counter intuitive that violent crime should rise in an area where more people are being found guilty. Therefore again these results may be spurious.[29]

Table 2.7 Police Force Area Models of Crime in England and Wales, Averaged between 1992-98

	Property Crime	Violent Crime
Proportion non-white	.178*** (.012)	.170*** (.015)
Proportion of 16-19 year olds in education	-1.60*** (.169)	.688*** (.180)
Proportion unemployed	.268*** (.067)	.826*** (.115)
Wage Inequality	1.22*** (.274)	-.381 (.374)
Proportion found guilty	.046 (.141)	.230** (.118)
Proportion jailed	.046 (.105)	-.014 (.090)
Police numbers	-.071*** (.016)	-.032 (.026)
Average sentence length	-.278*** (.106)	-.363*** (.135)
R-Squared	.997	.999
Sample Size	41	41

[27]This could also reflect student representation in city center areas where more drinking and likely victims are to be found.

[28] Less than 10% of all crimes per year are violent crimes.

[29] When the model breaks violent crime into its constituent parts (i.e. violence against the person, sexual offences and robbery) violence against the person is the only offence that attracts a statistically significant positive coefficient. Sexual offences has a positive but insignificant coefficient while robbery attracts a negative coefficient. This is likely to be due to the fact that violence against the person and sexual crimes tend not to be rational acts, while robbery is. Therefore, those committing robbery are more likely to respond to incentives or deterrence in much the same way as those committing property crimes.

While these findings are interesting, they tell us very little about the relationship between crime and its correlates. It is highly likely that a high crime area is also an area with high unemployment for example, which is why cross-sectional studies tend to find statistically significant relationships between crime and such variables at this level. However, these observed relationships may actually be produced by any number of intervening variables, many of which are unobservable. Using this type of methodology, there is no way to control for the presence and effect of these intervening variables. Thus, such models are highly likely to suffer from omitted variable bias, so the results should be viewed with caution. This may explain why some counter intuitive results emerge.

Moreover, because the picture observed is static (i.e. a snapshot at one point in time) it is not possible to generalise findings outside of the sample or to establish causal relationships. This means that from a policy perspective, few implications can be drawn about the relationship between crime and its determinants from these findings. What is needed is an examination of fluctuations in the crime rate, in an attempt to establish what lies behind these movements.

2.6.2 Within Area Variation in Crime: Area-level modeling

The results so far indicate that some areas are high crime areas while some are low crime areas and these patterns tend to persist over time. But it is also true that within these areas, crime rates fluctuate over time and it is thus important to establish what factors lie behind this movement. To do this, the permanent component of crime must be removed. As detailed in the methodology section, it is possible to do this with data measured at police force area level over time by controlling for area fixed effects. This, is done by holding constant factors that may differ across high and low crime areas, some of which we would otherwise be unable to observe. This makes it possible to better isolate associations between crime and its correlates. This is the methodological question which corresponds best to the theory. What happens to crime across areas if an hypothesised determinant of crime changes?

2.7 Area Level Models of Crime

There are a number of ways to estimate models that include fixed effects.[30] The first is to include dummy variables for each police force area. In this case, the model looks like:

$$C_{at} = \alpha + \beta_1 demo_{at} + \beta_2 labourmarket_{at} + \beta_3 deter_{at} + F_a + T_t + \varepsilon_{at}$$

where C is the measure of crime, α is the constant, *demo* is a vector for the demographic variables of interest, set out in the data section, *labourmarket* is a vector for the labour market variables of interest and *deter* a vector for the set of deterrence variables. F represents the area fixed effects, (measured using a dummy variable for each police force area (minus 1, as the constant α is included in the model)). T represents time dummies for each year (again minus 1). ε is the error term incorporating any factors that influence crime which are not included in the model (although the fixed effects and time trends will account for such variables, where they are constant across time in the case of the former and constant across area in the case of the latter).

The subscript 'a' indicates each police force area and the subscript 't' each time period. Note that the area fixed effect only has an 'a' subscript, because it controls for differences across areas that are constant through time, while the time trend only has a 't' subscript as it accounts for differences through time which are constant across areas.

[30] This Chapter focuses on two methods but other ways include demeaning the variables.

The second fixed effects model uses changes or differences in the variables of interest across time periods. Thus, from the above model we get:

$$(C_{at} = \alpha + \beta_1 demo_{at} + \beta_2 labourmarket_{at} + \beta_3 deter_{at} + F_a + \varepsilon_{at})$$

$$-$$

$$(C_{at-1} = \alpha + \beta_1 demo_{at-1} + \beta_2 labourmarket_{at-1} + \beta_3 deter_{at-1} + F_a + \varepsilon_{at-1})$$

Or:

$$(C_{at} - C_{at-1}) = \alpha + \beta_1 (demo_{at} - demo_{at-1}) + \beta_2 (labourmarket_{at} - labourmarket_{at-1})$$
$$+ \beta_3 (deter_{at} - deter_{at-1}) + (F_a - F_a) + (\varepsilon_{at} - \varepsilon_{at-1})$$

This can also be written more simply as:

$$\Delta C_a = \alpha + \beta_1 \Delta demo_a + \beta_2 \Delta labourmarket_a + \beta_3 \Delta deter_a + \Delta \varepsilon_a$$

Where Δ indicates the change from '*t*' to '*t-1*'. The area fixed effect F_a does not appear in the final equation as it has been 'differenced away' (i.e. $F_a - F_a$). Thus, this model is referred to as a 'first differenced equation' (Wooldridge 2000).

There is no general consensus as to which method is best, but usually where '*t*' is small, as in this case, dummy variables are thought to produce more efficient results. This Chapter will use both methods. If the findings are robust, both methods should give similar results.

Table 2.8 shows the relationship between property crime and a number of explanatory variables, while controlling for differences in areas characteristics and time trends with the use of dummy variables. The Table reports six specifications. The first (shown in column (1)) is a simple fixed effects regression of property crime on the demographic variables. The second (2) and third (3) regress property crime on labour market variables, while the fourth (4) and fifth (5) columns examine the effect of deterrence variables on property crime. The final column (6) shows the preferred model, where only the independent variables shown to have an effect on property crime are included.

The results from the first specification show that the measures of demography included here, ethnicity and education, do not have a statistically significant effect on property crime despite both being important predictors of crime in other research.

The second specification examines the effect of unemployment and then a measure of the top and bottom of the wage distribution. Results for this specification show that while the measure of unemployment attracts a negative sign, the coefficient is statistically insignificant. Thus, like much of the literature that emphasizes the fragile nature of the crime-unemployment relationship (see Freeman, 1999), there appears to be no evidence in this property crime model of a crime-unemployment link. This is an excellent example of how failing to control for area fixed effects (or looking at single cross-sections) can prove to be misleading. In the previous model, a positive relationship was found between crime and unemployment. That this relationship vanishes with the inclusion of fixed effects suggests that there are other characteristics of areas that explain the cross-sectional correlation.

The measure of the bottom end of the wage distribution, the 25th percentile (which effectively captures the extent of low pay in the area), attracts a negative sign, but is only significant in a two-tailed test. The 75th percentile wage, which can be thought of as a proxy for the stock on wealth in the area (for example, more disposable income, more goods to steal, lower guardianship of property because people are more likely to be out in the evening) attracts a positive sign, statistically significant at a greater than 1% level. In this specification an F-test on the 25th and 75th percentiles produces an F statistic of 4.97, which is statistically significant at the 5% level. This means we are unable to reject the hypothesis that the coefficients on the two variables are equal and opposite.

Thus, in the third specification the 25^{th} and 75^{th} percentiles are combined to create a wage inequality index, which is added to the specification along with the unemployment measure. Again, the coefficient on the unemployment variable, while attracting a negative sign remains statistically insignificant. On the other hand the wage inequality measure is positive and is strongly statistically significant at a greater than 1% significance level.

The fourth and fifth specifications examine property crime using two different ways to measure deterrence. Column (4) shows the results from looking at crime specific deterrence measures, those found guilty, those jailed and the average sentence length for property crimes only. The final deterrence measure in this specification is the number of police officers. This latter variable is the only measure of deterrence that attracts a statistically significant coefficient. Column (5) shows the same specification, but this time measured for all crimes. The proportion jailed and the average sentence length remain statistically insignificant, like the previous specification, but the proportion found guilty of all crimes in the area attracts a negative coefficient, statistically significant at the 5% level. Again, the coefficient on the number of police officers is negative and statistically significant at the 5% level. The fact that the proportion found guilty of all crimes has a greater deterrence effect on property crime than the crime-specific measure of deterrence suggests that if the rational choice theory is correct, people make decisions not having weighed up the actual costs and benefits of their action, but the perceived costs and benefits, which are often based on incomplete or even incorrect information.

The final specification (6) shows the preferred model, including the variables that remain statistically significant. Thus, included in this model is the wage inequality measure, which attracts a positive sign, statistically significant at the 5% level; the proportion found guilty of all crimes, which has a negative sign (significant at a greater than 1% level); and the number of police which also attracts a negative sign (significant at the 5% level).[31]

Table 2.9 reports a set of results for the same property crime specifications as above, but using changes over time rather than dummy variables to capture the fixed effects. Reassuringly, the results produced are very similar to those reported above. The statistically significant variables in the model are the same as before, so that in the final model the wage inequality measure attracts a positive coefficient, statistically significant at the 5% level, the proportion found guilty attracts a negative coefficient (significant at the 5% level) and the coefficient on the number of police officers shows a negative sign, significant at the 10% level. The magnitude of the coefficients from both models are very similar, although for all statistically significant measures they are slightly lower using the first differenced model (the wage inequality coefficient is .358 in the dummy model and .315 in the changes model, the equivalent figures for the proportion found guilty are -.139 and -.089 and for the number of police officers -.316 and -.201).

[31] Note the high R-squared – this is a result of including a dummy variable for each police force area, which means the model explains much of the variation in the data.

Table 2.8 Police Force Area Models of Property Crime in England and Wales, 1992-98 Including Area Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Basic Model with Demographic Variables	**Labour Market (Unemploy-ment and wages)**	**Labour Market (inequality)**	**Deterrence (Crime Specific)**	**Deterrence (Overall)**	**Final Model**
Proportion Non-White	-.015 (.013)					
Proportion of 16-19 year olds in Full Time Education	-.011 (.056)					
Proportion Unemployed		-.038 (.039)	-.045 (.038)			
25th. Percentile Wage		-.302 (.237)				
75th. Percentile Wage		.526*** (.201)				
Wage Inequality			.432*** (.179)			.358** (.171)
Proportion Found Guilty				-.006 (.044)	-.137** (.057)	-.139*** (.045)
Proportion Jailed				-.010 (.043)	-.022 (.057)	
Police Numbers				-.465*** (.149)	-.341** (.154)	-.316** (.153)
Average Sentence Length				.011 (.040)	.036 (.042)	
Area Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	.9997	.9997	.9997	.9997	.9997	.9997
Obs	287	287	287	286	286	286

Robust Standard Errors in parenthesis
* significant at 10%, ** 5%, *** 1%

Table 2.9 Police Force Area Models of Property Crime in England and Wales, 1992-98 Specified in First Differences

	(1)	(2)	(3)	(4)	(5)	(6)
Changes in:	**Basic Model with Demographics**	**Labour Market (Unemployment and wages)**	**Labour Market (inequality)**	**Deterrence (Crime Specific)**	**Deterrence (Overall)**	**Final Model**
Proportion Non-White	-.009 (.011)					
Proportion of 16-19 year olds in Full Time Education	.017 (.038)					
Proportion Unemployed		.003 (.028)	.000 (.028)			
25th. Percentile Wage		-.228 (.191)				
75th. Percentile Wage		.331*** (.156)				
Wage Inequality			.298** (.138)			.315** (.130)
Proportion Found Guilty				.021 (.033)	-.063** (.042)	-.089** (.036)
Proportion Jailed				-.030 (.030)	-.047 (.035)	
Police Numbers				-.215* (.130)	-.227* (.127)	-.201* (.122)
Average Sentence Length				-.023 (.025)	-.042 (.035)	
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	.687	.692	.9997	.693	.699	.703
Obs	246	246	246	245	245	245

Robust Standard Errors in parenthesis
* significant at 10%, ** 5%, *** 1%

Thus, both methods show that property crime is positively associated with wage inequality. Where wage inequality is greater or has increased the most property crime is higher or has increased the most. This supports the idea that relative deprivation (Stack 1984), not just being poor, but being poorer or having less than others around you, is an important predictor of crime. The results also show that property crime is negatively associated with the proportion of people in the area found guilty of all crime and the number of police officers. Where a greater proportion of people are found guilty of crime or where there has been a higher rise in those found guilty, and where there are more police officers or where there has been a rise in the number of police officers, property crime is lower or has declined by more. This supports rational choice and deterrence theories, which posit that the higher the likelihood of apprehension the more people will be dissuaded from breaking the law. It also provides evidence in favour of government policy to put 'bobbies back on the beat'.

Tables 2.10 reports the results from the fixed effects model for violent crime using dummy variables to control for area fixed effects. As with property crime, the Table reports six specifications. With the exception of the wage inequality measure (in this case replaced with the mean wage measure), the specifications are the same as the property crime model.

Column (1), which reports the coefficients on the demographic variables, shows that like property crime, neither ethnicity nor education have a significant effect on violent crime. The unemployment measure also remains statistically insignificant, as do both measures of the wage distribution (the 25^{th} and 75^{th} percentile), (column 2). As such, the inclusion of the inequality measure in the property crime model is not appropriate here. Instead a measure of the average wage in the area is added to the model in specification (3). As the results show this measure attracts a positive sign and is statistically significant at a greater than 1% level. This supports the findings of Cantor and Land (1985) who posit that violent crime is higher when people have more spending power to go drinking as alcohol consumption is so highly correlated with violent crime (Raphael and Winter-Ebmer 2001).

Of the deterrence measures, only the number of police officers attracts a negative coefficient that is statistically significant.[32] The final, preferred specification (6) thus contains only mean wages, which attracts a positive sign, statistically significant at a greater than 1% level, and the number of police officers, which attracts a negative coefficient, statistically significant at the 5% level.

The results from the fixed effect dummy variable model indicate that violent crime is positively associated with mean wages. Areas where average wages are higher or where the average wage rose by more are areas where there has been more violent crime, or where violent crime has risen by more. On the other hand, violent crime was found to be negatively related to the number of police officers. Areas with more police officers or areas where there has been a rise in the number of officers are the areas with lower crime or where violent crime had decreased by more.

However, these findings are not reproduced when the model is specified in first differences (Table 2.10). Indeed, in the first differenced model, none of the variables in the final specification (6) are statistically significant. Thus, for violent crime the findings do not seem very robust. This is in line with other work in the area that has found it difficult to establish the determinants of violent crime (for a discussion of this see Chiricos 1987).

[32] The proportion found guilty attracts a positive, statistically significant coefficient. This is counter intuitive.

The fact that the fixed effect and first difference models produce similar results for property crime, but not for violent crime, is in line with the idea that first differences exacerbates measurement error. The models produce very different results for violent crime, which is likely to contain more measurement error than property crime. For this reason, the fixed effects models probably deserve more attention.

Table 2.10 Police Force Area Models of Violent Crime in England and Wales, 1992-98 Including Area Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Basic Model with Demographics	**Labour Market (Wage distribution)**	**Labour Market (Mean Wages)**	**Deterrence (Crime Specific)**	**Deterrence (Overall)**	**Final Model**
Proportion Non-White	-.014 (.026)					
Proportion of 16-19 year olds in Full Time Education	-.135 (.112)					
Proportion Unemployed		-.048 (.071)	-.034 (.070)			
25th. Percentile Wage		.561 (.630)				
75th. Percentile Wage		.487 (.376)				
Mean Wages			1.13*** (.450)			1.22*** (.452)
Proportion Found Guilty				.281*** (.075)	.228* (.057)	
Proportion Jailed				-.056 (.078)	-.166 (.109)	
Police Numbers				-.798*** (.301)	-.639* (.328)	-.525** (.302)
Average Sentence Length				.078 (.059)	-.002 (.083)	
Area Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	.9997	.9997	.9997	.9997	.9997	.9997
Obs	287	287	287	286	286	286

Robust Standard Errors in parenthesis, * significant at 10%, ** 5%, *** 1%

Table 2.11 Police Force Area Models of Violent Crime in England and Wales, 1992-98 Specified in First Differences

	(1)	(2)	(3)	(4)	(5)	(6)
	Basic Model with Demographics	Labour Market (Wage distribution)	Labour Market (Mean Wages)	Deterrence (Crime Specific)	Deterrence (Overall)	Final Model
Proportion Non-White	-.005 (.017)					
Proportion of 16-19 year olds in Full Time Education	-.038 (.077)					
Proportion Unemployed		.027 (.059)	.041 (.056)			
25th. Percentile Wage		.115 (.533)				
75th. Percentile Wage		.470 (.291)				
Mean Wages			.660* (.393)			.622 (.392)
Proportion Found Guilty				.285 (.081)	.202** (.095)	
Proportion Jailed				-.045 (.053)	-.111 (.075)	
Police Numbers				.018 (.040)	-.362 (.353)	-.346 (.363)
Average Sentence Length				-.009 (.041)	-.023 (.058)	
Area Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	.203	.212	.212	.241	.216	.212
Obs	287	287	287	286	286	286

Robust Standard Errors in parenthesis, * significant at 10%, ** 5%, *** 1%

2.8 Incorporating Dynamics into Crime Models

Earlier findings indicated that crime is highly persistent over time. While the inclusion of area fixed effects will control for part of this, there may still be persistence above and beyond this. It is therefore important to include some measure of inertia in the models. One way to do this, is to include a measure of the lagged dependent variable in the model, in an attempt to account for historical factors which cause differences in the dependent variable that are otherwise difficult to account for (Wooldridge 2000).

One issue with first differencing models is that it necessarily produces serial correlation when a lagged measure of the dependent variable is added to the model. This is because a non-zero correlation is induced between the lagged dependent variable and the error term. The problem arises from the fact that the error term will pick up a range of factors that have not been included in the model (for example peer pressure). In a contemporaneous model, the error term is assumed not to be correlated with any of the explanatory variables. So peer pressure is represented by the error term as it is not reflected in any of the other right hand side variables. However, in a dynamic first differenced model, the contemporaneous error term may be correlated with the lagged dependent variable which may also include a measure of peer pressure. This will result in biased estimates. This can be seen more clearly in the model below:

$$(C_{at} - C_{at-1}) = \alpha + \beta_1(demo_{at} - demo_{at-1}) + \beta_2(labourmarket_{at} - labourmarket_{at-1})$$

$$+ \beta_3(deter_{at} - deter_{at-1}) + \delta(C_{at-1} - C_{at-2}) + (F_a - F_a) + (\varepsilon_{at} - \varepsilon_{at-1})$$

The potential correlation exists because:

$$\mathrm{E}[(C_{\mathrm{at\text{-}1}} - C_{at-2}), (\varepsilon_{at} - \varepsilon_{at-1}) \neq 0$$

This problem can be overcome using an instrumental variable technique suggested by Arellano and Bond (1991). However, a more simple procedure is to incorporate the lagged variables into the fixed effect dummy variable model, where no bias problem exists. This is done for property crime in Table 2.12. The Table reports two specifications. The first simply shows the preferred specification from the previous fixed effects dummy variable model for property crime. The second includes a lagged measure of the dependent variable.

The first thing to note is that the lagged measure of property crime is strongly positive and statistically significant at a greater than 1% level. The inclusion of the lagged dependent variable slightly reduces the coefficient on all the independent variables. However, with the exception of the wage inequality measure, all remain statistically significant. Thus, the results show that even after accounting for some persistence, property crime remains strongly persistent in the fixed effects model.

Table 2.13 shows the results from the dynamic models of violent crime. As with property crime the Table reports three specifications. The first is the preferred model from the previous fixed effects dummy variable model (column (6), Table 2.10), which for violent crimes contains a measure of the average wage in the area and the number of police officers. The second specification (2) adds in a lagged measure of violent crime in the area.

The results show that like property crime, violent crime is strongly persistent over time. Having already accounted for some persistence in the fixed effects model, the coefficient on the lagged violent crime variable attracts a positive coefficient statistically significant at a greater than 1% level. The coefficient itself is slightly larger in magnitude than the lagged measure of property crime at .580 compared to .472. Thus, violent crime, even more so than property crime, is heavily persistent.

Table 2.13 Police Force Area Models of Violent Crime in England and Wales, 1992-98 Using Dummy Variables and Including Lagged Variables

	(1)	(2)
	Preferred Model	**(1) Plus Lagged Crime Measure**
Wage Inequality	.358** (.171)	.186 (.150)
Proportion Found Guilty	-.139*** (.045)	-.118*** (.036)
Police Numbers	-.316** (.153)	-.256** (.101)
Property Crime – Lagged		.472*** (.054)
Area Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Test for Serial Correlation	Yes	Yes
R-Squared	.9997	.9999
Obs	286	246

Robust Standard Errors in parenthesis, * significant at 10%, ** 5%, *** 1%

Table 2.12 Police Force Area Models of Property Crime in England and Wales, 1992-98 Using Dummy Variables and Including Lagged Variables

	(1)	(2)
	Preferred Model	**(1) Plus Lagged Crime Measure**
Mean Wages	1.22*** (.452)	.873** (.434)
Police Numbers	-.525** (.302)	-.001 (.291)
Violent Crime- Lagged		.580*** (.105)
Area Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Test for Serial Correlation	Yes	Yes
R-Squared	.9997	.9997
Obs	286	246

Robust Standard Errors in parenthesis, * significant at 10%, ** 5%, *** 1%

2.9 Concluding Remarks

In an attempt to establish simple descriptive relationships between crime and its correlates in England and Wales in the 1990s, this Chapter has looked at two ways in which the crime rate varies: between police force areas, and within police force areas. Using different methodologies, it was found that the discovery of significant relationships was easier using cross-sectional data. However, these results are possibly misleading, do not allow causality to be established and as a result can offer few implications for criminal policy. Examining area level data over time has proven much more successful. It allows us to ask the conceptual question in the right way: If X changes what happens to crime?[33] Although more difficult to establish significant relationships, those that have been discovered are more robust, even to the inclusion of dynamic effects.

Thus, when using area level panel data to exploit cross-area changes in order to identify the determinants of crime, the results show that in the 1990s property crime in areas experiencing a growth in wage inequality rose by more. Crime has been lower in areas where the number of police officers was higher and it has been lower where the proportion found guilty of all crimes has increased.

Explaining violent crime rates has proven more difficult since their relative infrequency makes the results much noisier. Despite this, evidence has shown that violent crime is positively related to average wages, it is higher in areas where the average wage has been higher over the period under examination and lower in areas where the number of police officers has increased.

[33] The equivalent cross-sectional question is: Is crime high when X is high?

The results have also shown that both property and violent crimes are heavily persistent over time and that failure to account for this persistence may mean that some of the factors that help explain crime are ignored.

As well as highlighting which factors are most closely associated with different crimes, these findings point to the potential usefulness of area data in understanding crime. This will be utilised in the following Chapter, which further explores the relationship between crime and the labour market at area level.

3. Spatial Patterns of Crime: Can Labour Market Variables Explain Them?

3.1 Introduction

Residential location is a strong determinant of the level of crime. Indeed, the location of where you live strongly determines the level of crime you are likely to experience. In 1999, a person living in South Africa was nine times more likely to be murdered than someone living in the USA. A person in the USA was four times more likely to be a victim of homicide than someone living in the UK, who in turn was one and a half times more likely to be killed than someone in Norway (Home Office, 2001a).

The likelihood of being a victim of crime in England and Wales is documented in the British Crime Survey (BCS), a household survey that asks about people's experiences of crime. Figures from the 2000 BCS show that the risk of victimisation 'varies considerably across households with different characteristics and situated in different localities" (Home Office 2002). Those living in urban areas, inner city areas, areas of high physical disorder, in social housing and on council estates are consistently more likely to be victims of property crime (domestic burglary and vehicle related theft) than those living in other areas.

These findings are supported by the official crime statistics which show that while the average crime rate across all police forces in England and Wales (between April 2000 and March 2001) was 9,814 crimes per 100,000 of the population, the rate was higher for

Metropolitan forces (Metropolitan, City, West Midlands, Merseyside, Greater Manchester, West Yorkshire, South Yorkshire and Northumbria) where the average crime rate was 12,775 per 100,000. The highest rates were in Greater Manchester (14,104), West Midlands (13,892) and London (City and Metropolitan combined with 13,761 crimes per 100,000 of the population). This contrasts markedly with areas such as Dyfed-Powys, Surrey and Wiltshire, all of which had rates of less than 6000 crimes per 100,000 of the population (at 4,760, 5,874 and 5,989 respectively). But even within police force areas, crime rates vary across geographical location. Within greater Manchester (the highest crime police force area), the violent crime rate was as high as 2,600 crimes per 100,000 of the population in Manchester itself, while Stockport and Wigan had only 1,200 crimes per 100,000 of the population (Home Office, 2001b).

Such evidence highlights what the Chicago School drew attention to in the 1920s and 30s, and what has by now become a well known picture. Crime is massively unevenly distributed across geographical location. This Chapter, with the aid of mapping technologies, carries out an exploration into the spatial distribution of crime across local authorities in England and Wales. Using various statistical and Geographical Information Systems (GIS) mapping techniques, the Chapter focuses on two aspects of research in the geography of crime. The first is the examination of the spatial distribution of crime, and involves looking for spatial patterns of crime across different geographical locations. The second focuses on the extent to which the uneven distribution of crime can be explained by the distribution of a range of demographic, labour market and socio-economic determinants of crime.

3.2 Spatial Patterns of Crime: Theoretical Considerations

There are a number of reasons for thinking that crime is likely to be non-randomly distributed across the areas of England and Wales. The previous Chapter has shown that crime in an area will be dependent on a number of other characteristics such as the demographic and socio-economic make-up of that area. If factors such as these are associated with crime at this local level the distribution of crime is likely to reflect the distribution of these other structural characteristics. This may produce a number of possible distributions. Firstly, it is likely that areas that are geographically close to each other will share similar demographic and socio-economic characteristics. There are a number of theories that predict differential involvement in crime by groups with different labour market or socio-economic characteristics. Such theories (discussed at length in the previous two Chapters) include rational choice theory (Becker 1968), anomie (Durkheim 1933), strain theory (Merton 1968), differential opportunity (Cloward and Ohlin 1960) and social control theory (Hirshi 1969), all of which predict higher involvement in crime for those with weaker labour market positions. Thus, these theories would predict that areas that are geographically close and which share similar socio-economic characteristics, will produce clusters of areas with similar crime rates.

Alternatively, given that there are a finite number of criminals,[1] it may be the case that if crime is high in one area (if there are less police in that area, or the properties are less well protected, for example) then, as rational choice, social control or deterrence theory predicts, crime will be lower in the neighbouring areas than expected in a random distribution. On the other hand, if there is a police clamp-down on crime in an area, this

[1] In the sense that at any point in time only some people commit crimes.

may lead to the migration of criminals to surrounding areas, producing an area of low crime surrounded by high crime areas. All of these scenarios will produce non-random patterns of crime distribution. But if the geographical distribution of crime is produced solely by the location of these other area characteristics, once such differences are controlled for, there should be no spatial correlation between crime across areas and crime should be distributed randomly across the areas of England and Wales.

Other theories suggest that the spatial association of crime across areas depends not only on individual characteristics or individual situations within areas, but on the interaction of people with areas and with other people in the areas. For instance, one of the findings from the early work on the geography of crime in Chicago (Shaw and McKay 1942) is that crime in an area is associated with social disorganisation, which creates an atmosphere where criminal behaviour is culturally transmitted. This disorganisation, or social breakdown, which is very closely related to the situation of individuals, largely resulted from a lack of community. This can be elaborated with reference to social control theory (Hirshi 1969) which predicts that areas where the community is weaker will be associated with higher crime, as informal social controls which deter people from engaging in crime (such as fear of peer disapproval or stigmatisation) will be weaker in these areas.

According to subcultural theories (Cohen 1955), crime will be spatially associated across areas, not because of disorganisation, or social breakdown, but because some areas are much more heterogeneous than others, and therefore will have a greater number of subcultures. For Fischer (1984), cities have more subcultures than smaller rural areas and as urban areas are more populous not only will the subcultures in these areas be larger, they will also be more able to resist outside influences and more able to diffuse their subcultural beliefs to the wider society (Fischer 1995).

The diffusion of subcultures is strongly related to peer pressure (Hirshi 1969), where individuals are encouraged to behave in the same way their peers do. In larger urban areas, where subcultures exert more influence, peer pressure to adhere to the beliefs and behaviours of the subculture will be greater. Also, central to this, is the idea of differential association (Sutherland 1950) and differential opportunities (Cloward and Ohlin 1960). The first of these theories predicts that crime will be spatially associated across the areas that offer increased opportunities to learn criminal behaviour through face-to-face interaction. The second, that crime will be associated across areas that offer greater opportunities for involvement in criminal behaviour such as gang membership.

These theories predict that crime will be correlated across areas depending on the ability of areas to create an environment more (or less) favourable to the development of criminal attitudes and forms of behaviour. This is often strongly correlated with area or population size or population make-up (Fischer 1995). This is also an important factor for routine activities theory (Cohen and Felson 1979, Cohen and Cantor 1980) that stresses that criminal behaviour depends not only on motivated offenders, but also on the availability of suitable targets. This refers to the availability and vulnerability of potential targets of crime. Thus, area size is again important in predicting geographical association of crime across areas.

For example, urban areas provide more available targets by the simple fact that these areas are more populous (so there exists more targets for inter-personal crime) and as a result have a greater stock of goods to steal (providing more targets for property crime). Also, the fact that urban areas are more populous means that diverse groups are likely to be located closer together than in less populated areas. Thus, poor areas may be located close to wealthy areas thus creating tension arising from inequalities experienced across the different areas. These inequalities lead to feelings of relative deprivation that may manifest themselves in crime.

Targets are often more vulnerable in urban areas, where individuals often do not have the resources to protect their properties (having alarms or security locks installed, for example). Moreover, inner city areas (in particular areas of social housing and housing estates) are often easier targets because of the architectural design of the buildings themselves (Newman 1972) or the streets in which they are situated (Hillier and Hanson 1984). The fact that properties in large urban areas are often less well maintained than other properties also makes urban areas more vulnerable. Wilson and Kelling (1982) show how areas descend into crime if attention is not paid to maintenance. A broken window gives the impression that no-one cares, so more and more windows are broken. If nothing is done about the broken windows, the situation escalates into more and more serious disorder and crime, as criminals (such as drug dealers, pimps and prostitutes) are attracted to the area and the respectable people (who have the means) leave.

Routine activities theory (Cohen and Felson 1979) also predicts crime will be spatially associated across areas depending on the level of guardianship in these areas. City areas have a higher proportion of single occupied dwellings than elsewhere and multiple occupant dwellings are often made up of groups of single people rather than family units. This means that properties in these areas are more likely to be left unoccupied than in other areas. Larger urban areas are also less likely to have any form of 'protective neighbouring' (Schneider and Schneider 1978). There may also be a less developed sense of community in larger areas so it is less likely that neighbours will look out for one another or one another's property. They are less likely to be involved in community groups such as neighbourhood watch schemes; less willing to take action if they see a crime in progress; less likely to report a crime or suspicious behaviour; and less likely to cooperate with the police in the event of a crime (Conklin 1986).

There are a wide range of theories that predict spatial association of crime across areas. While they differ in their reasons for this predicted association, most suggest that the spatial association of crime can be accounted for by differences across areas in criminal determinants. It is a test of this prediction generated from these theories which forms the subject matter of this Chapter.[2]

3.3 Existing Empirical Work

Examining the geographical distribution of crime is not a new research activity. Although generally attributed to the Chicago School, maps locating the areas of crime date back to the previous century. Much of the early work on the geographical distribution of crime focused on the location of crime within a particular city. The most well known of course is Shaw and McKay's (1942) study of Chicago. Work in the UK around this time included mapping the location of crime in London (Burt 1925) and Liverpool (Jones 1934), and later on in Cardiff (Herbert 1977), Luton (Timms 1965) and Sheffield (Baldwin and Bottoms 1976).[3]

[2] The focus is on whether the spatial association of crime across areas can be accounted for by the location of other factors, rather than a test of which these theories is correct.

[3] For a more up to date studies which use crime mapping techniques see Hirschfield and Bowers 2001.

Since then data availability and statistical and mapping techniques have greatly increased the range and potential of spatial analytic studies. Over the more recent period spatial analysis has been used to examine the distribution of a wide range of phenomena, from fertility (Tolnay 1995) to disease (Marshall 1991) and child deaths (Gupta 1997), trade unions (Hedstrom 1994) and even the location of ant nests (Harkness and Isham 1983). A number of studies have looked at the spatial patterning of crime. Much of this work has been done in the US. For example, Spilerman (1970) looked at the distribution of racial disorders in 673 US cities between 1961 and 1968. He found that racial disorders were not random occurrences, but that cities differed in the likelihood of racial disorder. The distribution of these disorders could not be explained by the structural factors of the cities, but by the individual values held by the black population in the cities.

Messner at al (1999) examined the spatial distribution of homicides in the counties that make up the St. Louis Metropolitan Statistical Area (MSA), plus three other counties in the surrounding MSA's between 1979 and 1995. They relate the distribution of violent crime to the distribution of two principle components: a population structure component (which measures population size and density) and a resource component (measuring percentage black; percentage of families below the poverty line; median family income; the Gini coefficient of family income inequality; and the percentage of single parent families) and find clusters of high crime 'hot-spots' and low crime 'cool spots' which traditional correlates of crime are unable to account for.

Glaeser at al (1996) used crime recorded at city level in 1970, 1985 and 1986 and then New York data from 1993, to look at spatial differences in the propensities towards crime across cities. They found that even after controlling for underlying area characteristics, there remained geographical variation in the crime rates, which could not be explained. They attributed this variation to differences in social interactions.

Sampson and Raudenbush (1999) used videotaped observations of over 23,000 streets in Chicago along with census data, police records and a local survey of 3,500 residents to look at social and physical disorder in 196 neighbourhoods. They found that even after controlling for the structural characteristics of the neighbourhoods there remained differences in crime and disorder, which they argue could be explained by what they termed 'collective efficacy' (i.e. social cohesion among residents and the informal social control of public space).

Outside of the US, Murray et al (2001) used GIS crime mapping techniques to examine the distribution of crime in 541 suburbs around Brisbane, Australia in 1996. Their results show that crime is not randomly distributed. They identified clusters of areas with high crime rates, areas with low crime rates, areas of high crime surrounded by low crime and low crime areas surrounded by high crime which could not be explained by standard correlates of crime. They could only be explained by reference to geography, in particular the location of transportation routes and stops and the distance to the nearest police station.

In the UK a great deal of work that examines the geographical distribution of crime in the UK uses data from the British Crime Survey, which in the early periods identified the areas where the respondent resided. This made it possible for researchers to aggregate individual characteristics from the BCS to provide a picture of the area or neighbourhood (see for example Trickett et al 1992, 1995a,1998) or match BCS areas to Census data (see Hale et al 1994, Osborn et al 1992, 1996 Osborn and Tseloni 1998, Trickett et al 1995b). Thus, Trickett et al (1992) aggregated the 1982 BCS to area level and found that the distribution of crime was non-random, in particular it depended on whether the area had a high crime rate or a low crime rate. While in low crime areas crime appears to be randomly located, in high crime areas crime is clustered across particular households. Trickett et al (1995a), looking at differences between the 1982 and 1988 BCS, found that crime became more unevenly distributed across areas over time.

Osborn et al (1992) matched the 1984 BCS to 1981 Census data and, examining both household and area/neighbourhood characteristics, found that crime victimisation is unevenly distributed and that controlling for household and area characteristics only goes part of the way to explaining the distribution. Using data from the 1992 BCS matched to 1991 Census data Osborne and Tseloni (1998) found that crime victimisation remains distributed in a non-random fashion even when the household and area characteristics, which are related to victimisation risk, are controlled for.

Using data on crimes reported to the police Brimicombe et al (2001) used a combination of statistical and GIS mapping techniques to look at the geographical distribution of racially motivated crimes in 24 wards that make up the London Borough of Newham. They found that the distribution of racially motivated crimes is related to the ethnic composition of the area, but after controlling for this, some areas have higher rates of racial crime than expected.

3.4 Data and Descriptive Analysis

3.4.1 Crime Data

There are 43 police force areas in England and Wales and within each of these areas are a number of sub-areas referred to as Crime and Disorder Reduction Partnership areas (CDRPs). There are 376 CDRPs in England and Wales, although in this Chapter only 374[4] areas are considered. These areas correspond to Local Authorities.

While a number of studies have used data at police force area level (for example, Reilly and Witt (1996), Machin and Meghir (2000) and Hansen and Machin (2001)) there has been little work at this more disaggregate level (for exception see Bowers et al 2001 or Chainey 2001). Data at this level are only available since April 1999 so it is not possible to carry out a comprehensive time series analysis. However, the large number of areas at this level (374) provides an excellent base to look at cross-sectional geographical variation in crime and its correlates. Moreover, because each CDRP covers only a small area, the data are well suited to examine more localised relationships in particular areas rather than assuming characteristics are homogenous within counties.

The crime data are crimes reported to and recorded by the police at CDRP level. They are examined separately for property crimes (burglary, theft of a motor vehicle and theft from a motor vehicle) and violent crime (violence against the person, sexual offences and robbery). These figures come from the Home Office publications on notifiable offences that can be accessed on the web at: www.homeoffice.gov.uk/rds.

Because these are official statistics on recorded crime, as discussed previously, they are unlikely to represent the true level of crime, as not all crime is reported to or

[4] The Scilly Isles and the City of London have been dropped as there are too few observations in these two areas.

recorded by the police. Increased pressure on the public to report crime and on police to record it means that more crimes are appearing in the official statistics. As the data are for 2000, this will be especially true. Also as the data are a cross-sectional there is no concern about differences in reporting or recording practices over time. While some may believe that victimization surveys offer a more accurate reflection of crime, as Chapter 1 noted, it is not obvious that this is necessarily true, as these types of surveys are themselves associated with potential problems (also see Brantingham and Brantingham 1984 for more details). Moreover, official statistics form the only basis of nationally representative crime data at this very disaggregate area level.

The number of CDRPs within each police force area, along with aggregate property and violent crime rates, are shown in Table 3.1.

3.4.2 Labour Market Data

To these crime data are matched a set of possible correlates of crime. The first set of variables are labour market variables. As the crime data are available for a relatively short period of time, matching other variables over this period is an easier task than over longer periods. As such, the data are rich in regard to the correlates of crime. The labour market variables chosen for examination are the variables most often discussed in theory and found in existing empirical work to be the strongest predictors of crime.

Thus, a number of studies have found crime to be related to unemployment (Devine et al 1988, Pyle and Deadman 1994a, Levitt 1998). Others have shown that income is more important (Field 1998, Gould at al 2002), particularly wages at the bottom end of the distribution (Machin and Meghir 2000, Hansen and Machin 2001) and wage inequality (Hseigh and Pugh 1983, Fowles and Merva 1996).

Table 3.1 Police Force Area and Sub-Areas

Police Force	Number of Sub Areas	Aggregate Property Crime Rate (per 1000 of population) in 2000	Aggregate Violent Crime Rate (per 1000 of population) in 2000
Avon and Somerset	9	29.81	12.70
Bedfordshire	4	27.99	11.29
Cambridgeshire	6	21.59	10.23
Cheshire	8	18.02	6.61
Cleveland	4	37.42	7.61
Cumbria	6	12.82	8.99
Derbyshire	9	22.47	10.81
Devon and Cornwall	16	17.32	8.51
Dorset	8	18.68	6.63
Durham	8	18.54	9.31
Dyfed-Powys	4	5.88	11.96
Essex	14	15.53	7.48
Gloucestershire	6	20.42	10.15
Greater Manchester	10	46.48	20.15
Gwent	5	19.20	26.74
Hampshire	14	16.27	10.82
Hertfordshire	10	18.30	5.17
Humberside	4	33.11	12.20
Kent	13	20.02	9.46
Lancashire	14	21.74	9.73
Leicestershire	9	24.85	13.27
Lincolnshire	7	16.60	6.71
London	32	32.68	28.11
Merseyside	5	30.56	13.71
Norfolk	7	16.98	8.14
North Wales	6	14.24	9.00
North Yorkshire	8	15.35	7.19
Northamptonshire	7	24.36	9.76
Northumbria	11	19.98	9.26
Nottinghamshire	8	36.38	16.61
South Wales	7	26.51	11.48
South Yorkshire	4	31.55	7.74
Staffordshire	9	27.36	19.51
Suffolk	7	12.58	10.37
Surrey	11	12.90	8.36
Sussex	13	21.31	12.87
Thames Valley	16	26.50	8.48
Warwickshire	5	20.29	6.14
West Mercia	13	15.87	7.73
West Midlands	7	37.44	23.72
West Yorkshire	5	41.69	10.56
Wiltshire	5	12.06	8.26

Included in the data as labour market variables are ILO unemployment and a measure of the top and bottom of the income distribution in the area, measured as a standard deviation below and above the average income in the area. These measures come from a variety of sources including the Labour Force Survey and the Office for National Statistics regional data (all at Local Authority level) (see Appendix A for details). They capture not only labour market opportunities, but may also reflect residential segregation patterns i.e. packets of low price housing near high price housing created by area income inequality.

3.4.3 Demographic Data

The second set of variables matched to the crime data are population and demographic variables. As mentioned in the previous Chapter such variables are important because areas differ not only in their population size and density but also in the make-up of their population. All of these factors are likely to cause differences in crime across areas. The demographic variables considered in this model are the proportion male, the proportion non-white, the proportion under 25, the proportion of 16 to 19 year olds in full time education, the proportion of social housing and the proportion of lone parents.[5] These variables have been chosen because past empirical work has found they may be important determinants of crime. For example, significant differences have been discovered between the offending rates of males and females (Graham and Bowling 1995), whites and blacks (Blau and Blau 1982, Land, McCall and Cohen 1990) and whites and Asians (Graham and Bowling 1995, Flood-Page et al 2000). Differences in criminal participation by age have been well documented (Greenberg 1977, Hirschi and

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[5] Also included in the models is a variable that measures the extent of lone parents in the area claiming lone parent income support. This is designed to capture the financial burden of lone parents.

Gottfredson 1983 and Hansen 2001), as has the importance of gaining post-compulsory education (Lochner 1999 and Hansen 2001). Differences in housing tenure (Reilly and Witt 1996) and in family make up (Messner et al 1999, Levitt 1998, Levitt and Lochner 2001) have also been shown to be related to crime.

3.4.4 Deterrence Data

The final set of variables are deterrence measures. As mentioned in the previous Chapter, it is important to include a measure of deterrence in the area as economic theories of crime predict that this is very likely to be related to criminal activity in the area. Becker (1968) and Ehrlich (1973) predicted that deterrence is one of the main considerations for people deciding whether or not to commit a crime. Freeman (1983) and Freeman and Rogers (1999) found that deterrence measures have an ability to reduce crime and that the effects of deterrence measures are more important than labour market and other variables on crime. Moreover, failing to include a measure of deterrence in the model (even though it may not be of primary interest), will bias the results as deterrence is likely to affect crime and is potentially correlated with the explanatory variables (see Appendix B for further discussion of bias). The deterrence variable included in this data is the crime specific clear-up rate in the area.

3.5 Methodology

The focus of this Chapter is two-fold: firstly, it looks at the spatial distribution of crime at CDRP level and secondly, it examines the extent to which the distribution of demographic and socio-economic variables are able to account for observed variations in the crime rates. The first part involves identifying patterns of spatial association in the crime rates of areas. To do this, GIS mapping techniques are used to plot the crime rates in the 374 CDRP areas on a map of England and Wales. From these maps, visual inspection allows identification of the location of crime and the discovery of geographical patterns in the data. However, as Messner et al (1999) point out visual inspection of maps are unable to accurately detect patterns in the data. The human eye is biased towards discovering patterns where none exist. So this must be supplemented with tools that allow the more rigorous analysis of the spatial distribution of crime. In this case, the Moran's I statistic is used to identify significant spatial associations (see below for definition).

Having identified patterns in the distribution of crime, this Chapter goes on to examine which area characteristics are related to crime at CDRP level. This is done by carrying out a series of statistical regressions of property and violent crime on a number of possible explanatory variables (as detailed above). If any of these variables are associated with crime, controlling for them in the model should alter the geographical distribution of crime. To see if this is the case, the residual crime rates from the full model (i.e. the variation that can not be explained by the model) are plotted on a map of England and Wales and compared to the map of the raw crime rates. If the pattern looks more random with the inclusion of the explanatory variables, this means that the distribution of crime can be explained, at least in part, by the underlying area characteristics. Again Moran's I statistics and maps are used to examine whether patterns in the residual crime rates across areas are statistically significant.

3.6 Measures of Spatial Association

3.6.1 Raw Data Maps

The maps used in this paper are produced using a GIS package called ArcView, which allows the area crime data to be displayed on a map of England and Wales. Using graduated colour, where the colours change according to the amount of crime in each area, these maps are able to show the spatial location and distribution of crime. The distribution of property crime is shown in Figure 3.1. With the darker shading representing areas of higher crime, it is clear that property crime is higher in the more urbanised areas, with pockets of high crime around London, Birmingham and the areas surrounding Leeds, Bradford and Manchester. It is low in the geographically sparse areas such Wales.

The map for violent crime (Figure 3.2) produces similar results. Although violent crime looks more dispersed than property crimes, there remain clusters of high violent crime areas around London, Birmingham, Leeds and Manchester. There is also a pocket of high crime around Newport in South East Wales and Kings Lynn in East Anglia.

Figure 3.1 The Distribution of Property Crime

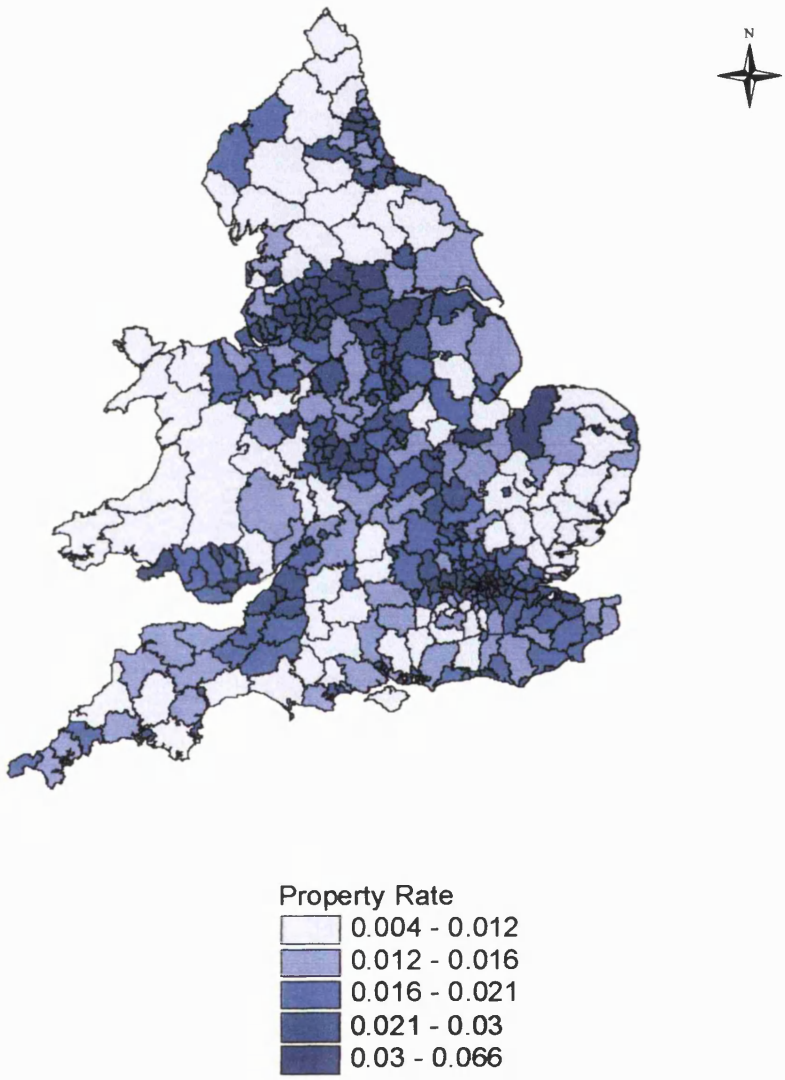
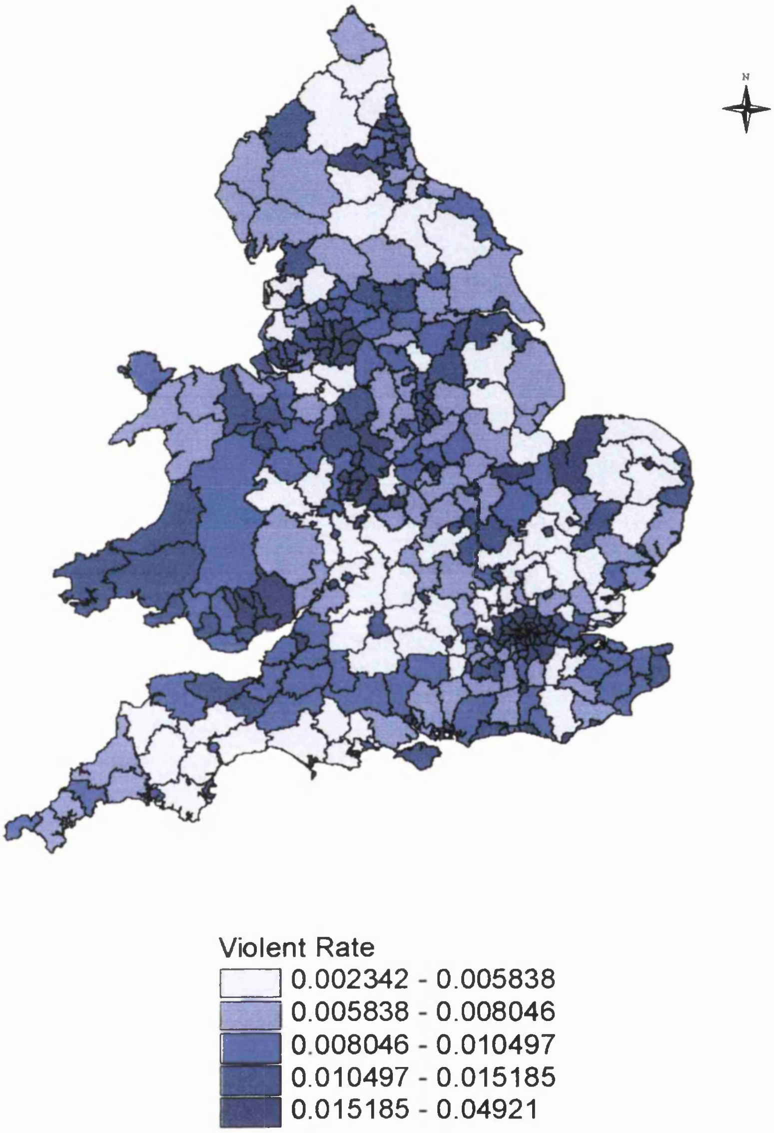


Figure 3.2 The Distribution of Violent Crime



3.6.2 Moran's I: Global Measure

While these maps provide excellent visual aids for examining the basic geographical distribution of crime, they do not provide a measure of the magnitude of spatial association, or any indication of whether the patterns observed could have occurred by chance. What is needed is a more formal measure of the spatial correlation of crime across areas. The classic indicator is the Global Moran's I statistic (see Cliff and Ord 1973 or Anselin 1999). This statistic measures the degree of spatial clustering in the data in terms of the correlation between area-specific crime rates and the average crime rates in 'neighbouring' area-groups. This can be written as:

$$I = \frac{Cov(X_i, \overline{X}_i)}{Var(X_i)} = \frac{\sum_i X_i \overline{X}_i}{\sum_i X_i^2}$$

where X_i is the crime rate in a specific area and $\overline{X}_i$ is the average crime rate in the neighbouring areas.

A given area's 'neighbouring' crime rate is constructed as an inverse-distance weighted average of all other areas in the data set. Neighbouring areas that are closer to the initial area are given higher weights, while areas further away receive lower weights.[6]

Thus, Moran's I is a statistical technique which, rather simply, tells us whether crime levels in an area are similar to crime levels in other areas. Just like the standard correlation coefficient, the statistic is bounded by –1 and 1. A value greater than zero indicates positive spatial correlation with high crime rate locations generally neighbouring other high crime rate locations, and low crime rate locations neighbouring other low crime rate areas. A negative value indicates that high crime areas tend to be

[6] Although other weights may be constructed based on spatial proximity weighting schemes. When this is done the basic results are unchanged.

close to low crime rate areas. If there is no systematic spatial pattern, the statistic is close to zero (the expected value with randomly distributed data is –1/(n-1) in small samples).

The Moran's I statistics for the raw data indicate some degree of positive spatial association in crime rates across England and Wales, though the degree of spatial association is quite low. The Global Moran's I statistic for both measures of crime is higher than expected. In the case of violent crime the Moran's I is .11837 (z = 17.463); for property crime it is .08146 (z = 14.589). Both are statistically significant at greater than the 1% level.

3.6.3 Moran's I: Local Measure

The results presented so far suggest that on the whole neighbouring areas tend to have similar rates of crime. However, this has little meaning when we consider that England and Wales covers some 150,000 square kilometers and that there are 374 CDRPs within this area. It may well be the case that although there is a positive spatial association overall, within this there are a number of different associations (see O'Loughlin at al 1994).

To examine this possibility a Local measure of Moran's I can be used to look for smaller pockets of spatial association within the overall picture. A local measure of Moran's I is produced in the same way as the global measure but where the global measure is:

$$I = \frac{Cov(X_i, \overline{X}_i)}{Var(X_i)} = \frac{\sum_i X_i \overline{X}_i}{\sum_i X_i^2}$$

In other words:

$$\frac{X_1 \overline{X}_1}{Var(X_1)} + \frac{X_2 \overline{X}_2}{Var(X_2)} + \ldots\ldots + \frac{X_n \overline{X}_n}{Var(X_n)}$$

The local measure just takes[7]:

$$I^L = X_i \overline{X}_i$$

Like its global counterpart the Local Moran's I^L measure not only identifies positive and negative spatial associations, but also tests whether these are statistically significant.

The null hypothesis is that there is no spatial association of crime rates across the areas of England and Wales. This is tested using a Bonferroni Correction method (see Ord and Getis 1995 for details). This is necessary as there are 374 areas which means that if we are interested in testing for statistical significance at the 5% level over 18 observations will show statistically significant spatial associations just by chance. The Bonferroni Correction simply tests for statistical significance at the 5% level by removing the element of chance (dividing 5 by 374). This reduces the chance of committing a type I error – rejecting the null hypothesis when it is in fact true.

Moreover, Local Moran's I can be mapped using ArcView in a similar way to the raw crime rates. This can be seen in Figures 3.3 and 3.4, this time the shading represents statistically significant positive spatial associations (darkest red shading) or statistically significant negative spatial associations (darkest blue shading) using the Bonferroni Correction Method. The lighter coloured shading represents statistically significant associations at the 5% level using the less stringent, uncorrected level of significance (where, as discussed earlier, the chance of committing a type I error is higher).

Figure 3.3 shows that for property crimes the clustering of positively associated crime rates around London and Manchester, Leeds and Pembrokeshire visible in Figure

[7] Thus the global measure is just the sum of all the local measures.

3.1 is statistically significant. Going back to Figure 3.1, we can see that for the first three areas the positive association identified is high crime areas with high crime areas. In Pembrokeshire the positive association refers to the clustering of low crime areas together. For violent crime (Figure 3.4) the Local Moran's I identifies fewer areas of spatial association, the predominant areas are those in London. There are smaller pockets of positive association in Manchester and South East Wales around Newport. These are all positively correlated high crime areas. The only areas of negative association are those areas around London which have low rates of violent crime compared to the high rates of crime in more central parts of London.

Figure 3.3   Local Moran's I for Property Crime

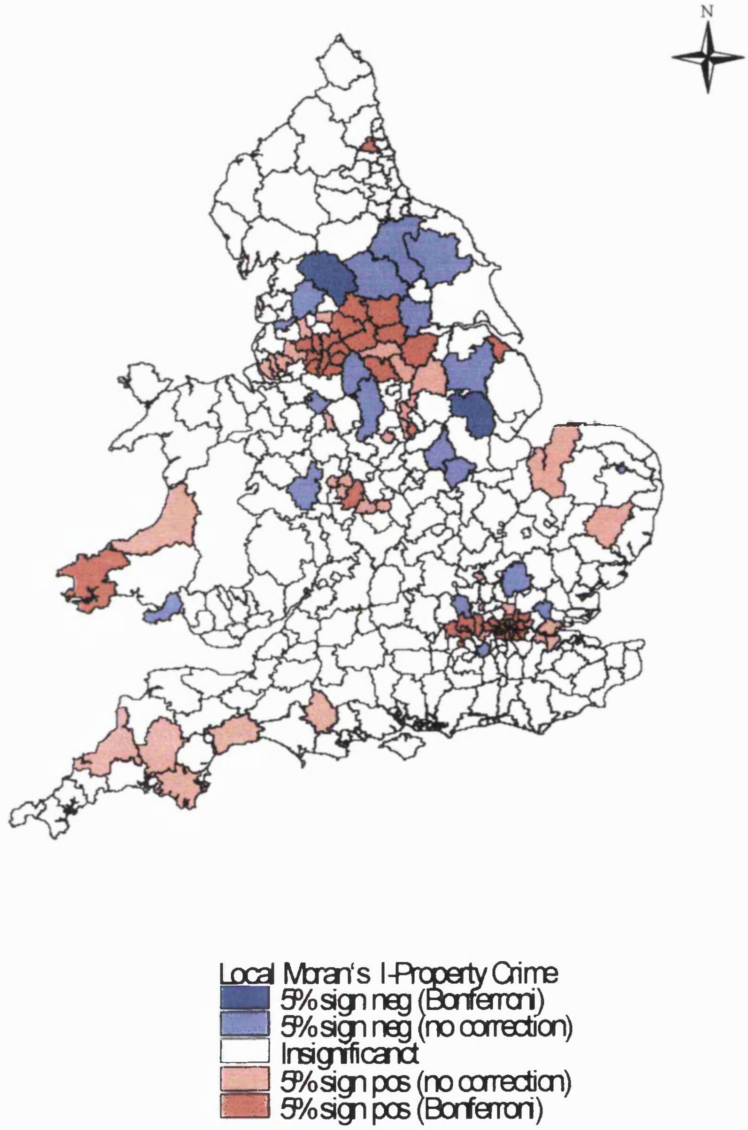
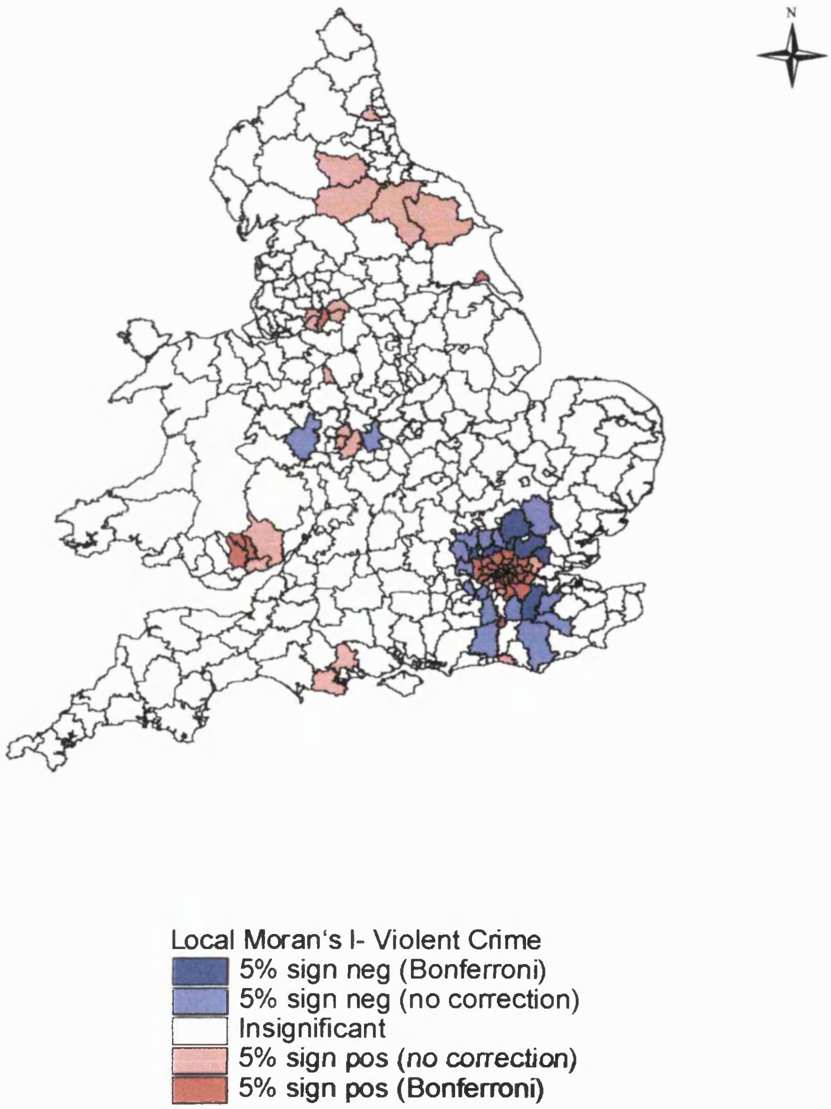


Figure 3.4 Local Moran's I for Violent Crime



3.7 Regression Results

It is likely that some of the spatial association of crime across areas can be explained, at least in part, by the relationship crime has to a number of observable or measurable variables and the geographical distribution of these variables. To examine which area characteristics are associated with crime at this level, regression analysis is carried out with crime as the dependent variable and a number of variables that may be related to crime as the independent variables.

Because individuals can act in one of two ways: either a crime occurs and is recorded or it is not, the model used is a probit. This model is based on the assumption that the probability distribution in question (i.e. the probability of committing an offence), is normal and predicts probability Y=1 (i.e. a person commits an offence) compared to Y=0 (not committing an offence). However, this model is based on the actions of an individual and the data are 'grouped data', that is, each observation at CDRP level consists of a number of individuals. So in this case a grouped probit or normit model must be used, where the dependent variable becomes the 'normit' of the proportion of individuals in an area who commit a crime (Greene, 2000).[8]

The regressions are carried out separately for property crime and for violent crime. Table 3.2 shows the results from the property crime model. There are four specifications. The first (column (1)) is a simple regression of area crime rates on a number of variables designed to represent the demographic structure of the areas. The second (2) includes labour market variables, while the third (3) looks at the effect of the property crime clear-up rate. The final specification (4) includes all the variables

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[8] This is just a transformation of the proportion, $\Phi(\Pi_i)$, where Π_i is the proportion and Φ is the normal

together.

The relationship between property crime and the demographic variables can be seen in column (1) of Table 3.2. The proportion of males in the area and the proportion of young people under the age of 25 are both positively associated with property crime. Both of these finding are statistically significant at a greater than 1% significance level. The proportion of social housing in an area and the proportion of single parents in an area also attract positive coefficients, statistically significant at a greater than 1 % significance level, while the proportion of 16 to 19 year olds in post compulsory education in an area is negatively associated with property crime. This finding again is statistically significant at a greater than 1% significance level.

Column (2) shows which labour market variables are related to property crime. The ILO measure of unemployment attracts a negative coefficient, but remains statistically insignificant, confirming the findings in the previous Chapter and much of the earlier work on crime and the labour market. Higher incomes at the lower end of the distribution reduce property crime, while income at the top end of the income distribution is positively associated with property crime. Both of these findings are statistically significant at a greater than 1% significance level. A fourth variable examined in this section is the proportion of people in the area claiming lone parent income support. This has been included to try to measure the effect of the relationship between single parent families and low pay and poverty (Desai et al 1999). This variable attracts a strongly positive coefficient, significant at a greater than 1% significance level.

Examining the coefficients on both income measures in column 2 it is clear that it

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cumulative distribution function.

is possible that both measures have an equal and opposite effect. When this is tested the F-test gives a statistic of 11.02, which is statistically significant at the 1% level. Thus, that the two measures are equal and opposite cannot be rejected. For this reason, as in Chapter 1, an inequality measure is constructed and entered into the model in column 3. This produces a positive coefficient on the measure of income inequality, which is statistically significant at a greater than 1% significance level. The results of the other labour market variables remain unaltered.

The property crime clear-up rate, shown in the fourth specification (4) attracts a positive coefficient (significant at the 5% level), which is counter-intuitive. This suggests that areas where a higher proportion of crimes are cleared up are also areas where more crimes take place. This may indicate that the variable is endogenous, thus giving spurious results produced by the fact that the data are a cross-section only rather than reflecting any true association. As discussed in the previous Chapter, cross-sectional methodology is susceptible to omitted variable bias, because it is unable to control for intervening factors that may be producing the relationship discovered. It may be the case that areas with more crime will have a larger police population with which to solve crimes.[9]

The final specification (5) examines the effect of all the independent variables on property crime. This full model slightly alters which factors are most associated with property crime at the local level, although many of the same factors discussed above remain important. Thus, the proportion of males in the area and the proportion of young people aged under 25, still attract a positive coefficient and remain statistically significant

[9] Ideally we would also like information on the number of police officers. Unfortunately, police numbers are only available from the Home Office at police force areas and not at CDRP level. Data cannot be used from surveys which record occupations such as the NES, because as a sample they will have too few observations at this level.

at a greater than 1% significance level in this full model. The proportion of 16-19 year olds in full time education is still negatively related to property crime (and is statistically significant at a greater than 1% level). The proportion of non-whites and the proportion of people living in social housing attract positive coefficients, but are statistically insignificant.

Both the proportion of lone parents in the area and the proportion of lone parents receiving income support attract positive statistically significant coefficients. But in terms of magnitude of effect the latter variable is clearly the more important of the two. Thus, the negative outcomes often attributed to the breakdown of the family and the rise of single parent families, such as crime, appear to be more related to the fact that single parent families are in greater financial need that many others in society rather than being a product of single parent families *per se*.

Of the labour market variables in the full model, the measure of income inequality remains unchanged from the previous specification. Income inequality is positively related to property crime. A finding which is statistically significant at the 5% level. In this final model, the measure of unemployment becomes statistically significant at the 5% level, indicating that areas with a larger proportion of the population who are unemployed, have lower property crime rates.[10] This full specification also alters the previous counter-intuitive effect of the clear-up rate. The coefficient in this final model remains statistically insignificant.

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[10] This may indicate less opportunity for crime in areas where more people are unemployed. For example, there may be less goods to steal or greater guardianship of property.

Table 3.2 Property Crime Regressions

	(1) Basic Model (with Demographics)	(2) Labour Market Variables	(3) Labour Market (inequality)	(4) Clear Up Rate	(5) Full Model
Proportion Male	.033*** (.033) [.002]				.027*** (.007) [.001]
Proportion under 25	.979*** (.326) [.052]				.834*** (.289) [.044]
Proportion of 16-19 year olds in Full Time Education	-.130*** (.053) [-.007]				-.131*** (.051) [-.007]
Proportion non-white	.163 (.106) [.009]				.146 (.118) [.008]
Proportion Social Housing	.398*** (.092) [.021]				.095 (.112) [.005]
Proportion Lone Parents	1.90*** (.324) [.101]				.992*** (.423) [.052]
Lone Parent Income Support		14.73*** (1.87) [.813]	14.72*** (1.86) [812]		8.39*** (2.27) [.440]
ILO Unemployment		-.325 (.495) [-.018]	-.343 (.484) [-.019]		-.940** (.440) [-.049]
Bottom End of the Income Distribution		-.417*** (.122) [-.023]			
Top End of the Income Distribution		.439*** (.143) [.024]			
Income Inequality			.412*** (.122) [.023]		.283** (.120) [.015]
Property Crime Clear up Rate				2.18** (.889) [.137]	.354 (.566) [.019]
Obs	**374**	**374**	**374**	**374**	**374**
R-squared	**.565**	**.484**	**.483**	**.587**	**.611**

Also includes controls for area size and population
( ) Robust Standard Errors
[ ] Marginal Effects

Table 3.3 reports the same set of specifications for violent crime. Thus, like the property crimes models, the first (column (1)) of Table 3.3 is a simple regression of area crime rates on a number of variables designed to represent the demographic structure of the areas. The second (2) includes labour market variables, the third (3) additionally examines a wage inequality measure, while the fourth (4) looks at the effect of the violent crime clear-up rate. The final specification (5) includes all the variables together.

As with property crime, the proportion of males in the area and the proportion of young people under the age of 25 are positively associated with violent crime (the first at a greater that 1% significance level, the second at the 10% level). However for violent crime the proportion of individuals in the area who are non-white also attracts a statistically significant positive coefficient. Again, as with property crime, in this demographic model the proportion of social housing and the proportion of lone parents in an area are both positively associated with violent crime and both statistically significant at a greater than 1% significance level.

Of the labour market variables shown in Column (2), the proportion unemployed and the measure of high income in an area are both positively associated with violent crime (significant at the 5% level). The indicator of low income attracts a negative coefficient, but remains statistically insignificant. This supports other research and findings in the previous Chapter that show violent crime to be more associated with higher disposable income (thus allowing people to go out more which increases the chance of personal violence). Moreover, when individuals do go out, they may be seen as more profitable targets for example, carrying more cash or mobile phones. The final labour market related variable is the proportion of individuals in the area claiming lone parent income support. This attracts a positive coefficient, statistically significant at a greater than 1% significance level.

As with the property crime specification the two income measures were tested against the hypothesis that they had an equal and opposite effect. When this was done the

F-test produced a statistic of 3.47, which although smaller than the property crime model, is statistically significant at the 10% level. Thus, column 3 includes a measure of income inequality, which attracts a positive, but statistically insignificant coefficient. Including the income inequality measure does not affect the coefficient on the proportion of lone parents claiming income support, but it does however affect the measure of ILO unemployment, which is forced to statistical insignificance with the inclusion of this new wage measure. The violent crime clear up rate remains statistically insignificant when entered into the model in column 4.

The picture is greatly altered when all of the independent variables are included in the full model in column (5). Of all the variables discussed above only three remain statistically significant in the full model. Once again, this supports previous research and the findings from Chapter 2 which show that it is much more difficult to establish the determinants of violent crime than property crime. Thus, in the final model (5), the proportion of males, the proportion of non-whites and the proportion of people claiming lone parent income support in an area are positively associated with violent crime in an area.

Table 3.3 Violent Crime Regressions

	(1) Basic Model (with Demographics)	(2) Labour Market Variables	(3) Labour Market (inequality)	(4) Clear Up Rate	(5) Full Model
Proportion Male	.045*** (.009) [.001]				.058** (.027) [.002]
Proportion under 25	.603* (.602) [.018]				.379 (.283) [.011]
Proportion of 16-19 year olds in Full Time Education	.021 (067) [.001]				.023 (.060) [.001]
Proportion non-white	.875*** (.128) [.026]				.802*** (.138) [.024]
Proportion Social Housing	.567*** (.115) [.017]				.163 (.133) [.005]
Proportion Lone Parents	1.32*** (.431) [.040]				.042 (.373) [.001]
Lone Parent Income Support		19.05*** (2.40) [.577]	19.09*** (2.67) [.582]		11.37*** (2.80) [.335]
ILO Unemployment		.938** (.452) [.028]	.706 (.458) [.022]		-.585 (.439) [-.017]
Bottom End of the Income Distribution		-.208 (.168) [-.006]			
Top End of the Income Distribution		.541** (.241) [.016]			
Income Inequality			.149 (.182) [.005]		.261 (.175) [.008]
Violent Crime Clear Up Rate				1.70 (1.10) [.065]	-.100 (.136) [-.003]
Obs	**374**	**374**	**374**	**374**	**374**
R-squared	**.660**	**.635**	**.601**	**.014**	**.713**

Also includes controls for area size and population
( ) Robust Standard Errors
[ ] Marginal Effects

3.8 Residual Crime Rate Maps

The regression results indicate that there are a number of measurable characteristics that are associated with both property and violent crime. However, the variables were not able to account for the total variation in either type of crime. Thus, there remain a number of other factors that affect both types of crime which remain unmeasured. The degree to which the measured determinants are able to account for variations in the crime rate is given by the coefficient of determination (or the R squared). More specifically, this measures the proportion of variation in the crime rate that can be accounted for by variation in the explanatory variables (Gujarati 1995). This coefficient is given at the bottom of Table 3.2 for property crime and Table 3.3 for violent crime. We can see that even in the final model the regressions do not fully account for the entire variation in the crime rates. The models account for 61% of the variation in property crime and 71% of the variation in the violent crime rate. The variation not explained by the model is referred to as the residual sum of squares, in this case the residual crime.

Using ArcView, it is possible to plot the residual variation of crime on a map of England and Wales and compare it to the original distribution of the raw crime rates (i.e. the distribution of crime before the effect of the measured determinants were taken out) in Figures 3.1 and 3.2. The previous results showed that the measured variables account for the majority of the variation in crime. Therefore, we should expect the residual crime rates to be distributed more randomly. By examining Figure 3.5, we can see that this is indeed the case, residual property crime appears to be more dispersed than the raw property crime rates. However, there remains clustering of high crime rates around some of the larger cities such as London, Manchester, Doncaster and Leeds and clusters of low crime around the more rural areas of East Anglia and West Wales. Figure 3.6 reveals similar patterns for the residual violent crime rates. Although the general pattern looks more dispersed than the raw violent crime rates in Figure 3.2, pockets of high crime remain around London, Manchester and the West Midlands.

The Global Moran's I for residual property crime of .04864 ($z = 9.799$) and .05123 ($z = 9.850$) for residual violent crime confirm that despite controlling for a range of factors which are associated with the location of crime, both types of crime remain positively spatially associated across England and Wales. However, the association is weaker than in the original data, indicating that controlling for the measurable area characteristics has reduced the overall level of spatial association of crime across areas.

Figure 3.5 Residual Property Crime

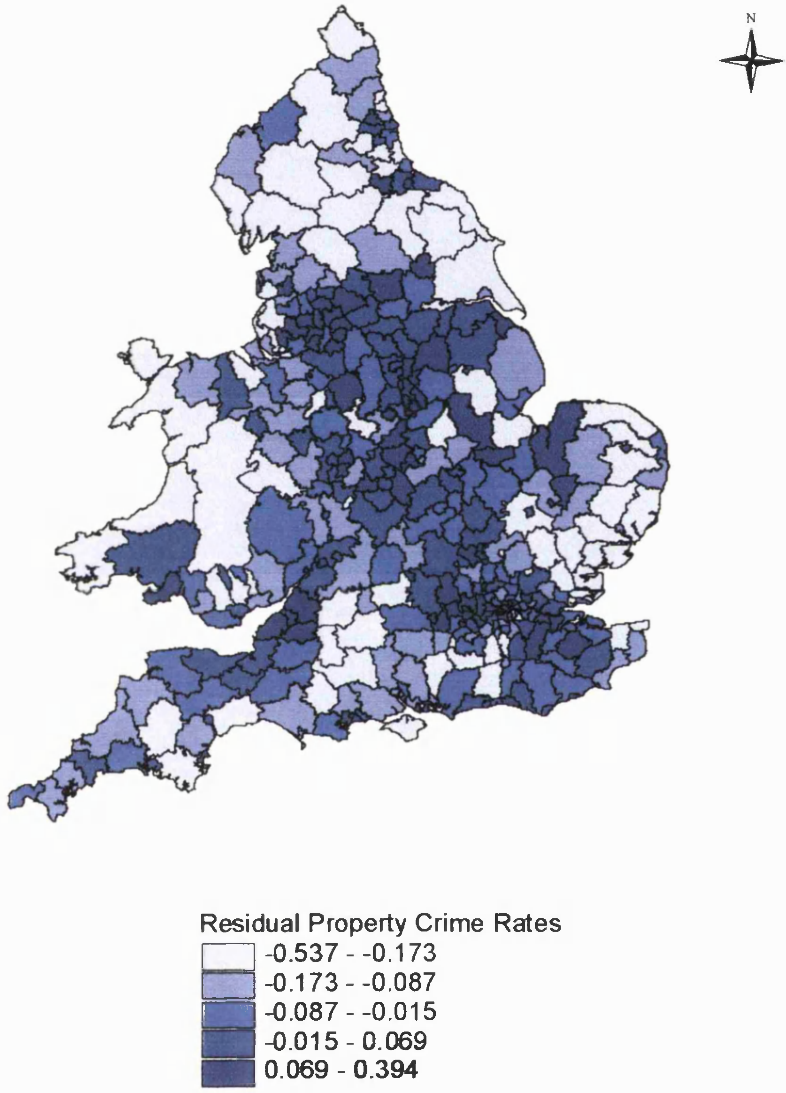
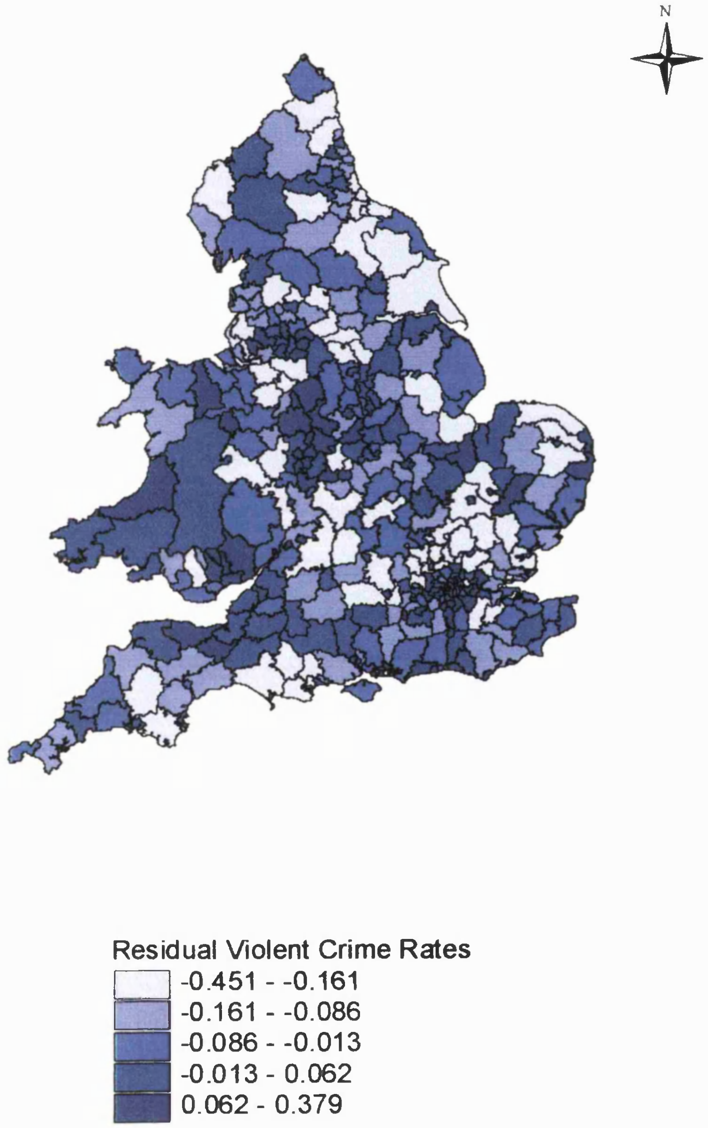


Figure 3.6 Residual Violent Crime



The areas of spatial association can be located by calculating Local Moran's I statistics for the residual crime rates and plotting them on a map of England and Wales. When this is done (in Figure 3.7) we can see that for residual property crime, there are fewer areas where crime is spatially correlated. However, there remains spatial association of property crime across a number of areas.

Areas of positive association are located around Windsor, Manchester and Nottingham. These are areas of high residual property crime surrounded by other areas of high residual property crime, where the areas characteristics have not been able to account for much of the crime in the area. There are also a number of areas with positive association where low residual crime rate areas are surrounded by other low residual crime rate areas. These are located in the extreme North East, around Berwick-Upon-Tweed. These are areas with low property crime rates once the area characteristics have been controlled for.

There are also some locations where residual property crime is negatively associated across areas. However, there are fewer of these than positive associations. Here areas with low residual property crime rates are surrounded by areas of higher residual crime rates. East Riding and some areas in the Midlands are examples of this type of spatial patterning.

Figure 3.8 shows the results of the Local Moran's I for residual violent crime on a map of England and Wales. It is clear that violent crime is less spatially associated across areas than property crime, though this was also true of the local measure of association in the original data.[11] For violent crime, the dominant pattern of spatial association is positive. The areas around St. Albans and Stockton-on-Tees are low residual violent crime areas surrounded by other areas of low residual violent crime. On the other hand, Staffordshire and Newport exhibit positive association of high residual crime rates. There is some evidence of negative association around Shropshire, which is an area of low residual violent crime surrounded by higher crime areas.

The interesting thing to note is that while spatial association remain in the residual data, the location of these associations are different from the original data. This suggests that the spatial association in the raw data, which was produced by the geographical distribution of the measurable determinants of crime, dominated other associations. Once the effect of the measurable characteristics were netted out in the statistical regression models, other forms of statistical associations were produced by the unmeasurable determinants of crime. In the raw crime rate data, the spatial patterns for both types of crime were dominated by positive associations of high crime rates around the large city areas such as London. In the residual data this is much less true. This possibly suggests that much of the rural / urban crime differential can be explained by differences in the characteristics of these areas.

11 To some extent this is to be expected violent crime is likely to be much more idiosyncratic and individual than property crime

Figure 3.7 Local Moran's I for Residual Property Crime

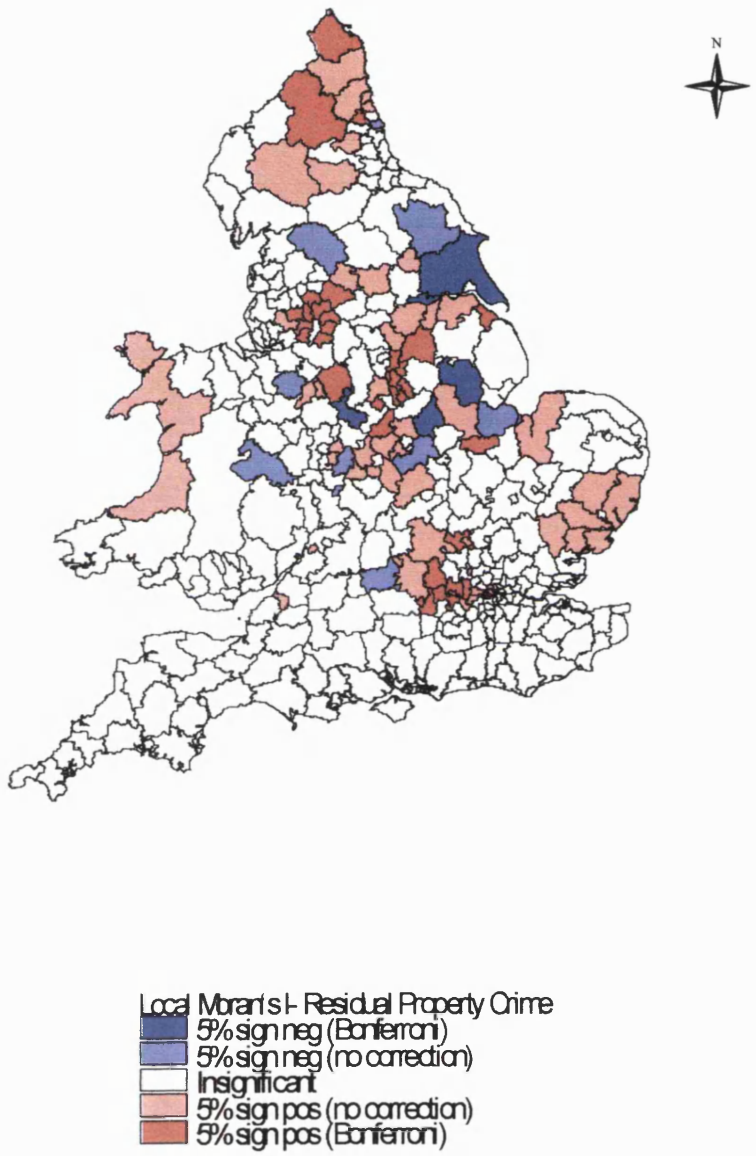
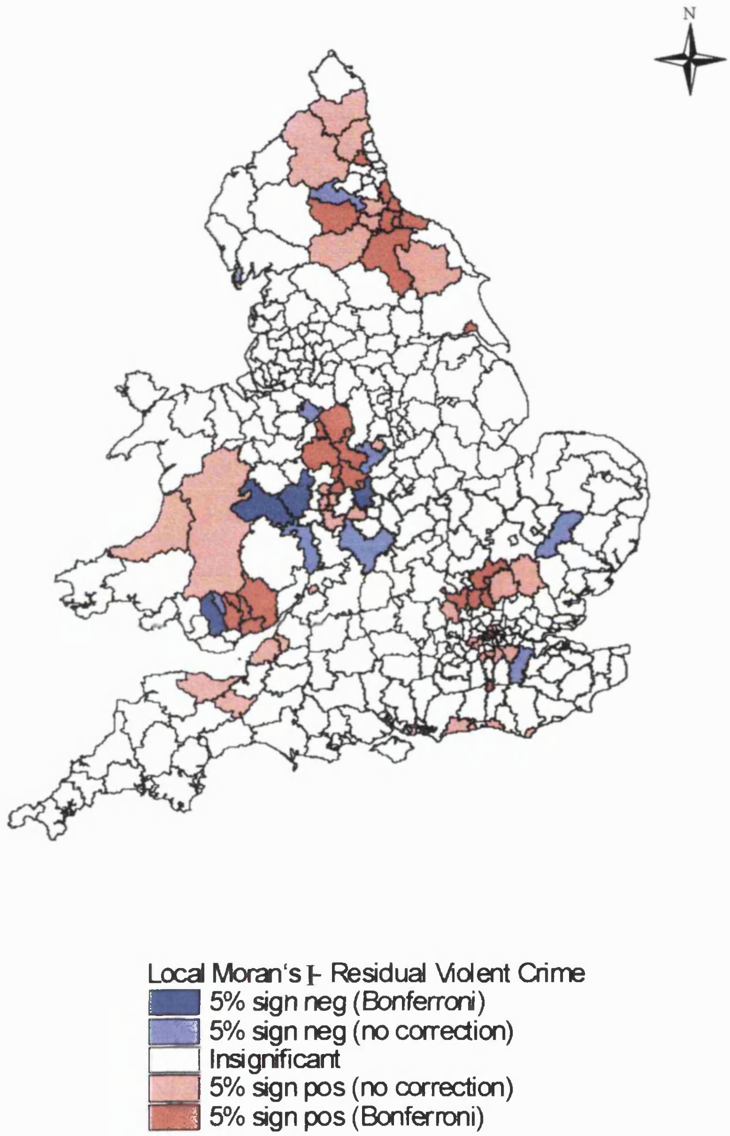


Figure 3.8 Local Moran's I for Residual Violent Crime



3.9 Concluding Remarks

This Chapter has examined the distribution of crime across 374 CDRP areas in England and Wales. The findings show that crime is not randomly located but that in general, as Moran's I statistic identified, there exists positive spatial association across areas. Areas of high crime are located near to other high crime areas and low crime areas are located near to other low crime areas. Using a local measure of Moran's I statistic clusters of both positive and negative association were discovered, although positive spatial associations were more prevalent.

Statistical regression analyses found that some of the spatial association could be explained by the variation in a number of measurable variables. The variables that were found to be statistically significant (and thus able to explain at least some of the spatial association of crime across areas for property crime), were related to the age, sex educational level, labour market position and financial situation of the individuals living in the area. Property crime was found to be higher in areas with a higher proportion of males in the area, a higher proportion of young people aged under 25 and a lower proportion of 16-19 year olds in full time education. Property crime was also higher in areas with a higher proportion of lone parents and individuals claiming lone parent income support; in areas where the income inequality is greater; and where a greater proportion of the population is unemployed.

Like the previous Chapter, it was harder to uncover the determinants of violent crime than property crime. Nevertheless, some factors were found to be significantly related to violent crime. Areas with a higher proportion of males, a higher proportion of non-whites and a higher proportion of people claiming lone parent income support had higher rates of violent crime than other areas.

After controlling for differences in the measurable area characteristics, the remaining spatial association of crime across areas was attributable to unmeasured factors.[12] Although on the whole, these unmeasured characteristics produced less spatial association (as indicated by the lower value of the global Moran's I), they did produce some spatial associations. Those that were produced were different in nature to the patterns produced by the measurable variables.

The spatial association produced by the measurable characteristics were dominated by positive associations of high crime rates around the large city areas such as London. This is not true of the spatial patterns produced by the unmeasurable determinants of crime. This provides evidence that much of the rural / urban crime differential can be explained by differences across these areas in their measurable characteristics.

While these findings shed light on the spatial association of crime across relatively small areas of England and Wales (which have not received much attention from researchers in the past), there are some limitations to this work. Because this is relatively early days in terms of data collection at this level, the analysis in this Chapter is based on a cross-section. The previous Chapter showed that statistical regression analysis, using such data, are vulnerable to omitted variable bias. The potential problem of omitted variable bias is reduced here by adding a large number of independent variables to the right hand side of the statistical regression models.

Thus, methodologically, this research should perhaps be viewed as a type of pilot

[12] These include any factors that have not been incorporated in the model, that have an affect on crime. At this stage we must rely on theory and common sense to inform us what such factors might be, but possible

study in the early days of data collection. The descriptive analysis brings to light some important issues that can be addressed with more rigorous testing approaches, when more data becomes available at this level.

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examples include peer pressure, non-residential land use, transportation nodes, or even the weather.

4. Crime and the Minimum Wage: A Quasi-Natural Experiment

4.1 Introduction

The way in which the volume of criminal activity moves over time, and what factors lie behind its evolution, have been important research and public policy questions for many years. Earlier Chapters considered the way a number of possible determinants of criminal behaviour could impinge upon crime and found low wages to be a robust indicator of criminal involvement. These findings are consistent with other work in the area of crime and the labour market.

This Chapter focuses on the relationship between crime and low wages in a rather different way than previous research on crime and the labour market. If one thinks that differential wage opportunities matter for crime, then presumably the best way of testing for the existence of a crime-wage link is to look at a situation where people on the margins of criminal participation receive a (potentially large) wage increase. Such a situation is offered when a binding Minimum Wage floor is introduced to a labour market that was not previously regulated by Minimum Wage legislation. This was the case when a National Minimum Wage (NMW) was introduced to the UK labour market in April 1999. If labour market conditions are related in an important way to crime, or an individual's propensity to commit criminal acts are altered by changing labour market opportunities, then one may well see changes in crime occur in the time period surrounding Minimum Wage introduction.

4.2 Empirical Work on Crime and the Labour Market

Early empirical work in this area tended to focus heavily on links between crime and unemployment. Surveys of this work by Freeman (1999), Box (1987) and Chiricos (1987) report that the relationship between crime and unemployment appears fragile at best. Some studies have detected a positive relationship between crime and unemployment (Land, McCall and Cohen 1990, Levitt 1998), but this is often more easily found in studies using individual longitudinal data (see, for example, Thornberry and Christenson 1985; West 1982 for the UK). The same is true if specific[1], rather than aggregate, unemployment rates are examined. However, other studies that show a statistically significant unconditional correlation between crime and unemployment, find that once other variables are taken into account, the relationship between crime and unemployment disappears (examples are Butcher and Piehl 1998 for the US and Machin and Meghir 1999 for England and Wales). Even stronger than this, others have found there to be no relationship between crime and unemployment at all (Cullen and Levitt 1999).

This weak pattern of results is not so surprising when one realises that there are a number of conceptual reasons why unemployment may not be the most appropriate labour market variable to examine in relation to crime. Because criminal participation is unlikely to be something that most individuals enter into lightly crime may well be more responsive to long term labour market measures than to short run ones such as contemporaneous unemployment (Gould et al 2002). Indeed, there is a much larger group of individuals who, although in employment, are in insecure low paid, low skill jobs, or in part time or temporary work; who are economically and socially marginalized. Moreover, by the very fact that they are employed and socially connected, these people may be in a better position to commit crimes than the unemployed (see Box 1987, Fagan and Freeman 1999, Grogger 1998).[2]

Because of this a number of studies have looked at broader measures of crime and the labour market. Using the 1939 Boston Cohort Sampson and Laub (1993) find job stability to be negatively related to subsequent criminal behaviour. Looking specifically at violent offences, Crutchfield (1989) finds labour instability to be a significant predictor of overall violence, murder, assault and robbery. The link between job stability and crime has also been highlighted in UK research by West and Farrington (1977) and Farrington (1986).

Along the same lines, Allan and Steffensmeier (1989) find the quality of work to be important in relation to crime. For young adults there is a strong association between working less than the preferred number of hours and crime. In his UK study, Hale (1999) finds that changes in the structure of employment are related to crime, in particular shifts from manufacturing to the service sector, increasing part time and temporary jobs and changes between male and female employment. Similarly, and again based on UK data, Farrington et al (1986) find that individuals are more likely to offend if they work in low status jobs.

A related issue explored in other research is the role of economic incentives. The US evidence of Fowles and Merva (1996) and Hsieh and Pugh (1983) find poverty to be

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[1] This is usually the unemployment rate of young males (as in Freeman and Rogers (1999) and Allan and Steffensmeier (1989) for the US and Reilly and Witt (1996) for the UK).

[2] In the 1980 wave of the National Longitudinal Study of Youths (NLSY) over half of those working reported that they had committed some crime and one fifth of those working had committed at least 1 income producing crime (Fagan and Freeman 1999, Grogger 1998). In Fagan's (1992) study more than 25% of drug dealers were also working.

positively related to crime (the latter looked at violent crimes only). Other US studies link the rise in crime to widening wage inequality, which has been experienced since the 1970s as a result of a decline in both relative and absolute wages at the bottom end of the market (Fowles and Merva 1996, Blau and Blau 1982, Hsieh and Pugh 1983). Similarly, Witt, Clarke and Fielding (1999) look at police force area data in England and Wales from 1988 to 1996, and find that changes in wage inequality are positively correlated with changes in crime.[3]

By looking at the wage rates of low skilled workers a more recent body of work has concentrated on those at the bottom of the wage structure rather than looking at the gap between the top and the bottom of the wage or income distribution. Gould et al (2002) look at the relationship between changes in crime and changes in wages across areas in the US between 1979 and 1995 and report that the falling wages of unskilled men in this period led to a rise in burglary of nearly 14%, a rise in larceny/theft of around 7%, a 9% increase in aggravated assault and an 18% rise in robbery. From data on the police force areas of England and Wales between the mid- 1970s and mid- 1990s, Machin and Meghir (2000) look at cross-area changes in crime in relation to changes in the 25th percentile of the area wage distribution. They find a negative correlation between particular types of crime (theft and handling, burglary, vehicle crime and total property crime) and low wages, even after controlling for other variables such as measures of demographic change and measures of deterrence. Finally, Grogger (1998) uses data from the US National Longitudinal Survey of Youth to look at the relationship between wages and property crimes for young people. He reports results which show falling real wages

[3] A smaller body of work has looked at other measures of economic activity. For example, Witt and Witte (2000) consider the relation between crime and female labour supply, reporting results based on US time series showing common trends in crime and female labour force participation.

not only offer an explanation of the rise in youth crime in the 1970s and 1980s but also of the differences in criminal involvement between age and ethnic groups.

These latter findings are clearly in line with the idea that economic incentives are important for crime. Moreover, they also suggest that wage measures, especially measures for workers towards the lower end of the wage distribution, may provide better measures of the state of the labour market for people on the margins of crime than unemployment.

This Chapter also looks at crime and wages, but by adopting a different methodological approach compared to other work. Examining what happened to crime before and after the introduction of the National Minimum Wage (NMW) to the UK labour market in April 1999. This provides a good testing ground for looking at the impact of a wage change for people deciding whether to participate in, or desist from, crime as the wage increases received by low wage workers were sizable. Metcalf (1999) estimates that about 2 million workers would receive wage gains from the imposition of the NMW. Moreover, the average wage gain for workers paid less than the NMW of £3.60 per hour (£3.00 for 18-21 year olds) before its introduction was estimated to be of the order of 30 percent.[4]

4.3 Why Should There Be A Link Between Crime and Low Wages?

Theoretically there are a number of reasons for thinking that low wages should be related to crime and how the introduction of a Minimum Wage would affect this relationship. Firstly, as Chapter 1 discussed simple choice theoretic models of crime (e.g.

[4] That a large number of workers (though probably not as high as Metcalf's 9 percent) benefited is borne out by the *ex-post* study of Labour Force Survey data before and after minimum wage introduction by Dickens and Manning (2001). Their study shows a significant impact of the minimum wage on the wage distribution, with around 6 to 7 percent of workers getting wage gains. Interestingly, whilst they show sizable gains at lower percentiles of the distribution, they also report very little evidence of spillover effects up the wage distribution.

Becker 1968 or Ehrlich 1973) propose that individuals have a choice between crime and work, or more generally they choose to allocate their time across crime-work space. These decisions are a function of a number of factors, including expected earnings from crime, expected earnings from the labour market, and perceptions of the severity of the punishment if one gets caught. Seen as a simple work/crime decision this explains why people with no work may decide to partake in crime. But at a more complex level, this can also shed light on how individuals who are employed may decide to commit crimes and the extent to which they allocate their time between work and crime (as already noted above, we know that many people do both). Thus, an increase in legal wages brought about by the introduction of the National Minimum Wage should reduce the incentive to participate in illegal activities, thus bringing the crime rate down. Also by raising wages workers now have more to lose by getting caught, which should also act to discourage criminal activity and reduce crime.[5]

Of course, these simple choice based models of crime have themselves been called into serious question for their relatively simplistic assumptions about criminal behaviour. But other theoretical approaches generate a relation between crime and low wages. For example, anomie and strain theory (Merton, 1957), predicts that people with low wages are likely to suffer financial hardship, sometimes in similar ways to those who are unemployed. This financial hardship means that low paid individuals are encouraged by society to strive for culturally approved goals such as material success but are unable to achieve these goals because of their weak labour market position. This disjunction between what Young (1999) referred to as 'cultural inclusion' but 'structural exclusion', (i.e. the difference between the desire to and ability to achieve goals), causes anomie,

[5] It is something of an unanswered question as to whether the economic model is only relevant to non-violent crimes for which monetary incentives may alter behaviour or whether it can also be extended to the

normlessness or strain. This may well encourage individuals to commit acquisitive crimes either for themselves or to sell for cash in order to obtain the goods they cannot afford. It may also lead to feelings of frustration or anger, which may well manifest themselves in violence. Thus, we would expect low wages to be associated with relatively high rates of both property and violent crimes. An increase in wages brought about by the introduction of the Minimum Wage may ease the strain, which may well lead to a reduction of both types of crime.

Over and above the disjunction between the goals and the means faced by the low paid, their situation is worsened by the fact that most of them will be in jobs where promotion or career advancement is hard (if not impossible). Thus their opportunities to have money and status may appear blocked. Unable to achieve success legally, these individuals may be forced to resort to illegal methods. Moreover, such individuals are more likely to live in poorer areas where it is possible illegal opportunities to achieve goals are more abundant than legal opportunities (Cloward 1959). In these areas, there may also be peer pressure to get involved in crime (Cloward and Ohlin 1960) or increased opportunity for learning criminal behaviour through association and interaction with other criminals (Sutherland 1924, Akers 1964). As noted above, the introduction of the Minimum Wage in the UK raised wages of the low paid by a sizable amount and, in doing so, may well have reduced the need to turn to crime to achieve success or status. Eventually, it may even give people the power to migrate to better areas where there is less criminal peer pressure, although this would be much more long term.

Moreover, by increasing the wages of the low paid, the Minimum Wage may provide enough of an increase in spending power and financial security to dissuade the

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case of violent crime. Various researchers have taken different stances upon this (though see Grogger 2000 for an interesting attempt to apply the economic model to violent crime).

low paid from turning to the black market for goods. In this way, by reducing the demand for crime, the Minimum Wage would lead to a reduction in crime.

Finally, as employment is one of the major institutions through which social bonds are formed between individuals and society, social control theory predicts that employees with low paid jobs may be less attached to society (Hirshi 1969, Box 1971). Thus, crime rates may be high amongst those in low paid jobs as social controls will be less able to deter them from breaking the law. If wages are increased due to the implementation of the National Minimum Wage, this may act as a mechanism for strengthening the social bonds between the low paid and society. More tied to society and therefore more constrained by social controls this group will be less likely to commit crimes.

Thus, there are a number of potential explanations as to why the introduction of the Minimum Wage may influence crime and help us try to pin down a link between crime and the low wage labour market. These ideas form the basis of the hypothesis that the introduction of the Minimum Wage may have the potential to reduce crime.

4.4 Methodology

The empirical methodology utilised in this Chapter involves comparing what happened to crime rates before and after the Minimum Wage introduction in the police force areas of England and Wales. Changes in various crime rates before and after Minimum Wage introduction are related to the initial proportion of low wage workers (i.e. those paid less than the Minimum Wage prior to its introduction) in those areas. This is much the same methodology as that adopted in some US work (notably Card 1992) to look at the relationship between employment and minimum wages in US states before and after the large federal Minimum Wage increase of April 1990. Identification of the minimum wage effect comes from the fact that there are more low wage workers in some areas than others and therefore the Minimum Wage should be thought of having more of an effect there than in areas where there are fewer low wage employees. As Card puts it:

> *'From an evaluation perspective……a uniform minimum wage is an under-appreciated asset. A rise in the federal minimum wage will typically affect a larger fraction of workers in some states than in others. This variation provides a simple natural experiment for measuring the effect of legislated wage floors, with a "treatment effect" that varies across states depending on the fraction of workers initially earning less than the new minimum'.*
>
> Card, 1992 p.22

This approach to looking at crime and the labour market is founded upon the idea that a sizable change in labour market opportunities has the potential to alter an individual's incentive to participate in crime. The theoretical approaches outlined in the previous section highlights an individual's propensity to commit crime, say C,[6] will depend on a number of factors. In general terms, $C = C(W_c, p, S, W, Z)$ where W_c is the earnings from a successful crime, p is the probability of being caught, S is the punishment, W is the earnings available on the legitimate job market and Z are other factors relevant for crime. According to the theoretical approaches, the C(.) function depends positively on W_c and negatively on p, S and W. It therefore reveals a clear trade off between perceived earnings from crime and formal labour market activities. One can aggregate the C(.) function to area-level so that C(.) becomes the area-specific crime rate

[6] C may reflect a discrete 0-1 choice between work and crime or may reflect the allocation of hours per week between formal labour market activity and criminal actions (see, for example, Ehrlich 1973). As the focus is on wages and crime, the latter is probably more appropriate.

(= the number of people engaging in crime divided by the population). The empirical approach, based on looking at the differential impact of the Minimum Wage introduction across areas, can be thought of as providing a positive (and sizable) increase in W. As long as its impact is not offset by coincidental changes in W_c, p, S or Z (which seems highly unlikely in the short time period considered), one should see crime fall in areas where W has the potential to rise by more.

The main factors in Z (i.e. the other determinants of crime), are likely to be those other factors that influence both the supply and demand for crime. In a simple supply-demand framework, the demand side can be thought of as being characterised by an inverse relation between crime and criminal earnings, while the supply side is driven by the wage and criminal justice system variables. The demand for crime is likely, at least to some extent, to be shaped by demographics (e.g. if there are more well-off consumers perhaps the pickings from crime may be more lucrative) and so demographic changes over the short time period are also considered.[7]

Thus, in summary, the empirical approach in this Chapter will compare changes in area-specific crime rates before and after the introduction of the NMW in April 1999. The quasi 'natural experiment' created by the fact that some areas have more low wage workers than others will be exploited to see if the Minimum Wage had the potential to reduce crime in the time period surrounding the Minimum Wage introduction.

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[7] These are: change in average age, change in the population share of young (<25) men, change in proportion black, change in population share with no educational qualifications, change in proportion female, change in share of public sector jobs.

4.5 Data on Crime and the Labour Market

4.5.1 Crime Data

The crime data used in this Chapter are offences reported to and recorded by the police at police force area level in England and Wales over a two year period. The first period is the financial year prior to the introduction of the National Minimum Wage (April 1998 to March 1999) and the second is the year following its introduction (April 1999 to March 2000).[8]

As noted previously, there are 43 police force areas in England and Wales. However, as in Chapter 2, these are aggregated to form 41 areas. This is done for two reasons. First of all the, City of London and Metropolitan police force areas are aggregated to a single London area because the low resident population produces artificially high crime rates in the City of London.[9] Secondly, because of a boundary change that occurred in Gwent and South Wales in the mid-1990s (and because some of the models use data from earlier periods), these two Welsh police forces are analysed together as well.

Four different types of crime are examined: the total number of notified offences; the number of property crimes (defined as burglary plus theft and handling); vehicle crimes (theft of a vehicle, theft from a vehicle, aggravated vehicle taking, vehicle

[8] As has been discussed in Chapter 1, using the official statistics may mean we are overlooking the crimes that are either not reported to, or recorded by the police. However, because of increased public awareness and legal requirements to report crimes, coupled with more precise recording practices by the police, most crimes that do not appear in the official statistics are the more trivial offences. These issues were discussed at length in Chapter 1 and again in Chapters 2 and 3, but for a recent discussion and more details on possible under-reporting problems, described as the 'dark figure' of crime, see McDonald (2001). Moreover, as Chapter 1 also noted in England and Wales the official statistics provide the only source of data on crimes by police force area. The British Crime Survey (which as a victim survey, some argue, captures, at least partially, the 'dark figure' of crime) does not have (publicly available) information on areas. A particular strength in this Chapter is that most of the analysis is based upon changes over short time periods which means that the results are unlikely to be contaminated by reporting biases of this kind. (See Appendix B for further discussion of bias). Indeed, McDonald (2001) makes the very point that time series analyses may suffer from bias problems because the under-reporting of crime varies systematically with the economic cycle. The short time period of study is a clear advantage in this regard.

interference and criminal damage to a vehicle); and violent crimes (violence against the person).

As the focus of this Chapter is on the possible links between crime and monetary measures, then one may plausibly ask why this analysis looks at violent crimes as well as non-violent crimes. Although the justification for looking at non-violent crimes is very clear from the economic model, many commentators would argue that violent crimes are much less likely (if at all) to be shaped by monetary factors (Devine et al 1998, Gould et al 2002). However, this is essentially an unresolved issue and one can put forward arguments both ways. A number of studies find that economic incentives matter for violent crime (see for example, Blau and Blau 1982, Merva and Fowles 1996, Grogger 2000). This relationship is often mediated through the link between crime and drugs (Merva and Fowles 1996, Wilkinson 2001). Hence, this Chapter presents empirical models of both property and violent crime.

4.5.2 Labour Market Data

The labour market variables are obtained by aggregating individual-level data to police force area. This was done using data from the Labour Force Survey (LFS), matched using a county level identifier to the police force areas. The principal measure used to look at whether the Minimum Wage introduction had a differential effect by police force area, is a variable which measures the proportion of workers paid beneath the hourly minimum in the year before its introduction (£3.60 for people aged 22+, £3.00 for 18-21 year olds). This variable is used to gauge the extent to which there is a differential impact of the Minimum Wage across police force areas. Towards the end of the Chapter, other variables measuring the nature of the low wage labour market are also considered as a robustness check of the main findings.

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[9] This actually makes no difference in practice, as the descriptive statistics and regression results are

The empirical models also control for a number of other factors which theory and past empirical work inform us could be influencing the relationship between crime and the introduction of the Minimum Wage. These include changes in the demographic structure of areas or in the likelihood of detection that could be occurring during the time period examined. The demographic variables considered come from the LFS and are area measures of average age, the population share of women, of young (<25) men, of those with no educational qualifications and the share of public sector jobs in total employment. The crime clear-up rate (namely the proportion of crimes that were solved by the police in each area) is used to capture changes in detection rates that may coincide with the time periods of study.

One other variable of particular interest, which is derived from the LFS, is the area unemployment rate. It is possible that connections exist between changes in crime and changes in the unemployment rate. There are at least two reasons why this research needs to examine this possibility. First, a lot of the existing crime research has focused on the link between crime and unemployment. Secondly, there has been a great deal of discussion as to whether the Minimum Wage would actually increase unemployment by pricing workers out of jobs. There is only very weak and fragile evidence on the first question but the nature of the data means we can take another look at it here. With regard to the second point, and more importantly, to date there is little evidence that the introduction of the UK Minimum Wage was detrimental to jobs (Stewart 2001) except in some sectors that are very vulnerable to the Minimum Wage due to having large numbers of low wage workers (such as the care homes sector studied in Machin et al 2001). However, it is important here to allow for a possible unemployment effect of the

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population weighted. But it seems neater and more natural to aggregate the two London areas together.

Minimum Wage that may arise due to its differential impact on wages across areas. This is done in the empirical work presented in this Chapter.

4.6 Descriptive Analysis

Table 4.1 begins the empirical analysis by showing the relationship between area wage structures and the extent of low pay prior to the introduction of the Minimum Wage. This is done by dividing areas into groups on the basis of the proportion of people paid beneath the National Minimum Wage in the year prior to its introduction. The police force areas of England and Wales were divided up into four areas described as 'most low pay' (where over 11.7 percent of workers were paid beneath the minimum in the initial period), 'second most low pay' (between 10.2 and 11.7 percent beneath the minimum), 'second least low pay' (between 7.5 and 10.2 percent) and 'least low pay' (less than 7.5 percent below the minimum). The Table shows the hourly wage at different percentile points of the wage distribution for each of these areas and then changes over time for each area, together with gaps in the change between the 'most low pay' and 'least low pay' areas. These latter changes (given in bold) can be thought of as 'difference-in-difference' estimates of the impact of the Minimum Wage on different points of the wage distribution.

The upper panel of the Table focuses on the 10^{th} percentile of the hourly wage distribution, whereas the lower panels consider the 25^{th}, 50^{th} and 90^{th} percentiles. The upper panel of the Table shows there to have been quite sizable wage increases at the 10^{th} percentile in the period surrounding Minimum Wage introduction. Furthermore, the scale of these increases was different across areas, with the 'most low pay' area 10^{th} percentile increasing by 35 pence per hour and the 'least low pay' area also increasing significantly, although only by 18 pence per hour. The difference-in-difference estimate of 17 pence per hour (which is statistically significant) shows a stronger beneficial impact of the Minimum Wage on the 10th percentile to have occurred in low wage areas.

However, like other research in this area (notably Dickens and Manning, 2001) the Minimum Wage does not seem to impact higher up the distribution. There are no differences across areas at the 25th percentile where the changes in hourly wages are very similar across areas (the difference-in-difference estimate now being only 1 pence, and completely insignificant). The same is true at the median. At the top of the distribution the opposite occurs and the 90th percentile grows by more in the 'least low pay' areas, though this will be for reasons unconnected to the Minimum Wage introduction. Nevertheless there is an important impact on wage structures that differs across areas at the lower end of the distribution.

Table 4.2 looks at changes in crime rates (defined as crimes per 1000 population) across the same group of four areas as in Table 4.1. Looking at the difference-in-difference estimates (given in bold), a very clear pattern emerges. For all four types of crime, there seems to be a reduction of crime in the 'most low pay' areas as compared to the 'least low pay areas'. For example, the year-on-year change in the total crime rate was around 11.6 crimes lower per 1000 people (comparable numbers for property, vehicle and violent crimes being 6.3, 3.2 and 1.6 respectively). Furthermore, for the non-violent crimes, this gap seems to be driven by crime falling in the areas with more low paid workers and rising in the areas with few low paid workers. For violent crimes, the crime rate appears to increase across all areas, but by less where there are more low wage workers.

Table 4.1 The Introduction of the National Minimum Wage And Area Hourly Wage Structures

	Year Before Introduction	Year After Introduction	Change (Standard Error)
10th Percentile			
Most Low Pay	3.25	3.60	.35 (.03)
2nd Most Low Pay	3.43	3.70	.26 (.03)
2nd Least Low Pay	3.58	3.82	.24 (.06)
Least Low Pay	3.96	4.13	.18 (.10)
Most Low Pay – Least Low Pay	-.71*** (.06)	-.54*** (.08)	**.17* (.06)**
25th Percentile			
Most Low Pay	4.17	4.40	.23 (.06)
2nd Most Low Pay	4.39	4.61	.22 (.07)
2nd Least Low Pay	4.63	4.90	.27 (.12)
Least Low Pay	5.22	5.45	.23 (.18)
Most Low Pay – Least Low Pay	-1.06*** (.13)	-1.05*** (.15)	**.01 (.06)**
50th Percentile			
Most Low Pay	5.80	6.09	.30 (.11)
2nd Most Low Pay	6.13	6.47	.34 (.12)
2nd Least Low Pay	6.55	6.97	.42 (.25)
Least Low Pay	7.51	7.81	.30 (.38)
Most Low Pay – Least Low Pay	-1.71*** (.26)	-1.72*** (.29)	**-.01 (.10)**
90th Percentile			
Most Low Pay	12.19	12.59	.41 (.24)
2nd Most Low Pay	12.63	12.97	.34 (.36)
2nd Least Low Pay	14.07	14.67	.55 (.53)
Least Low Pay	16.22	17.44	1.22 (.90)
Most Low Pay – Least Low Pay	-4.03*** (.69)	-4.84*** (.63)	**-.81 (.35)**

Notes: Areas are split into four (almost) equal sized groups of police force areas (3 groups of 10 and one of 11 areas). The groupings are based upon the proportion of workers paid less than the Minimum Wage in the year prior to its introduction. Areas in the Most Low Pay group have over 11.7 percent of workers beneath the Minimum Wage. Areas in the 2nd Most Low Pay group have between 10.2 and 11.7 percent of workers beneath the minimum. Areas in the 2nd Least Low Pay group have between 7.5 and 10.2 percent of workers beneath the minimum. Areas in the Least Low Pay group have less than 7.5 percent of workers beneath the Minimum Wage.
Standard errors are in parentheses.
* significant at 10% level, ** 5%, *** 1%.

Table 4.2 The Introduction of the National Minimum Wage and Area Crime Rates (Per 1000 Population)

	Year Before Introduction	Year After Introduction	Change (Standard Error)
Total Crime Rate			
Most Low Pay	98.47	96.04	-2.43 (11.54)
2^{nd} Most Low Pay	100.11	101.94	1.83 (14.73)
2^{nd} Least Low Pay	102.52	105.52	3.00 (13.06)
Least Low Pay	99.11	108.24	9.14 (22.03)
Most Low Pay – Least Low Pay	-.64 (16.22)	-12.21 (18.80)	**-11.56*** (3.54)**
Property Crime Rate			
Most Low Pay	63.50	60.24	-3.26 (8.99)
2^{nd} Most Low Pay	60.93	59.08	-1.86 (8.99)
2^{nd} Least Low Pay	66.26	65.21	-1.05 (8.04)
Least Low Pay	57.73	60.75	3.03 (9.61)
Most Low Pay – Least Low Pay	5.77 (8.91)	-.51 (9.69)	**-6.28***(1.95)**
Vehicle Crime Rate			
Most Low Pay	28.12	26.04	-2.08 (3.39)
2^{nd} Most Low Pay	30.28	30.25	-.03 (5.55)
2^{nd} Least Low Pay	31.02	30.70	-.32 (4.22)
Least Low Pay	27.13	28.26	1.13 (3.55)
Most Low Pay – Least Low Pay	.99 (3.43)	-2.22 (3.51)	**-3.21*** (.80)**
Violent Crime Rate			
Most Low Pay	8.33	8.91	.58 (1.04)
2^{nd} Most Low Pay	10.03	11.60	1.58 (1.69)
2^{nd} Least Low Pay	8.51	9.87	1.36 (1.82)
Least Low Pay	11.47	13.61	2.15 (4.86)
Most Low Pay – Least Low Pay	-3.14 (3.19)	-4.70 (3.79)	**-1.56 (.65)**

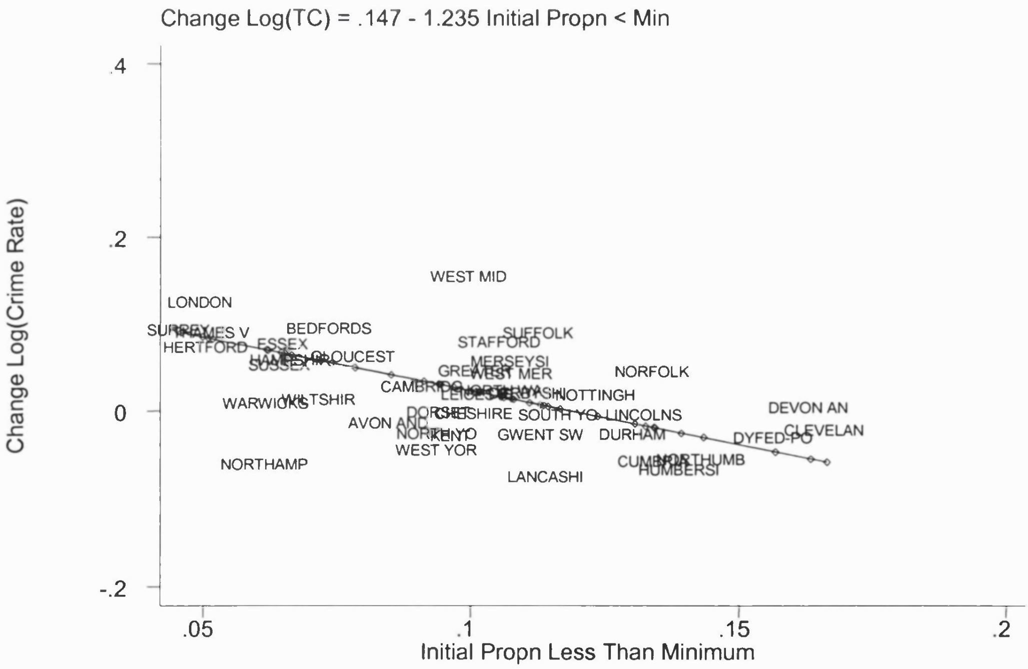
Notes: As for Table 4.1.

Thus, the descriptive statistics seem to indicate that the introduction of the Minimum Wage operated as we would expect, increasing wages at the bottom end of the wage distribution thereby reducing wage inequality more in areas with a higher proportion of workers paid beneath the minimum level before its introduction. Furthermore, crime seems to have been moderated (in relative terms) in those areas more affected by the introduction of the Minimum Wage (i.e. those with a higher proportion of workers paid beneath the minimum level before April 1999).

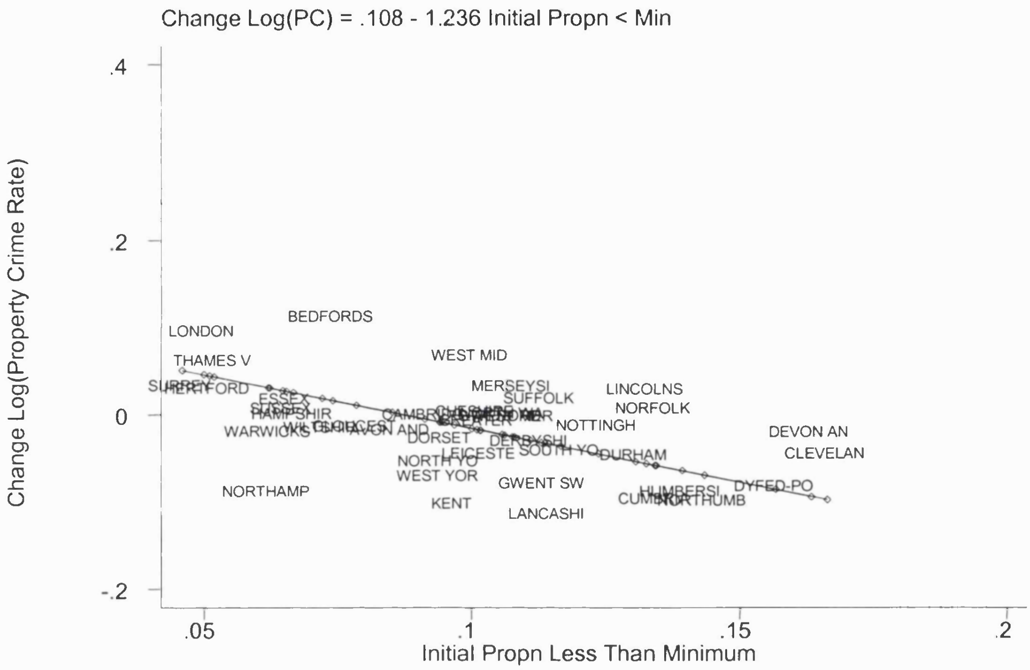
This pattern is confirmed in Figure 4.1, which plots the change in the crime rates against the initial proportion of low paid workers, over the period prior to, and post, the Minimum Wage introduction. This is shown separately for total, property, vehicle and violent crime. For all crime types, the graphs show crime went up by less in the areas with more low paid workers in the period before the Minimum Wage was introduced. All the regression lines fitted through the data points show there to be a negative relationship between changes in crime and the initial low pay proportion. The next section puts these findings to a more rigorous test by subjecting the data to a range of statistical tests.

Figure 4.1 Changes in Crime Rates And The Initial Proportion Low Paid, Between April 1998–March 1999 And April 1999-March 2000

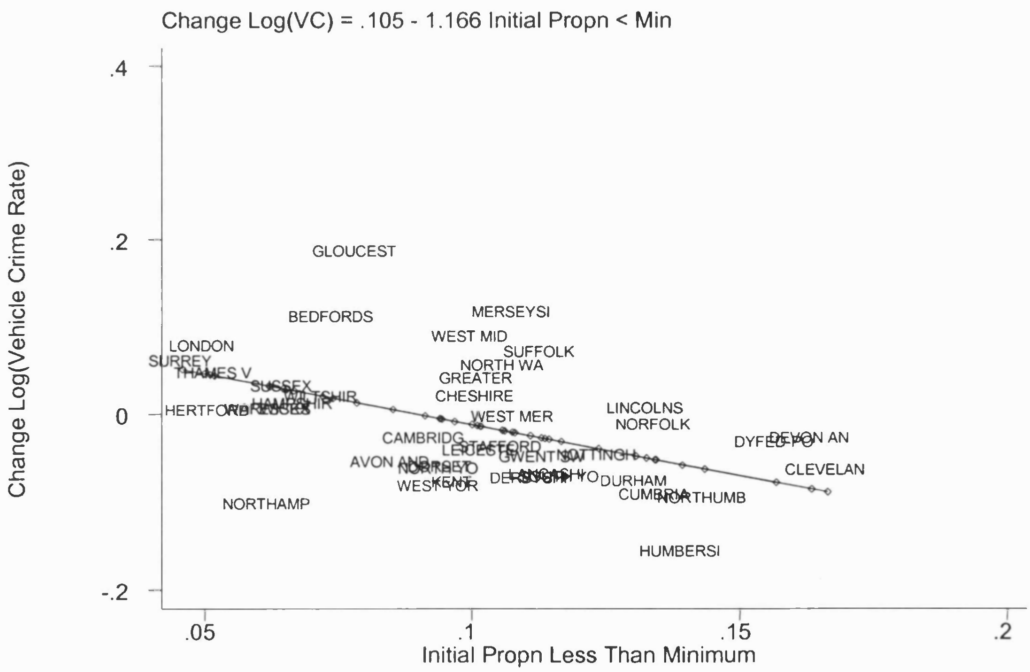
Total Crime



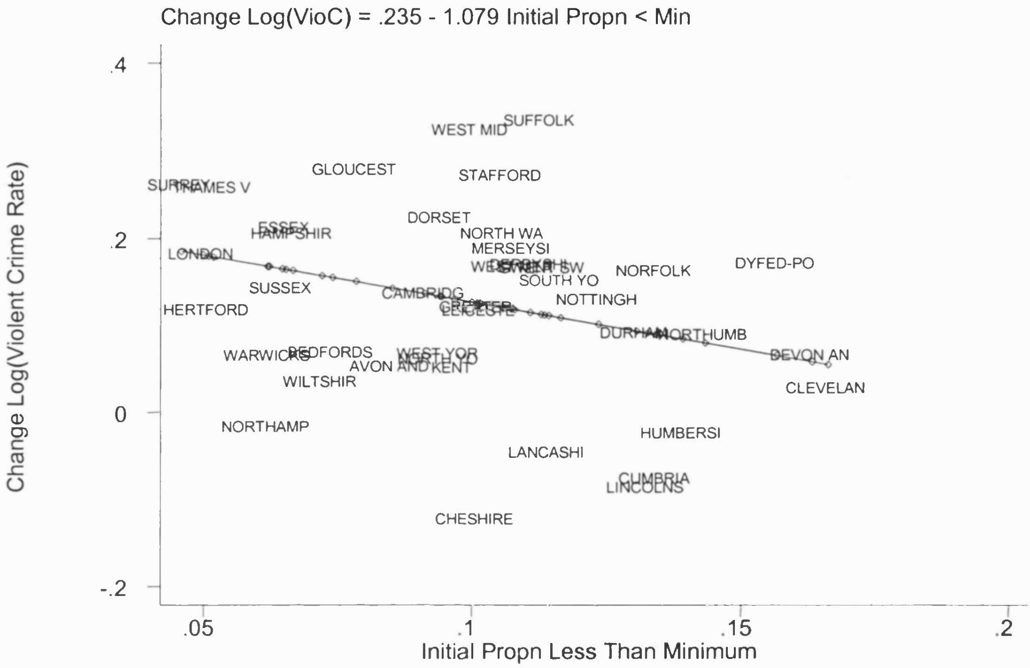
Property Crime



Vehicle Crime



Violent Crime



Notes: Population weighted regression line fit through data points

4.7 Regression Results

4.7.1 Basic Regression Results

Table 4.3 shows the results of regressions of changes in crime on the proportion of workers paid less than the minimum in the period before the Minimum Wage was introduced. Three sets of specifications are reported for each category of offence. The first is a simple regression of the change in crime on the initial period proportion of workers paid beneath the minimum. This is simply the slope of the regression lines fitted through the data points given in Figure 4.1. The second specification shows how this is affected by adding in the demographic controls[10] and the change in the crime clear-up rate. The third specification additionally adds in the change in the unemployment rate.

A comparison of column (1) and (2) shows the negative relationship between the change in crime (using all four measures) and the initial low pay proportion is not wiped out by the inclusion of the extra variables. In all cases, although the estimated coefficient on the initial low pay proportion falls (in absolute terms), it remains statistically significant. The coefficient on the change in the clear-up rate is interesting, as it appears to suggest negative deterrence effects for non-violent crimes but displays no association with changes in violent crimes. Nonetheless, the estimates reported in column (2) reinforce the earlier descriptive analysis, showing relative falls in crime occurring in the lower wage areas that were more affected by the introduction of the Minimum Wage.

The final specification (in column (3)) adds changes in the log(unemployment rate) as an explanatory variable. This is important because as noted above a critical question surrounding the introduction of the National Minimum Wage is its likely impact on unemployment. There was much speculation on this before the introduction of the wage floor as opponents of minimum wage legislation argued that minimum wages tend to hurt those they set out to initially help as the imposition of a Minimum Wage prices workers out of jobs.[11] Were this to be true there would be another mechanism we would need to consider here, namely that there would be more unemployed workers who could not get jobs who may then turn to crime. In this case, the Minimum Wage may raise crime rates. For this reason, it is important to also control for changes in unemployment that may have occurred differentially across areas, in case we are biasing the coefficient

[10] The estimated coefficients on these variables are not reported as the main concern is with the initial proportion low paid variable.

[11] Of course there has been a lot of (sometimes acrimonious) debate about the economic effects of minimum wages, especially their impact on unemployment. This is not of major concern here, but see Metcalf's (1999) discussion of the UK debate.

on the low pay proportion by neglecting another route in which crime may be affected by the labour market.

The inclusion of unemployment into the model has little effect on the coefficient on the initial low pay proportion, which remains negative and statistically significant for all four crimes (though it is very much on the margins of significance for violent crimes). For total, property and vehicle crime, there is no statistically significant association between changes in crime and changes in unemployment. However, for changes in violent crime the coefficient on the change in the unemployment rate is estimated to be positive and significant. This is the only place where an unemployment effect is found, supporting the discussion in Freeman (1999) that the relationship between crime and unemployment is a hard one to uncover.

Table 4.3 Regressions of Changes in Log(Crime Rates)on the Initial Low Pay Proportion Across Police Force Areas in the Years Before and After Minimum Wage Introduction

	(1)	(2)	(3)
Change in Log(Total Crime Rate)			
Proportion Paid Beneath Minimum Wage in Year Before Introduction	-1.235*** (.268)	-.980*** (.239)	-1.007*** (.250)
Change in Clear Up Rate		-.170* (.078)	-.175* (.081)
Change in Log(Unemployment Rate)			.080 (.088)
Demographic Controls	No	Yes	Yes
R-Squared	.400	.468	.486
Change in Log(Property Crime Rate)			
Proportion Paid Beneath Minimum Wage in Year Before Introduction	-1.236*** (.337)	-.894 *** (.235)	-.910*** (.239)
Change in Clear Up Rate		-.257*** (.076)	-.260*** (.078)
Change in Log(Unemployment Rate)			.045 (.071)
Demographic Controls	No	Yes	Yes
R-Squared	.400	.572	.578
Change in Log(Vehicle Crime Rate)			
Proportion Paid Beneath Minimum Wage in Year Before Introduction	-1.166*** (.253)	-1.012*** (.282)	-1.002*** (.283)
Change in Clear Up Rate		-.157* (.091)	-.156* (.092)
Change in Log(Unemployment Rate)			-.029 (.101)
Demographic Controls	No	Yes	Yes
R-Squared	.292	.378	.380
Change in Log(Violent Crime Rate)			
Proportion Paid Beneath Minimum Wage in Year Before Introduction	-1.079*** (.281)	-1.005** (.471)	-1.053** (.520)
Change in Clear Up Rate		-.003 (.126)	-.012 (.133)
Change in Log(Unemployment Rate)			.141 (.064)
Demographic Controls	No	Yes	Yes
R-Squared	.121	.261	.285

Notes: Coefficients (heteroskedastic consistent standard errors) reported. The sample size in all regressions is 41 police force areas. All regressions weighted by area population. The demographic controls entered were – change in average age, change in the population share of young (<25) men, change in population share with no educational qualifications, change in proportion female, change in share of public sector jobs. * significant at 10% level, ** 5%, *** 1%.

4.7.2 Using other Wage Measures to gauge the initial Proportion Low Paid

The results so far point to a negative association between changes both in property and vehicle crime rates and the incidence of low pay over the period of Minimum Wage introduction. This suggests that shifts in the nature of low wage labour markets do have the potential to affect crime. However, a potentially relevant consideration is that, to date, the analysis has used measures of the extent of low pay in the overall area labour market. Whilst these measures are a useful barometer of the state of the low wage labour market in these local areas, it is also the case that most people do not commit crimes and that those that do or those who are on the margins of criminal choice, are disproportionately males, young and are likely to be in low skilled jobs.

Taking these considerations into account Table 4.5 shows the results from regression models (comparable to column (3) of Table 4) that refine the nature of the initial low pay variable. The Table reports estimated coefficients on three different measures of low pay in the period prior to Minimum Wage introduction. Column (1) reports the estimated coefficient from a model incorporating a measure of the proportion beneath the minimum for males employed in occupations where the mean wage is below the 25th percentile of the average male wage. This is referred to as the low skilled males low pay measure. Column (2) uses the initial low pay proportion for males under the age of 25 only. Finally, column (3) returns to the full sample of people in a police force area but, rather than using the headcount measure considered so far, computes how far the wage bill would need to be raised to take all people initially beneath the minimum up to the Minimum Wage. Potentially, this will give different results to the headcount if the wage shortfall differs across areas.

Because the focus is on specific sub-groups then one should note that the magnitude of the estimated coefficients will differ from earlier results and indeed that is what happens in Table 4.5.[12] But the general thrust of the earlier results is certainly borne out. There is seen to be a more pronounced negative relationship between changes in crime and the initial low pay proportion in the period surrounding Minimum Wage introduction in the police force areas of England and Wales.

Table 4.4 Using Other Measures of Low Pay

	(1)	(2)	(3)
	Low Skill Males Low Pay Measure	Young Males Low Pay Measure	Wage Bill Share Measure
Change in Log(Total Crime Rate)			
Proportion Paid Beneath Minimum Wage in Year Before Introduction in Period Surrounding Introduction	-.882*** (.315)	-.387*** (.179)	-6.660 (2.291)
R-Squared	.432	.423	.431
Change in Log(Property Crime Rate)			
Proportion Paid Beneath Minimum Wage in Year Before Introduction in Period Surrounding Introduction	-.969*** (.301)	-.439*** (.142)	-6.920 (2.267)
R-Squared	.592	.571	.578
Change in Log(Vehicle Crime Rate)			
Proportion Paid Beneath Minimum Wage in Year Before Introduction in Period Surrounding Introduction	-.798** (.367)	-.311* (.177)	-5.941** (2.683)
R-Squared	.556	.547	.550
Change in Log(Violent Rate)			
Proportion Paid Beneath Minimum Wage in Year Before Introduction in Period Surrounding Introduction	-1.292* (.776)	-.813** (.313)	-9.071* (5.062)
R-Squared	.240	.248	.239

Notes: These are extensions based upon the same specification as column (3) of Table 4.3. Other notes as for Table 4.3.

4.7.3 Benchmarking Against Earlier Time Periods

A potentially very important concern that emerges from considering the results presented so far is whether these results really identify any change resulting from studying the Minimum Wage period. For example, it might be that crime rates have not

[12] In fact the means of the three variables in the pre-introduction year were: low skill males .08; young males .15; wage bill .01. Hence the differences in scale of the reported coefficients.

been rising as fast in low wage areas in time periods when the Minimum Wage was not present. Were this to be the case, the results may be spurious.

This possibility is explored by looking at regression models specified in the same way as those considered to date for earlier time periods. In the simplest specification reported above (in column (1) of Table 4.3), the regression relationship between changes in property crime and the proportion below the Minimum Wage in the initial period for the periods around Minimum Wage introduction was as follows (standard error in parentheses):

$$\text{Change in Log(Property Crime)} = \underset{(.268)}{-1.235} \text{ Proportion Paid Less Than The Minimum Wage in Period 1}$$

For earlier periods of change [(financial year 1996-1997) – (financial year 1997-1998)] and [(financial year 1995-1996) – (financial year 1996-1997)] the regression relationship is:

$$\text{Change in Log(Property Crime)} = \underset{(.171)}{-.272} \text{ Proportion Paid Less Than The Minimum Wage in Period 1}$$

So, in this earlier time period there is a (weak) negative association between changes in property crime and the initial low pay proportion, but it is nowhere near as marked as around the Minimum Wage introduction period. Indeed, the regression line fit through the points has a slope four and a half times as large (in absolute terms) in the period surrounding Minimum Wage introduction.[13] This shows a tilting of the crime low

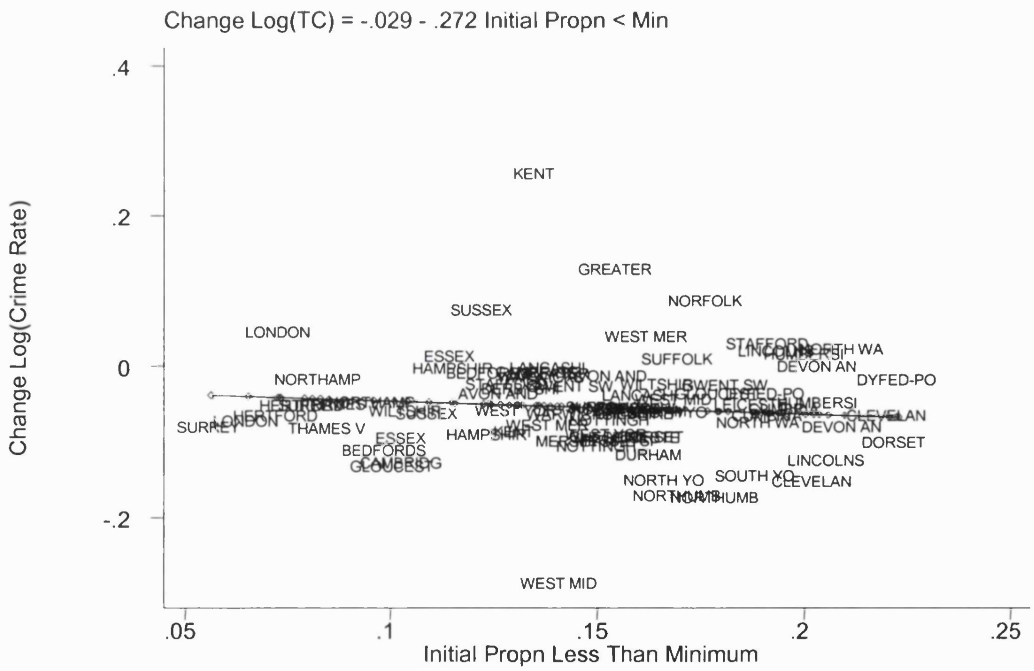
[13] Of course, as the periods not surrounding minimum wage introduction are pooled, the regression slope is the average slope across all periods. However, if each period is taken individually, the slope is always markedly steeper in the period surrounding minimum wage introduction.

pay relationship such that the relationship between changes in crime and low pay becomes stronger in the period when the Minimum Wage was introduced.

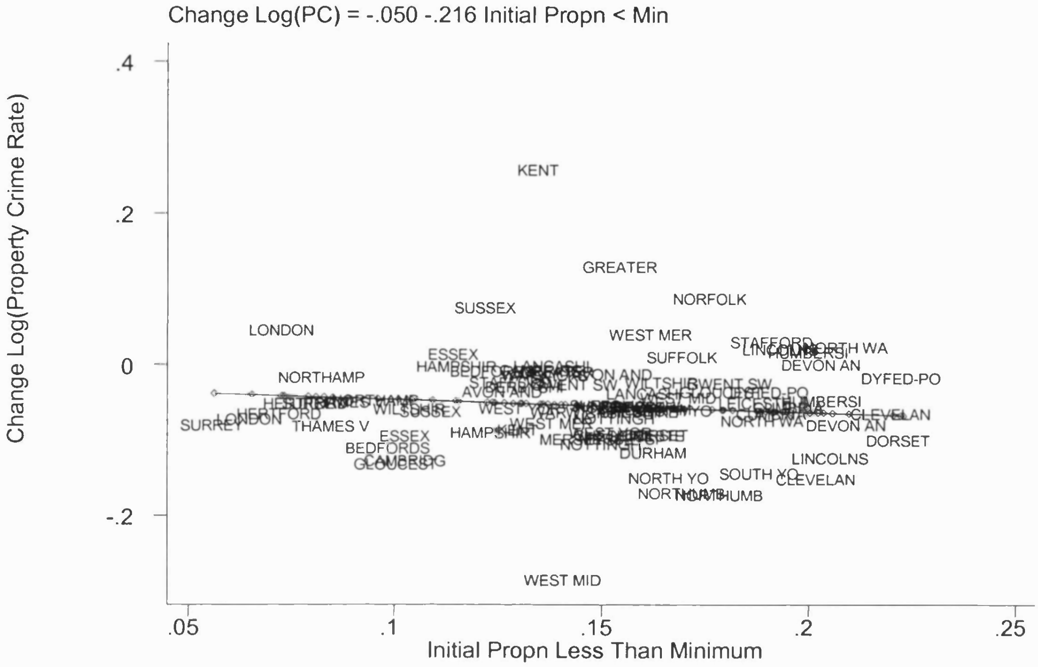
These differences can be seen in Figure 4.2 which plots the relationship between crime and the proportion low paid in periods prior to the Minimum Wage. When this is compared to Figure 4.1, which charts the same relationship but over the Minimum Wage introduction period, it is clear that there is a much stronger negative association in the period surrounding the Minimum Wage than in previous periods.

<u>Figure 4.2 Changes in Crime Rates and the Initial Proportion Low Paid in Earlier Time Periods</u>

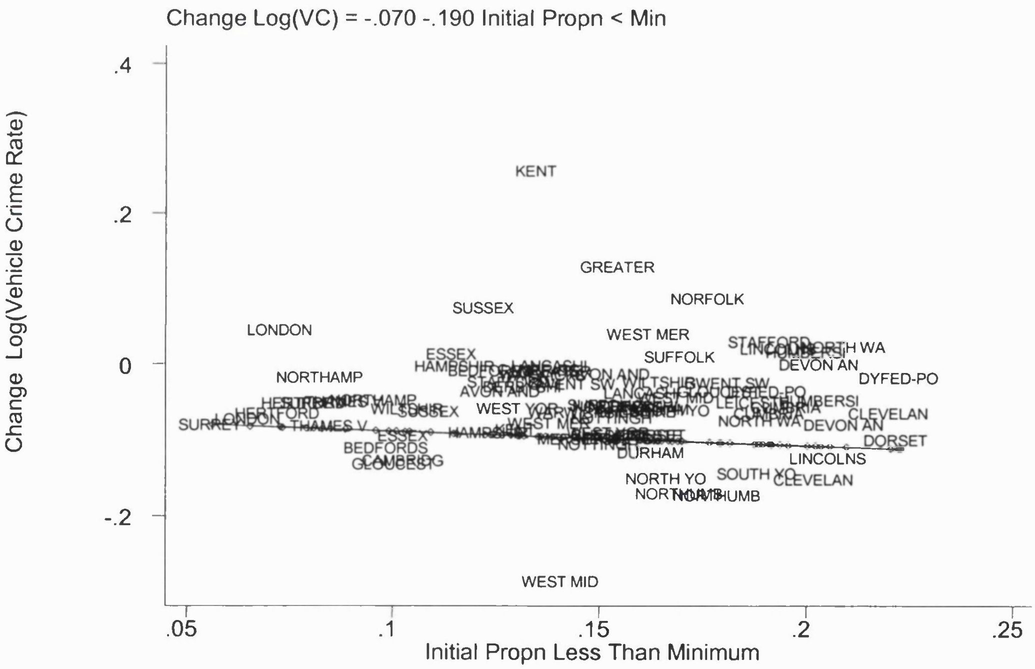
Total Crime



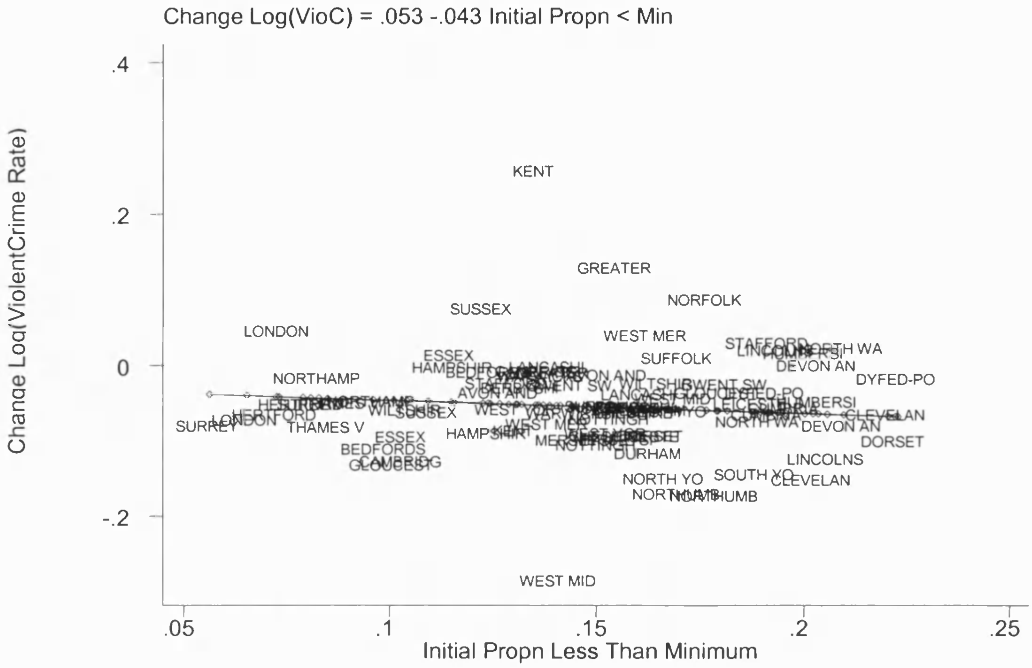
Property Crime



Vehicle Crime



Violent Crime



Notes: Population regression line fit through data points

A more formal way of thinking about this is to explicitly couch the modelling approach in a "difference-in-differences" framework. The analysis covers two distinct time periods, one where the Minimum Wage raised wages by more in low wage areas (which we can call period M), and one where no minimum wage legislation was in place (period NM). It is therefore possible to benchmark the measures of the change in crime from the period surrounding Minimum Wage introduction ΔC^{M} against the measure of the change in crime from the non-minimum wage period ΔC^{NM}. Thus, Table 4.5 shows a set of results from regressions that benchmark the basic results against the relationship between changes in crime and the initial low paid proportion in earlier time periods. As these add a further differenced set of data in the control periods where there was no minimum wage legislation in operation, one can think of these estimates as triple differenced, or difference-in-difference-in-difference estimates.[14] For the case of changes in total crime, the estimator is simply the gap between the coefficients on the initial low pay proportion variable across the two specifications (for the example considered, this is $-1.235 - \{-.272\} = -.963$).

Thus, Table 4.5 reports coefficients on the initial low pay proportion in the period surrounding Minimum Wage introduction from five specifications for each model of crime. Columns (1) to (3) are the same specifications as in Table 4.3, but benchmarked against earlier time periods. The change in the period surrounding Minimum Wage introduction (from financial year 1998/99 to financial year 1999/2000) is compared to changes in two earlier time periods (the change from financial year 1996/97 to 1997/98 and the change from 1995/96 to 1996/97). The reason for these choice of benchmark periods is a change in the way crime statistics were collected by police force areas that occurred in 1998 prevents us from being able to calculate the change from financial year 1997/98 to 1998/99.[15] However, the Home Office has published scaling factors (for total crimes) that can bridge this gap (as they collected crime numbers on the old and new reporting basis) and so the scaled change for these financial years is also included in the control group in column (4). Column (5) then implements a very stringent test by additionally including into the column (3) specification a full set of police force area trends.

[14] Or alternatively one can think of the estimates as difference-in-difference estimates of the change model (i.e. double-differenced in changes rather than triple-differenced in levels). As such they compare the relationship between changes in crime and the initial low pay proportion in the treatment period surrounding minimum wage introduction with the same relationship in the earlier (non-minimum wage) control periods.

[15] This is because April 1998 saw a change in the way crimes were counted and classified under Home Office rules. The changes, and their effects on crime by area and type of crime, are discussed in detail in Annex A of Home Office (1999). The principal motivation for the change was to try and get crime statistics to measure one crime per victim and to widen the definition of a notifiable offence (to include all indictable and triable-either-way offences plus some related summary offences). The Home Office reports that the definition change mostly affected violent crime, drug crime and fraud and criminal damage. Notice that the latter three crimes are not included in the analysis but, for the crimes analysed, the counting rule changes

The coefficients reported in the first three columns of the Table make it clear that the earlier estimates are not picking up a relationship that existed in earlier time periods. For total, property and vehicle crimes, the coefficient on the low pay proportion is seen to be significantly more negative in the period surrounding Minimum Wage introduction than in the comparison periods. The coefficient in the violent crime equation is also negative but the standard error is large, making the estimates very imprecise.

As already noted, the first three columns of Table 4.5 exclude the period measuring changes across financial years 1997/1998 to 1998/99 (the period directly preceding that surrounding Minimum Wage introduction) due to the change in the way that crimes were counted that occurred from April 1998.[16] However, as previously discussed, there exists a set of scaling factors reported by the Home Office (1999) that make it possible to compute the change for this period in a manner consistent with the Minimum Wage introduction years to see whether this definitional change matters or not for the main findings. The results produced by incorporating the scaled data from this extra period are given in column (4).[17] They tend to confirm the earlier picture, as the coefficients on the initial proportion low paid actually become slightly more negative (though reassuringly they remain insignificantly different from those in column (3)).

The nature of the data, on the same areas followed through time, means that one can also adopt an even more stringent test by including area-specific trends in the estimating equation. Therefore, the final column of the Table additionally includes 41 area trend variables. The coefficients are reduced in this specification and, of course as one would expect, the standard errors rise. Yet the main findings remain robust to this.

are more likely to affect the total and violent crime rates whilst being relatively unimportant for property and vehicle crimes.

[16] In practice, the reporting change means that we are unable to compute crime numbers for the financial year 1997/98 on the same basis as the 1998/99 and 1999/2000 financial years.

Overall, it seems that benchmarking against earlier time periods acts to reinforce the findings presented earlier. There appears to be a stronger negative relationship between crime and low pay in the period surrounding the Minimum Wage introduction. This is a robust finding for most crimes (i.e. except for violent crime, where the data are much noisier) and is in line with the idea that the altering of economic incentives brought about by the introduction of the Minimum Wage may well have caused individuals on the margins of crime to desist.

Table 4.5 Benchmarking Against Earlier Time Periods

[Change in financial year 1998/99 to 1999/2000 benchmarked against change in financial year 1996/97 to 1997/98 and change in financial year 1995/6 to1996/7 in (1), (2), (3) and (5);
Change in financial year 1998/99 to 1999/2000 benchmarked against change in financial year 1997/98 to 1998/99 (scaled by Home Office factors for reporting changes), change in financial year 1996/97 to 1997/98 and change in financial year 1995/6 to1996/7 in (4)]

	(1)	(2)	(3)	(4)	(5)
	Basic Specification	(1) + Clear Up and Demographics	(2) + Unemployment	(3) + Add Definition Change Year	(3) + Area Trends
Change in Log (Total Crime Rate)					
Proportion Paid Beneath Minimum Wage in Year Before Introduction in Period Surrounding Introduction	-.963*** (.317)	-.770*** (.255)	-.764*** (.257)	-.917*** (.270)	-.479 (.298)
R-Squared	.372	.421	.437	.284	.615
Change in Log (Property Crime Rate)					
Proportion Paid Beneath Minimum Wage in Year Before Introduction in Period Surrounding Introduction	-.962*** (.359)	-.806*** (.250)	-.809*** (.249)	-1.209*** (.388)	-.667*** (.214)
R-Squared	.488	.591	.595	.540	.763
Change in Log (Vehicle Crime Rate)					
Proportion Paid Beneath Minimum Wage in Year Before Introduction in Period Surrounding Introduction	-.850*** (.331)	-.657** (.300)	-.656** (.302)	-.853*** (.287)	-.596* (.355)
R-Squared	.461	.558	.558	.782	.686
Change in Log (Violent Crime Rate)					
Proportion Paid Beneath Minimum Wage in Year Before Introduction in Period Surrounding Introduction	-.962* (.581)	-1.104* (.645)	-1.098* (.645)	-1.155* (.599)	-1.121 (.720)
R-Squared	.186	.235	.245	.319	.480

[17] Notice that the scaling factors are for total crimes and they are not available for the specific crimes considered in the lower panels of the Table. The scaling factors are applied to the other crimes but clearly one should focus more on the total crime equations in column (4) of the upper panel of the Table.

Notes: Coefficients (heteroskedastic consistent standard errors) reported. Sample sizes are 123 for columns (1), (2), (3) and (5) and 164 for column (4). All regressions weighted by population. The demographic controls entered were – change in average age, change in the population share of young (<25) men, change in population share with no educational qualifications, change in proportion female, change in share of public sector job. All equations include dummy variables for time period and the proportion low paid variable.
* significant at 10% level, ** 5%, *** 1%.

4.8 Concluding Remarks

The main focus of this Chapter is to identify empirically the links between crime and the labor market. To do so, a rather different approach to that taken in the existing literature is adopted. The key question posed is what happened to crime before and after a large regulatory change was made in the UK, namely when the government introduced a minimum wage floor to a labour market previously unregulated by minimum wage legislation. This Minimum Wage introduction benefited a sizable number of workers. The Chapter examines whether the wage gains resulting from Minimum Wage introduction were able to alter incentives to participate in crime.

This is not only what one would expect from simple economic models of crime where shifting the relative monetary gains between legal and illegal activities can alter an individual's likelihood of committing crime, but it is also what a number of criminological theories suggest will be the case. These predictions are tested by noting that there were more beneficiaries from the Minimum Wage introduction in some police force areas of England and Wales than in others and using these differences to examine changes in crime rates across police force areas in the period before and after Minimum Wage introduction to the proportion of workers beneath the Minimum Wage before its introduction.

The results uncover a statistically significant negative relationship, showing relative crime reductions in areas that initially had more low wage workers. This finding remains robust to controlling for other relevant determinants of crime, to benchmarking against earlier time periods and to using initial period wage measures that look at the types of individuals one thinks are more likely to be on the margins of crime. Overall the results are in line with theoretical predictions that crime and low wages are related and that by improving the position of the low paid one does see a reduction in crime.

5. Rising Crime and Improvements in the Socio-Economic Position of Women: Are they Related?

5.1 Introduction

One of the most noticeable changes in the labour market in the last thirty or forty years has been the increased participation of women. Estimates from the Family Expenditure Survey show that in the UK only 38% of all employees between the age of 16 and 64 were female in 1970, by 2000 this figure had risen to almost 50%. In 2000, only 19% of females were defined as economically inactive. This figure represents a significant decline in economic inactivity since 1970, when 41% of females were not active participants in the labour market.

If we believe that crime is related to labour market opportunities the movement of females into the labour market may have an effect on crime. In the past most theoretical and empirical work in this area has focused on the effect of this movement on female crime, arguing that increases in female labour supply should shift the total share of crime committed by women, either generating more or less female crime compared to male crime (Steffensmeier et al 1989). While this is an interesting area of research, females make up only a relatively small fraction of those who engage in crime (around 13% of those found guilty of indictable offences in 1997 (according to convictions data on those found guilty at Magistrates and Crown

Courts)[1]. Therefore, examining the effect female labour force participation has on female crime is likely to uncover only a very small part of the impact shifts in female labour supply have on crime. For example, if increased female labour force participation in any way damages the labour market position of males, and there exists a connection between crime and the male labour market, this will imply a larger effect of female labour force participation on the overall crime rate.

Earlier Chapters have already shown that weak labour market positions are positively related to crime. This Chapter examines the effect of rising female employment on crime by assessing the impact it has on crime and examining the mechanisms through which any connection may work.

5.2 Traditional Explanations of why Improving the Labour Market Position of Women Should Affect Crime?

Typically work in this area has focused on female crime as the outcome of changes in female labour force participation (Steffensmeier et al 1989). Criminological theory predicts that if economic incentives are important for crime, changing patterns of female employment should affect women's participation in crime and we should see a movement in the amount of crime committed by females.

5.2.1 Predictions from Traditional Theories

Many of the more traditional theories suggest that shifting the economic incentives of an individual or group is likely to affect decisions to engage in crime. Improving the labour market situation is usually associated with a decline in crime. Thus, many of the theories that have been discussed at length in previous Chapters, such as rational choice (Becker 1968, Ehrlich 1973), anomie (Durkheim 1938) and

[1] Convictions data is used here as it is not possible to break down notifiable offences by gender as the perpetrator is unknown. Arrest data is not available consistently for the period under examination.

strain (Merton 1957) for example, predict that a rise in female labour force participation should be associated with a decline in female crime.[2]

However, many of these theories have been criticized in the past for their failure to address issues of female criminality. For example, it is argued that women place less emphasis on material success and feel less pressure to provide for their family. They are less exposed to delinquent peers, have stronger bonds and their behaviour is more supervised (see Steffensmeier and Allen 1996). As a result, there has been a call for theories aimed specifically at female crime (see discussion in Steffensmeier and Allen 1996).

However, Smith (1979) found that in general, the main criminological theories are able to account equally well for male and female crime. Moreover, 25 years after the Equal Pay and Pay Discrimination Acts (passed in December 1975), improvements in the position of women both in the labour market and society more generally have taken place which mean that many of these arguments are now outdated. Such changes include later age marriages, rising divorce rates and the rise of single mothers, which mean that many women are now the sole providers for families. Improvements in qualifications gained by females mean that females are now out-performing males in terms of educational attainment (Epstein et al 1998). Highly skilled women are now more represented in higher ranking occupations (Blau and Kahn 2000). As generations progress, these changes will be reinforced by parenting, which will render these criticisms even more out of date.

Changes such as those described above are used by gender equality theory to predict that as the socio-economic position of women improves female crime will

[2] Empirical evidence in support of the idea that female crime is related to the marginalized position of women in the labour market can be seen in the work of Box and Hale (1983, 1984) who, using data from England and Wales between 1951 and 1979, find female unemployment to be positively related to female crime. See Steffensmeier (1978) for evidence from the US.

increase (Adler 1975, Simon 1975). As women gain mobility, power and confidence these theories predict that they will develop attitudes traditionally thought to be more masculine, such as risk taking, which are positively related to crime. In addition, employment in the public sphere opens up crime opportunities outside the home; not just work related crimes, but also theft from shops and fraud, for example. Employment also allows women to develop networks and contacts outside of the home that may facilitate criminal interactions. Moreover, increased involvement in drug taking will bring women into contact with the illegitimate realm from which they have been excluded in the past.

Influenced by these ideas, power-control theory (Hagan 1993) emphasises how differences in labour market positions of males and females influence parenting patterns, thereby encouraging male and female children to develop different behaviours, which in turn lead to different rates of offending between males and females in later life. In more traditional families, which are headed by a working male where the wife does not work, household power is unevenly distributed. This inequality is reproduced among children so that male and female children are encouraged to develop different attributes, which lead to differences in levels of offending in later life. In more equal households, where both parents are employed in similar positions or both non-employed, differences in the way male and female children are brought up are minimised. Equality between the male and female role models is reproduced among the children so that gender differences in crime in later life are reduced. These ideas are based on the premise that equality of power for mothers results in greater equality for daughters (Singer and Levine 1988). This equality means that over time females will act in a similar way to males and differences in their rates of offending will be reduced.[3]

Empirical support for these ideas can be seen in the work of Fox and Hartnagel (1979) who used Canadian data between 1931 and 1968 to show that measures of female liberation, such as labour force participation, were positively associated with female crime. This relationship was particularly strong for theft. Although in the UK Box and Hale (1983, 1984) find no evidence of a relationship between factors associated with female liberation and crime.

5.2.2 An Alternative Explanation

Each of the existing theories predict that increased participation of females in the labour market should affect the amount of crime committed by women. This Chapter argues that as the amount of crime committed by females is small relative to that committed by males, the effect of increased female labour force participation on crime may not just be limited to female crime. If increased female labour force participation has a detrimental effect on the labour market position of males then rising female employment may have a wider impact on the overall level of crime than previously thought.[4]

Historically, women's involvement in the UK labour market was confined to a relatively small number of women working in a limited number of female dominated occupations (for example typists, nurses and primary school teachers) (see Blau and Kahn 2000). Women have been paid less than men and have been less likely to achieve promotion. As technologies were developed in the home, women's time became freer and more women began to enter employment (Goldin 1999). Anti-

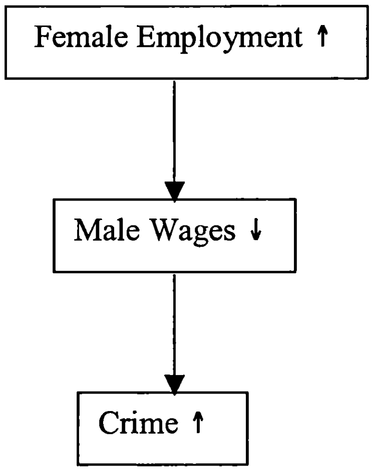
[3] This suggests that the rise of dual earner households is important and should be an area of future research.
[4] This is not a unique idea. For earlier studies which examine the effect of female labour force participation on total crime see Braithwaite et al 1992, Hale 1999 and Kapuscinski et al 1998.

discriminatory legislation that was set in place,[5] coupled with improvements in the education system, encouraged more and more women to train and enter traditionally male jobs in a wider range of occupations (Blau and Kahn 2000, Goldin 1999).

At the same time, economic restructuring[6] shifted the focus of the economy away from manufacturing and toward the service sector where demand for physical strength was reduced and demand for female skills, such as computing, greatly increased (see Kreuger 1993). While, improvements in education meant that the supply of suitably qualified males and females was increasing, so women and men had to compete for jobs.

It is possible that if this is the case, improvements in the labour market position of females will have a negative effect on the labour market position of males (for example, by lowering wages). As previous Chapters have shown, if crime is related to low wages by reducing male wages increased female participation in the labour market will have a negative impact on crime (see additionally Hansen and Machin 2001, 2002 or Machin and Meghir 2000 for the UK. Grogger 1998 or Gould et al 2002 for the US). This mechanism is depicted below:

[5] The Equal Pay Act and Sex Discrimination Act were passed in December 1975.
[6] There are debates to the main cause of this restructuring. It is widely believed that technological change was the driving factor behind the movement (see Berman et al, 1998), other explanations include the reduction of international trade barriers, or institutional changes such as de-unionisation (Freeman, 1992).



This mechanism works through substitution. This idea is discussed in more detail later in the Chapter, but basically this means that if males and females are competing for the same jobs, if they are both capable of doing the job as well as one another, they are substitutes. In other words an employer can hire either a male or a female to do a job. The advantage of hiring a male is that in general, males tend to have more labour market experience. However, on the other hand because females tend to have less labour market experience they are likely to receive slightly lower wages. If this makes females more attractive employees than males, females will be employed to do the job.

Alternatively, if females are discriminated against in the labour market, they will receive lower wages than similar males. This means that an employer can hire a more productive female for the same wage as a less productive male. Again, the employer will usually opt for employing the more productive female in preference to the less productive male.

In these cases, females and males are not good substitutes. To re-address the balance at an individual level and allow men and women to compete for jobs more equally (making them better substitutes), males may have to take a job at a lower wage. This may mean that in the wider economy, in occupations, industries and areas where there has been a large increase in female employment, we would expect to see a relative fall in male wages, particularly among the less skilled men.

5.3 Data

5.3.1 Labour Market Data

This Chapter uses a variety of data to test these hypotheses. Firstly, numbers on female labour supply come from three sources. The main source (matched to the crime data) is the New Earnings Survey (NES). As discussed in Chapter 2, this is a 1% sample of employees in employment who are members of Pay-As-You-Earn (PAYE) income tax schemes. Individuals are sampled according to the last two digits of their National Insurance number, which produces a random sample of around 160,000 individuals per year. In addition to labour market information, the NES contains a number of demographic and socio-economic variables that makes it possible to control for shifts in factors that may influence the relationship between female labour force participation and crime. Additional sources of labour market data include the Department of Work and Pensions Labour Market Trends tables (which are published quarterly and can be accessed on the web: www.dwp.gov.uk). And the Family Expenditure Survey (FES), which is a self-report survey of around 7,000 households in the UK.

5.3.2 Crime Data

Unfortunately, there are no corresponding crime data at the individual level with which to examine the effect of female labour force participation on crime. Instead, official data at police force area level are matched to individual level labour market, socio-economic and demographic data aggregated to police force level.

The official crime data used are notifiable offences reported to and recorded by the police.[7] Since, in most cases, there is no way to identify the perpetrator of the crime, notifiable offences include crimes committed by both males and females. As this Chapter is primarily concerned with the effect of female labour supply on male crime, sex-specific convictions data are also used to capture crime committed by males. Convictions data may reflect the level of crime in society less well than notifiable offences (since they not only depend on the accuracy with which crimes are reported to and recorded by the police, but also processing by the criminal justice system and the courts ability to find individuals guilty). On the other hand, they do enable the examination of the differential participation in crime by gender[8], which using notifiable offences does not[9]. Using both crime data makes it possible to compare and contrast results from the notifiable offences with male convictions data.

While some authors find that economic factors are important for violent crime, (for example, see Crutchfield 1989, Messner 1980 or Blau and Blau 1982) the evidence presented in this thesis consistently finds labour market factors to have a greater effect on property crime than violent crime. This is supportive of other work on crime in the UK which has found an association between property crime and labour market variables but not violent crime (see for example Hansen and Machin 2001).[10]

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[7] As discussed in earlier Chapters this is unlikely to cover all crimes as a number of crimes are not reported to or recorded by the police.

[8] Arrest rates are often used in the US, because these do not rely on court processes. In the UK however, arrest statistics are not available for the time period this Chapter examines.

[9] Notifiable offences are those reported to and recorded by the police, so there is no information on the perpetrator of those crimes such as gender.

[10] This is not to deny that rising female labour force participation may affect violent crime. Indeed, Bourgois (1996) argues very convincingly that the rise in female labour force participation may very well lead to a rise in the incidence of violent crimes against women such as rape and domestic abuse; as economically marginalized men try to reassert their authority by the physical domination of women. A similar argument is posed by Kapuscinski et al (1998) who find a strong positive relationship between female employment and homicide. In addition Macmillan and Gartner (1999) show that in households where the female works but the male does not the risk of spousal abuse is higher than in households

For this reason the crime data used are property crimes (burglary and theft and handling) reported to and recorded by the police and male property crime convictions (i.e. males convicted of theft and handling, burglary, fraud and forgery in Crown Court and Magistrates Courts). These convictions data are also used as a measure of deterrence when notifiable offences are used as the measure of crime. The number of police officers are also included as a measure of deterrence. All these data are compiled at police force area level between 1975 and 1997.

5.4 Descriptive Statistics

5.4.1 Female Labour Force Participation

Table 5.1 shows clearly how female labour force participation has increased in the last thirty years. Between 1970 and 2000 the number of women in the workforce increased by 44%, from 9,444,000 in 1970 to 13,556,000 in 2000. The number of female employees show similar trends going from 8,962,000 in 1970 to 12,544,000 in 2000[11] a rise of 40%. In 1970, females constituted 36% of the workforce and 38% of employees. By 2000, these proportions had increased to 46% and 49% respectively.

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where both partners have the same employment status. However, these types of violent crimes are unlikely to be well represented in officially recorded crimes (for example, only 9,000 rapes were recorded by the police in 2001/2002, while the BCS (which is likely to be a much better indicator of the extent of these types of crimes) estimated that around 635 cases of domestic violence had occurred between 2001/2002). To test the effect on these types of crimes research would need to use a more qualitative approach in an attempt to enumerate the extent of this type of violence against women, even then it is likely that women would be reluctant to talk about such crime, especially when they are committed by people known to the victim (Home Office 2002).

[11] The employees numbers are smaller than the labour force numbers as they exclude the self employed.

Table 5.1. UK Employment (in thousands) 1970-2000

	1970	1980	1990	2000	Change	% Change
Work Force						
Total	26414	26997	28913	29280	2866	10.9
Female	9444	10856	12762	13556	4112	43.5
% Female	*35.8*	*40.2*	*44.1*	*46.3*	*10.5*	
Employees						
Total	23783	24322	24254	25513	1730	7.3
Female	8962	10347	11604	12544	3582	40.0
% Female	*37.7*	*42.5*	*47.8*	*49.2*	*11.5*	

Source: Labour Market Trends, Department of Work and Pensions

These results indicate that female employment has been rising, while male employment has been declining. However, for rising female employment to have an effect on the male labour market (and thus on crime), it is important to ensure these trends are not simply the result of demographic change. For example, a decline in the male population could also produce a fall in the numbers of employed males. This would be independent of the rise in female employment, or perhaps even be a causal mechanism encouraging the rise in female employment as women enter the labour market to fill the jobs left by the declining male population.

To explore this possibility, Table 5.2 compares trends in male and female employment rates over time.[12] The results confirm the rise in female labour force participation identified above, showing an increase in the female employment rate from 61% in 1977 to 72% in 2000. This represents an 11 percentage point increase. On the other hand, the male employment rate actually declined by about 9 percentage points over the same period. These differing trends have led to a narrowing of the gap between the male and female employment rates. This evidence is in line with the possibility that in more recent times employers may be favouring women, thus leading to a rise in female employment rates relative to those of males.

[12] This is only possible to do since 1977.

The lower panels of Table 5.2 break male and female employment rates down by education level. This is important if we believe that education is a proxy for labour market skill, as it allows us to see in which part of the labour market employment gains and losses have been made. Thus, the middle rows of Table 5.2 show male and female employment rates for those with no educational qualifications, while the lower rows show the employment rates of those educated to degree level or above.

It is clear that the largest decline in employment has been among the least skilled males. In 1977, the employment rate for males with no qualifications was 88%. By 2000, it had decline to 60%, a fall of 28 percentage points. The employment rate for unskilled females with no qualifications also declined over this period, but the fall (of less than 9 percentage points) was nowhere near as marked as for males. This means that for those with no qualifications the gender gap in employment rates has narrowed.

The Table also shows that the employment rate of the most skilled men has fallen, but again by a fairly small amount compared to unskilled males. In 1977, the employment rate for males educated to degree level or above was 96%. By 2000, this had fallen to 91%. On the other hand, female employment at this educational level rose from 72% in 1977 to 87% in 2000. These employment shifts over time for those with a degree mean that by 2000, the employment rate for females was only slightly lower than for males.

These results reflect occupational shifts that favour a more highly skilled workforce and reward female type skills. It is clear that employment gains have been made by women, and at least to some extent, these have been at the cost of male employment, particularly unskilled male employment.

Table 5.2. Male and Female Employment Rates 1977-2000

	1977	1981	1985	1990	1995	2000	Percentage Point Change
				All			
Male	91.2	87.5	80.7	84.5	79.1	82.3	**-8.9**
Female	60.6	60.1	60.1	67.7	67.4	71.7	**11.1**
				No Qualifications			
Male	87.9	81.1	68.4	72.1	60.5	59.9	**-28.0**
Female	56.8	53.9	50.0	56.1	50.1	48.2	**-8.6**
				Degree Level			
Male	96.0	96.1	92.7	93.4	89.4	91.0	**-5.0**
Female	71.5	72.5	74.5	81.9	84.8	86.5	**15.0**

Source: Labour Force Survey

However, it may be thought that because many women work part time and move between part time and full time employment looking only at the number of women in the labour market or the female employment rate is not a true reflection of the extent of female labour force participation. If true, a better measure may be provided by looking at the changes in the total hours worked by women (Hakim 1996) or the share of the total hours worked by women. Looking at the data in this way also makes it possible to break down the increase in female labour force participation into full-time and part-time employment. This is important because if as some people have argued (McRae 1997) female growth in employment has been concentrated in part time jobs it will be less likely that women will be competing with males for the same jobs.

Using data from the NES and FES, Table 5.3 shows an increase in the share of total hours worked by women between 1970 (1975 for NES) and 2000. A potential issue with the NES is that because it contains information on wages from employers, it only contains information on those who pay National Insurance contributions. As a consequence, it under-samples those with low paid or part-time positions, many of whom will be women. On the other hand, the FES contains self-reported information from everyone sampled. Thus, it will include more people, but because information is self-reported, they may contain measurement error. Despite these potential differences, both data produce very similar numbers. Both sources show an increase in the share of total hours worked by women from around 30% in the 1970s to 41% in 2000. Moreover, while the Table shows very slight increases in the share of part-time jobs the data also show that the majority of the increase in hours worked (60%) has been in full time employment.

Table 5.3. Share of Total Hours Worked by Women 1970-2000

	Total Hours Worked		**Part Time**	
	NES	FES	NES	FES
1970*	30.6	29.5	19.0	22.1
2000	41.1	41.4	23.7	25.8
Change	10.5	11.9	4.7	3.7

*1975 for NES

These findings, although only descriptive, show a number of interesting facts. Firstly they reveal an increase in female labour force participation witnessed in the economy over the last thirty years. Secondly, they show that the majority of the growth in female employment has been in full time work (historically the domain of males). Thus, all these results point to the possibility that progress made by females in the labour market has, at least to some extent, been at the expense of males.

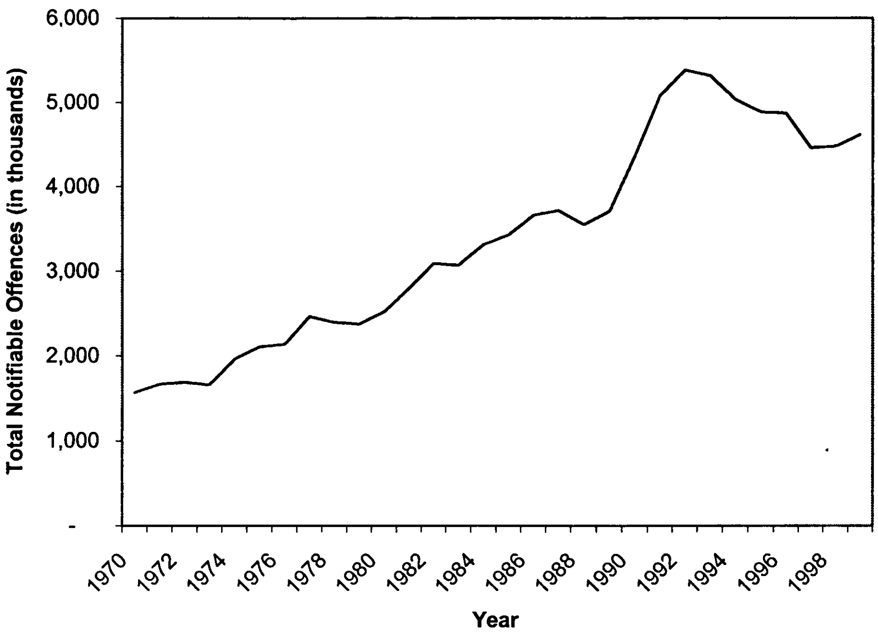
5.4.2 Crime

5.4.2.1. Notifiable Offences

Over this period, total notifiable offences rose from a relatively small base of around 1,568,000 in 1970 to a peak of 5,383,000 in 1992. After this time a decline occurred. This trend over time can be seen in Figure 5.1.

Property Crimes (measured as theft and handling and burglary), which make up a large number of total notifiable offences (88% in 1970, 80% in 1985 and 69% in 1998)[13] followed the aggregate trend, rising from 1,376,000 in 1970 to 4,207,000 in 1992, before subsequently falling. This trend in property crime (as well as the breakdown of property crime into its constituent parts) can be seen clearly in Figure 5.2.

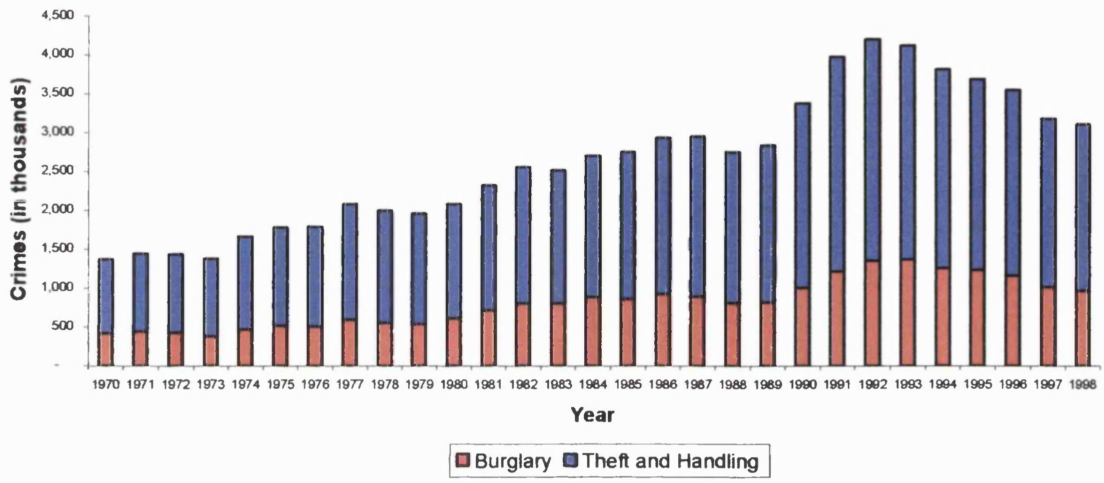
Figure 5.1. Trends in Total Notifiable Offences in England and Wales between 1970 and 1998



Source: Home Office

[13] Indicating a shift in the structure of crime.

Figure 5.2. Trends in Property Crime in England and Wales between 1970 and 1998



Source: Home Office

5.4.2.2 Convictions Data

Examining trends in notifiable offences offers no information on the share of crimes committed by males and females. For this we need to look at convictions data (the numbers of males and females processed by the criminal justice system).[14] This is done in Table 5.4, which shows the number of males and females found guilty of all offences and the number males and females found guilty of property crime offences in both Magistrates and Crown Courts. The Table shows quite clearly that patterns of convictions at Crown and Magistrates courts have evolved differently over time. The number of males and females found guilty of all crimes at Crown Court has increased while there has been a decline in the number of males and females found guilty of all crimes at Magistrates Courts. This decline has been larger for property offences than others. This supports the idea that there may have been a compositional change across

[14] We would like to use arrest data, as work in the US has done, but the arrest data has not been consistently collected in England and Wales by sex over time which would allow us to do this.

crimes over this period already indicated by the notifiable offence data. This evidence may suggest that as crime rose over this period the criminal justice system was forced to focus its attention on the more serious crime (i.e. those dealt with by the Crown Courts rather than the Magistrates and more violent offences rather than property crimes).

The share of those convicted who are female is fairly constant over time and across the type of Court. Of those convicted, of all crimes at Magistrates Courts, the percentage who are female only shifts between 14 and 16% over all time periods considered. The proportion of those found guilty at Crown Courts who are female fluctuates by about the same amount, between 7 and 9%. The percentage of those found guilty of property offences varies even less over time. At Magistrates Courts, between 18 and 19% of those found guilty are female, while at Crown Courts, the percentage who are female is between 9 and 10%.

The fact that the share of those found guilty who are female has remained fairly constant over time and that the crime rates for males and females have followed a similar pattern suggests that the large increase in female labour supply (which as traditional criminological theories predict is highly likely to affect the amount of female crime), is also likely to be exerting some influence on male crime. Thus, the share of female crime remains relatively flat despite huge changes in factors predicted to determine crime. This is very much in line with the hypothesis that shifts in female labour supply may have an impact on crime by influencing male offending via labour market substitution effects.

Table 5.4 Numbers found guilty at Crown and Magistrates Courts in England and Wales Between 1975 and 1997

	Total Found Guilty at Magistrates Courts		**Total Found Guilty at Crown Courts**		**Found Guilty of Property Crime at Magistrates Courts**		**Found Guilty of Property Crime at Crown Courts**	
	Male	Female	Male	Female	Male	Female	Male	Female
1975	293279	56615 (16.2)	48846	3741 (7.1)	224660	51424 (19.3)	29520	2549 (9.2)
1980	333013	62357 (15.8)	53560	5415 (9.2)	235254	54431 (17.8)	32992	3905 (9.8)
1985	307547	52032 (14.5)	74961	7007 (8.5)	213222	44632 (17.3)	47069	5038 (9.1)
1990	222401	37011 (14.3)	76265	6998 (8.4)	129093	28600 (17.1)	37735	4295 (9.8)
1997	212231	35696 (14.4)	64255	6544 (9.2)	114680	24758 (17.8)	25026	2685 (9.7)

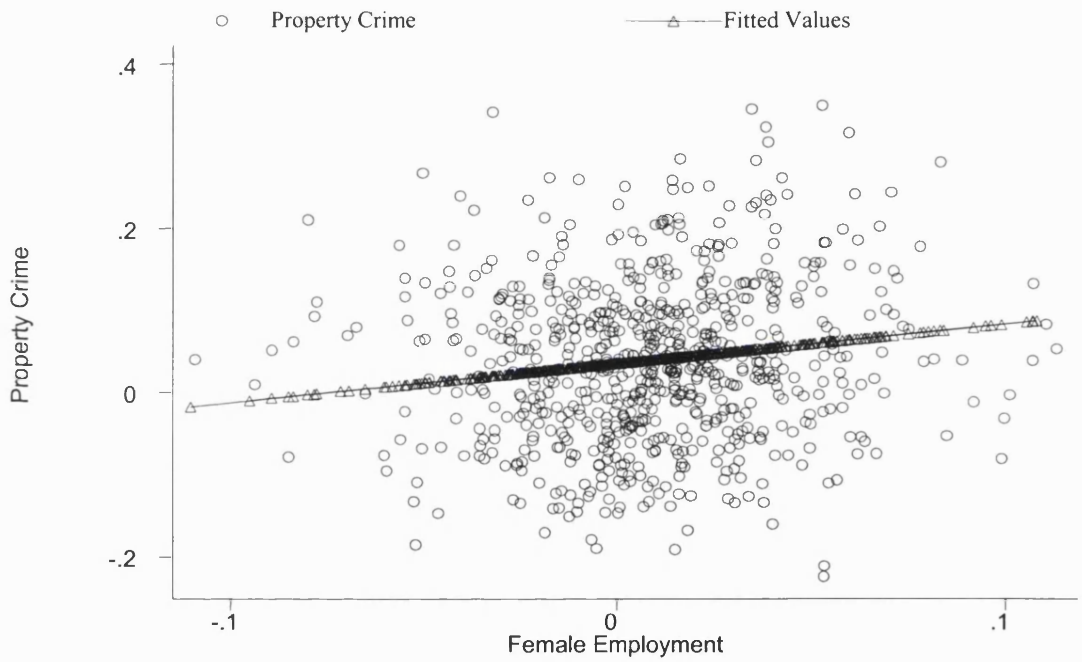
Percentage who are female in parenthesis

5.4.2.3 Graphing Changes in Female Labour Force Participation and Crime

Having examined trends in female labour force participation and crime it is now possible to look at the effect of rising female participation on property crime by graphing the changes in these two variables over time. This is shown in Figure 5.3, which plots the change in the female share of employment between 1975 and 1997 along the X axis and the change in the property crime rate along the Y axis. The line represents the fitted values, which are the predicted change in property crime given a change in female employment. The exact slope of this line is simply the regression coefficient on the female employment variable, which is .259. This means that there is a positive relationship between changes in female employment and changes in property crime between 1975 and 1997. In other words, the areas where the female share of employment rose, are also the areas where property crime increased.

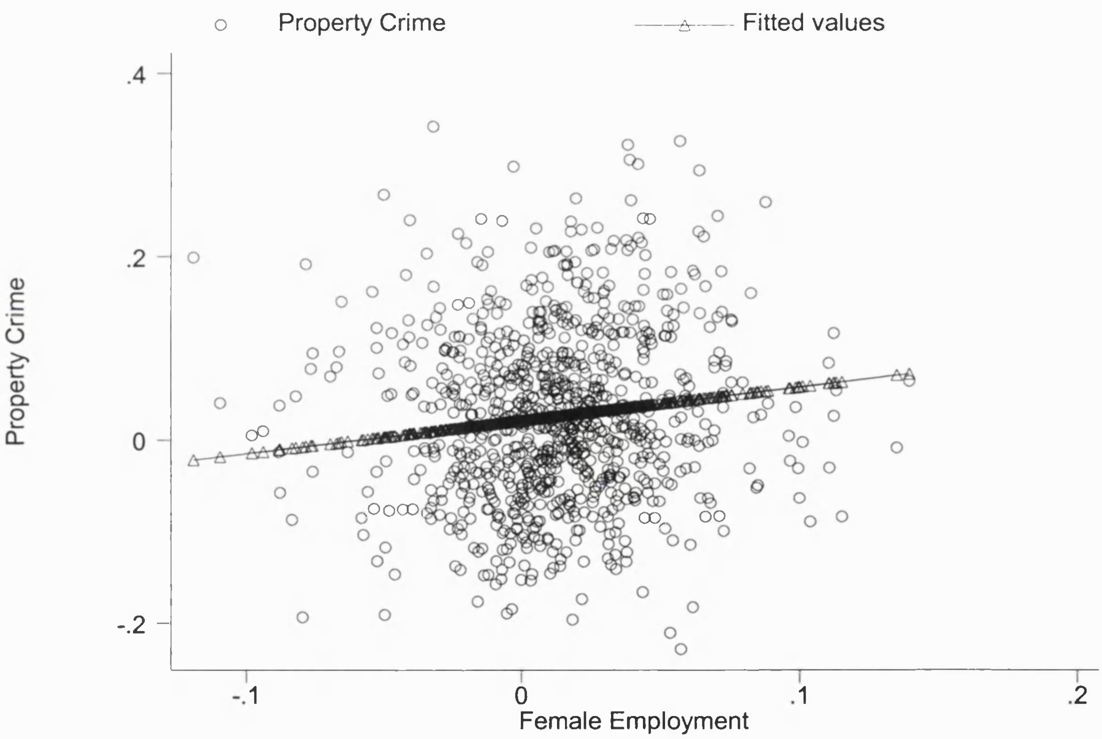
Criminological theory suggests that if economic incentives matter for crime, then rising female labour market participation should reduce the amount of crime committed by females (see Chesney-Lind and Shelden 1992 or Steffensmeier 1980). That the results show a positive relationship suggests that rising female employment is positively related to male crime and that this relationship is the dominant force.

Figure 5.3. Changes in Female Employment and Property Crime between 1975 and 1997



Using the convictions data, it is also possible to examine the effect of rising female labour supply on property crime carried out by males. This is done in a similar way to that illustrated in the above graph. The same measure of the change in the share of female employment lies along the X axis, but this time the Y axis measures changes in the male property crime conviction rate (i.e. the number of males convicted of property crimes/all males). The results of this are shown in Figure 5.4. A similar picture to the aggregate crime rate emerges. A positive relationship between changes in female labour force participation and changes in male property crime is produced. Areas where female labour supply rose the most saw the largest rise in male convictions for property offences. The regression line is slightly steeper in this graph (compared to Figure 5.3), reflecting a larger coefficient on the independent variable (.364 compared to .259).

Figure 5.4. Changes in Female Employment and Male Property Crime Between 1975 and 1997



The descriptive statistics not only demonstrate trends in female employment and crime over the period under examination, but also point to a possible negative relationship between female employment and the male labour market, and between female employment and property crime. Such relationships can be examined more rigorously by carrying out multivariate regression analysis. Multivariate analysis has an advantage over bivariate regression analysis (which has been used to produce the graphs), as it allows the model to take account of other changes that may be happening at the same time and that may affect the relationship between the variables of primary interest.

5.5 Statistical Regression Analysis

5.5.1 Crime Equations

Statistical regression analysis makes it possible to establish more precisely the relationship between increases in female employment and crime, while controlling for other variables that may be correlated with the key variables of interest. In addition, because of the nested nature of the data (at police force area level across time), it is possible to control for factors that are constant across areas and over time that may not be measurable in other ways. This has been discussed in detail in previous Chapters but an example of the former would be macro-economic shocks that hit the economy as a whole, while the latter may include factors specific to areas such as those related to geography.

Thus, the aim is to regress crime rates on female employment while controlling for a number of other factors that may influence the relationship. The model which make this analysis possible is specified for area '*a*' and time '*t*' as follows:

$$C_{at} = \alpha + \beta_1 Femp_{at} + \beta_2 Demo_{at} + \beta_3 Deter_{at} + F_a + T_t + \varepsilon_{at}$$

where *C* is the log(crime rate), *Femp* is a measure of female labour force participation (the female share of total employment), *Demo* is the controls for shifts in demographic characteristics of areas, and *Deter* is the controls for shifts in deterrence. F denotes controls for area fixed effects, measured by the inclusion of area dummies (excluding one due to the inclusion of the constant α in the equation). T represents time specific effects (again measured by the inclusion of (t-1) dummy variables for year). ε is an error term which reflects the fact that although the model includes a number of independent variables as well as controls for area and time effects, it is still unlikely to fully explain all the variation in the dependent variable. The subscripts '*a*' and '*t*' indicate that the model uses data at police force area measured over time.

The results of this model are given in Table 5.5. There are five model specifications. The first (1) is simply the fixed effects regression of property crime on the share of female employment, controlling only for time and area effects. The second specification (2) also controls for the demographic structure of the area (specifically the proportion of young people in the area aged under 25), that may influence the relationship of primary interest. The third (3) and fourth (4) model specifications add in deterrence measures: (3) controls for the proportion of the population found guilty of a crime; while specification (4) controls for the number of policemen in the area. The final specification (5) controls for demographics and includes both deterrence measures.

In the basic model (1), the coefficient on female employment attracts a positive, fairly sizable coefficient of .287, which is statistically significant at the 5% level. Because this is an area fixed effects model, the results can be interpreted as a change relationship. In other words, in those areas where female employment has risen, there has also been an increase in property crime. This supports the idea that despite the possibility that female employment reduces female crime, the overall effect of rising female employment has been to increase crime.

This finding is robust to the inclusion of controls for the demographic make-up of the area. When this is taken into account in specification (2), the coefficient on the share of female employment is slightly reduced (.242), but remains statistically significant at the 5% level.

Adding in additional controls for the proportion of the population found guilty of a property crime (specification (3)) does not alter the coefficient on the female share of employment from model (2). It remains .242, although in (3) it is only significant at the 10% level. The coefficient on the variable measuring the proportion found guilty attracts a negative coefficient of -.057, but is statistically insignificant.

The picture is somewhat different in specification (4), when the second deterrence measure, the number of police officers in the area, is added to the model. The inclusion of this variable actually increases the magnitude of the coefficient on the female share of employment to .256. This is statistically significant at the 10% level. Like the coefficient on the proportion found guilty, the number of police officers attracts a negative sign of similar magnitude (-.056). But unlike the previous deterrence measure, this result is strongly statistically significant at a greater than 1% level.

These results indicate that areas where female employment has risen have seen increases in property crime, even after controlling for the fact that areas where the number of police officers has risen have seen relative declines in the property crime rates.

Table 5.5 Property Crime Rates and Female Employment

	(1)	(2)	(3)	(4)	(5)
Female Employment	.287** (.136)	.242** (.135)	.242* (.135)	.256* (.134)	.255* (.134)
No. of Police Officers				-.056*** (.018)	-.055*** (.019)
Proportion Found Guilty			-.057 (.063)		-.039 (.072)
Controls for Demographics	No	Yes	Yes	Yes	Yes
Time Controls	Yes	Yes	Yes	Yes	Yes
Area Fixed Effects	Yes	Yes	Yes	Yes	Yes
R Squared	.958	.958	.959	.959	.959
Observations	943	943	943	943	943

Robust standard errors in parenthesis, *** significant at 1%, ** 5%, * 10%

5.5.2 Male Crime Equations

In the previous model, notifiable offences for property crime were related to the share of female employment (and other factors). Thus, the results produced include any effect female employment has on crimes committed by females as well as males. As already noted, while females only constitute a small fraction of individuals who commit crimes (between 15% and 17% for property crimes) and this is stable through time, there remains the possibility that their inclusion may be affecting the results.[15] To investigate this issue, it is possible to carry out a similar regression to the one above using only male crime as the dependent variable (with the convictions data) and including other male specific controls and population weights. The model now becomes:

[15] Indeed, it is likely that female employment by improving the position of women will decrease their involvement in crime (Chesney-Lind and Shelden 2000). If this is the case by including female crime the model will underestimate the true effect that shifts in female employment has on male crime.

$$MC_{at} = \alpha + \delta_1 Femp_{at} + \delta_2 MDemo_{at} + \delta_3 Deter_{at} + F_a + T_t + \varepsilon_{at}$$

where *MC* is the male-specific log(conviction rate) for property offences, *Femp* is the same measure of female labour force participation, *MDemo* controls for shifts in demographic characteristics of males in the area, and *Deter* controls for the number of police officers. Again, F denotes controls for area fixed effects, *T* controls for time specific effects and ε is the error term. The subscripts '*a*' and '*t*' indicate that the model is calculated using data across police force areas measured over time.

The results of this model are shown in Table 5.6. There are three different model specifications. The first (1), like the previous model, is a simple regression of the male property crime rate on female convictions with area and time fixed effects. The second (2), additionally controls for the demographic structure of areas; while the third (3), includes the number of police officers in an area as a measure of deterrence.

As with the notifiable offences, the basic convictions model uncovers a positive coefficient on the share of female employment. This is statistically significant at the 5% level. The magnitude of the coefficient is slightly larger when the male-specific crime rate is the dependent variable rather than all notifiable offences for property crimes (.331 compared to .288 in the previous model).

The inclusion of controls for area demographics causes the coefficient on the share of female employment to increase slightly, moving from .331 in the basic model (1) to .361 in the model that controls for demographics (2). This remains statistically significant at the 5% level. Additionally, controlling for deterrence by including the number of police officers to the model in (3), again leads to a slight increase the coefficient on the share of female employment, which is now significant at the 10% level. The coefficient on the number of police officers is -.029, which is significant at the 5% level. A possible reason for the smaller magnitude of the coefficient (compared to that of the previous model) may be related to bias (produced if the number of police in an area is negatively correlated with the convictions in an area).[16]

Thus, the results from this model, as shown in Table 5.6, very much reconfirm the earlier picture. Areas where the share of female employment showed a higher increase saw a higher increase in male property crime.

Table 5.6 Male Property Crime Rates and Female Employment

	(1)	(2)	(3)
Female Employment	.331** (.108)	.361** (.107)	.369* (.107)
No. of Police Officers			-.029** (.014)
Controls for Demographics	No	Yes	Yes
Time Controls	Yes	Yes	Yes
Area Fixed Effects	Yes	Yes	Yes
R Squared	.987	.987	.987
Observations	943	943	943

Robust standard errors in parenthesis *** significant at 1%, ** 5%, * 10%

5.5.3 Interaction between the Male and Female Labour Markets: Male Wages and Female Employment

Having established a positive relationship between rising female labour force participation and crime across areas and time we now need to establish why this relationship exists. We can try to do this by examining a possible mechanism through which higher female labour force participation increases crime. Earlier Chapters have

[16] If the number of police is negatively related to convictions (i.e. more police officers, less crime, therefore fewer convictions) the bias will be downwards and the coefficient on the number of police officers will be an underestimate of the true effect. It may be possible that the two variables are positively related. In this case the bias would work in the opposite direction. There may be some concern about the possible relationship between the number of police officers and the convictions and as a result the number of police would be an endogenous measure. However, we can see from Table 5.6 that the inclusion of the variable that measures the number of police officers does not alter the coefficient on the measure of female employment

already identified low wages to be positively associated with crime. If increasing female labour supply lowers male wages, and low wage men are more likely to commit crime, this is may to lead to an increase in crime. One way to examine this is by regressing male wages on female employment.[17] A model which allows us to do this is:

$$MW_{at} = \alpha + \theta_1 Femp_{at} + \theta_2 Demo_{at} + F_a + T_t + \varepsilon_{at}$$

where MW_{at} is the Log (Male mean wage), *Femp* is a measure of female labour force participation (the female share of total employment) and *Demo* controls for shifts in demographic characteristics of areas. As with the previous models, F denotes controls for area fixed effects, T represents a control for time-specific effects and ε is the error term. Again the subscripts 'a' and 't' indicate that the model is to be estimated for each area and each time period.

Table 5.7 reports two specifications that examine this question. The first is the basic area and time fixed effects model (1). The second (2) additionally controls for the demographic make-up of an area. The first specification produces a negative relationship between female employment and male wages (-.405) which is statistically significant at a greater than the 1% level. Additionally controlling for the demographic structure of an area slightly reduces the coefficient to -.368, but it remains statistically significant at a greater than 1% level. These results strongly indicate that areas where female employment has risen most have also seen the greatest fall in average male wages.

[17] This is important because we want to establish that female labour force participation is positively related to crime because it lowers male wages. There are other ways female labour force participation may increase crime by simply increasing the stock of goods or reducing the guardianship of property for example (see routine activity theory (Felson 1994).

Table 5.7 Male Mean Wages and Female Employment

	(1)	(2)
Female Employment	-.405*** (.079)	-.368*** (.072)
Controls for Demographics	No	Yes
Time Controls	Yes	Yes
Area Fixed Effects	Yes	Yes
R Squared	.996	.996
Observations	943	943

Robust standard errors in parentheses
*** significant at 1%, ** 5%, * 10%

5.5.4 Interaction between the Male and Female Labour Markets: Focus on Low Skilled Occupations

The previous sub-section shows average male wages grew by less in areas where female employment rose by more. This suggests a deterioration in the male labour market. However, it may well be the case that it is males in less good jobs (i.e. paid beneath average wages) who are more likely to engage in crime (Farrington 1986).[18] If this is the case, increasing female labour supply should have a greater effect on crime in these low skilled occupations than in other occupations.

This analysis becomes more important if, as a number of researchers argue (Topel 1997, Grant and Hamermesh 1981, Borjas 1986) more educated women, substitute for less skilled men since they tend to have less labour market experience than their male counterparts (or because they face labour market discrimination). If this is the case, increased female labour supply will lead to competition for jobs performed by less skilled males. As the females are more educated than the males they are competing with for jobs, employers are likely to favour the women,

[18] This was shown to be the case in Chapter 4.

particularly given they may receive lower wages (either as a result of having less labour market experience or on account of discrimination). For the males to compete favourably with the females, they may have to accept lower wages. In this way, the increase of females in the labour market will have a disproportionate effect on males at the bottom end of the labour market, who (as previous Chapters of this thesis have shown) are already more likely to be on the margins of crime.

To examine whether this is the case, Table 5.8 replaces the original measure of the female share of employment with the proportion of females in occupations where the male wage in the initial time period (1975) was below the 25th percentile of the male wage distribution. The first specification (1) is simply the fixed effects regression of property crime on the share of female employment, controlling only for time and area effects. The second specification (2) additionally controls for the demographic structure of the area (specifically the proportion of young people in the area aged under 25) that may influence the relationship of primary interest. The third (3) and fourth (4) model specifications add in deterrence measures: (3) controls for the proportion of the population found guilty of a crime; while specification (4) controls for the number of policemen in the area. The final specification (5) controls for demographics and includes both deterrence measures.

As with the original measure of the share of female employment (in Table 5.5), the basic specification produces a positive relationship between the share of female employment in low skilled occupations and property crime. In this case, the coefficient is slightly larger in magnitude at .333 (compared to .287) and is statistically significant at the 5% level. This supports the hypothesis that it is the males at the bottom of the earnings distribution who are most affected by the increase in female labour force participation.

When the model additionally controls for the demographic structure of areas (specification (2)), the coefficient increases to .353 and remains statistically significant at the 5% level. The coefficient further increases to .366 in specification (3), with the inclusion of the proportion of people found guilty of a crime. This result is statistically significant at a level greater than 1%. However, as with the previous model, while the coefficient on the proportion found guilty attracts a negative sign (which seems intuitive), it remains statistically insignificant.

Adding in a control for the number of police in model (4) slightly reduces the coefficient on the share of female employment in low skilled occupations, but it remains statistically significant at the 5% level. The coefficient on the number of police officers attracts a negative coefficient of -.051 which is significant at a greater than 1% level (reassuringly, this is very close to the magnitude of the same coefficient in Table 5.5 which is -.055). In the full model, in specification (5), the coefficient on the female share of employment is .328, which remains significant at the 1% level. The number of police officers also remains significant at the 1 % level, attracting a negative sign of -.050.

Table 5.8 Property Crime and Female Employment in Low Wage Occupations[19]

	(1)	(2)	(3)	(4)	(5)
Female Employment in Low Skill Occupations	.333** (.137)	.353** (.137)	.366*** (.138)	.317** (.135)	.328*** (.136)
No. of Police Officers				-.051*** (.018)	-.050*** (.018)
Proportion Found Guilty			-.066 (.063)		-.048 (.063)
Controls for Demographics	No	Yes	Yes	Yes	Yes
Time Controls	Yes	Yes	Yes	Yes	Yes
Area Fixed Effects	Yes	Yes	Yes	Yes	Yes
R Squared	.958	.959	.959	.959	.959
Observations	943	943	943	943	943

Robust standard errors in parenthesis, *** significant at 1%, ** 5%, * 10%

Because wages tend to be lower in female dominated occupations this measure, which identifies low paid males, is likely to include a number of males working in female dominated occupations. If these men differ in any way from males working in non-female dominated occupations, it is important to construct another measure of low paid occupations, which will not pick up males working in traditionally female occupations.

Therefore, Table 5.9 reproduces Table 5.8, replacing the existing definition of low skilled occupations, with one that measures the share of females in occupations where the average male wage was beneath the 50th percentile of the male wage

[19] Occupations where the average male wage was beneath the 25th percentile male wage distribution in 1975.

distribution in 1975 and where at least 50% of the workforce was male in the initial period.

The results produced by this model are very similar to those in Table 5.8. A strong positive association between the share of female employment and crime is discovered in all five model specifications. As we would expect, this model produces coefficients on the share of female employment that have larger magnitudes than in previous models (.406 in the final specification compared to .328 in the low skilled 25th percentile measure and .255 using the original share of females in all occupations). This is to be expected since traditionally the occupations examined here are strongly male dominated (see Appendix A for the percentage of males and females in these occupations over time). The increase of females is likely to have the greatest effect on the males within such occupations than in other occupations where female presence is more commonly observed.

As with the other models, the proportion found guilty attracts a negative, but statistically insignificant coefficient. The coefficient on the number of police officers is negative and strongly significant. It is very similar in magnitude to all the other models. The robustness of these findings is reassuring given the different ways the share of female employment is measured across models.

These results are supportive of other findings in earlier Chapters of this thesis (Chapters 2, 3 and 4) that also indicate that males at the lower end of the employment structure are the most vulnerable to crime.

Table 5.9 Property Crime and Female Employment in Low Wage Occupations[20]

	(1)	(2)	(3)	(4)	(5)
Female Employment in Low Skill Occupations	.382*** (.067)	.415*** (.066)	.419*** (.066)	.402*** (.065)	.406*** (.065)
No. of Police Officers				-.046*** (.018)	-.044** (.018)
Proportion Found Guilty			-.074 (.061)		-.058 (.061)
Controls for Demographics	No	Yes	Yes	Yes	Yes
Time Controls	Yes	Yes	Yes	Yes	Yes
Area Fixed Effects	Yes	Yes	Yes	Yes	Yes
R Squared	.960	.961	.961	.962	.962
Observations	943	943	943	943	943

Robust standard errors in parenthesis, *** significant at 1%, ** 5%, * 10%

5.6 Concluding Remarks

This Chapter has examined the effect increased female labour force participation has on crime. Traditionally, work in this area has focused almost exclusively on the effect of female labour supply on female crime. However, the results here indicate this approach has only touched on a small proportion of the impact increasing female labour supply has on crime. Because the amount of crime carried out by females is relatively small compared to that done by males, examining the outcome of increased female labour supply on male crime uncovers a much larger overall impact on crime than previously thought.

[20] Occupations where the average male wage was beneath the 50th percentile male wage distribution in 1975 and where at least 50% of the workforce were male in the initial period.

The results show that in areas where female employment rose, crime also rose. This result is robust to crime measured as all notifiable offences for property crimes and when measured as male property crime convictions. The results are stronger for male-specific crimes, probably due to the fact that including even a small number of female crimes is likely to bias the coefficient downwards, as female employment and female crime are likely to be negatively related.

Findings suggest that the positive relationship between female labour supply and crime may be produced as a result of the influence of higher female employment in reducing male wages. The fact that results are stronger when female employment is measured as the share of women in low skilled male occupations suggests that it is the wages of the least skilled males that are most affected. This is supportive of the idea that women substitute for less skilled men, thus increasing pressure on males who are already likely to be on the margins of crime and thereby leading to an increase in crime.

While a positive relationship between female labour supply and crime has been shown, this does not mean that female employment necessarily produces bad outcomes. And policy makers interested in reducing crime would be misled if they thought that reducing female employment would solve the problem. The results suggest that the real issue may be that females entering the labour market are substituting for low skilled males. It is likely that as females continue to improve their educational qualifications and accumulate labour market experience, they will compete for jobs with males who are further up the employment ladder and who are thus less likely to be on the margins of crime. It is likely that as women substitute for males higher up the employment ladder the effect of increasing female labour supply on crime will become weaker.

6. Age Differences in Crime: Are They Explained by Education?

6.1 Introduction

The peaking of aggregate crime in adolescence or early adulthood and its subsequent decline with age has become an established pattern.[1] Whilst this is fairly uncontentious, the exact nature of the crime-age relation, and whether there are potential differences across different groups of people, is much more controversial. For example, Hirshi and Gottfredson (1983) argue that the relationship between crime and age is not only invariant across time and place, but is also independent of other correlates of crime. For Hirshi and Gottfredson, age has a direct influence on crime which cannot be explained by other variables.

Others (such as Kercher 1987) argue age is related to crime because it is associated with particular stages in an individual's life cycle, which influence attitudes and behaviour and act to encourage or discourage criminal involvement. But such factors have differential effects on individuals or groups, which means that crime-age profiles will not be the same across different groups of people. Greenberg (1977) points out that changes which have taken place in the family, education and the labour force since the 1940s have made it increasingly difficult for young people to make the transition to adulthood. Thus, current crime-age profiles are different from crime-age profiles produced in earlier time periods. Profiles also vary for different types of crime (Steffensmeier et al 1989), as property crimes peak earlier than violent crimes, which themselves peak earlier than sexual crimes. We also see differences in the crime-age profiles between different ethnic or social groups (Greenberg 1977), or between males and females (Graham and Bowling, 1995) because the factors which encourage and discourage criminal activity amongst these groups are likely to be different.

This Chapter addresses Hirshi and Gottfredson's invariance thesis in a different way from previous studies, by examining the distribution of crime and age for two groups of young males: those who have more education and those who have less. As a critical part of the childhood years is children's exposure to the education system, the focus of this Chapter is on potentially different crime-age profiles for people with different levels of educational attainment.

6.2 Education and offending

According to a report by HM Chief Inspectorate of Prisons (1998) there were 10570 young people under the age of 22 in the custody of the prison services in England and Wales in 1997. This represents a 5% increase on the previous year. The report points out 'most of the youngsters had been failed by the education system' (Chapter 3, paragraph 3.12). Around two thirds of these youths had no formal qualifications, many had regularly truanted from school and over 50% had been excluded (or left voluntarily) before the age of 16.

These findings highlight an important link between education and offending which has been found in many empirical studies (e.g. Rutter 1979, Thornberry et al 1985). For example, in an analysis focusing on the importance of completing school,

[1] Although there are authors who disagree such as Cain (2000).

Lochner (1999) found that high school graduation[2] reduced criminal participation among young males in the US, even after differences in ability were controlled for. He also found that young male high school graduates were 30% less likely to earn an income from crime than those who did not graduate. Moreover, high school graduation reduced the probability of being arrested by around 60% and incarceration by between 85-95%. In the UK Farrington *et al* (1986) found offending was slightly lower amongst youths still at school.

There are a number of ways education can be thought to affect offending. The most pessimistic is that whilst youngsters are at school, they are being kept off the streets[3]. This separates them from their more delinquent peers (who are likely to be absent from school) and enforces some level of discipline upon them. At the same time, they are encouraged by the idea of meritocracy to have aspirations, and to create goals which, by working hard at school, they will be able to achieve. This encourages children to develop a stake in their own future and in society more generally. All of these act to minimise offending by youngsters in education.

Perhaps more importantly, education allows children to develop skills and acquire knowledge and training which will affect their future success in life. Their ability to communicate and forge relationships, their post compulsory educational choices, the jobs they will do and the wages they will receive over the life cycle potentially depend on skill formation and human capital accumulation whilst still at school. If children want to maximise their future success, they will be less likely to offend as youngsters. If they secure successful jobs with good wages as a result of their educational success, they will also be less likely to offend as adults.

[2] In the US high school graduation signifies the successful completion of 12 years compulsory schooling and usually takes place when individuals are 17 years old.
[3] Although this is not to deny that children can, and do, offend at school by bullying for instance.

However, not all youngsters have positive experiences of their time spent at school. It has been argued that problems at school increase delinquency for some young people (Cohen 1955, Greenberg 1977). This is likely to be particularly true for working class children who tend to be less well prepared for school because of the lack of educational stimulation and resources at home. Moreover, working class children often do not have the role models that encourage them to do well at school. If the people they see around them are unemployed or insecurely employed in unskilled jobs, they may see little point in investing in their future through education if that is all the future holds. Thus, for working class children these factors affect not only their ability to learn but also their motivation to succeed at school. Their experience of school can just serve to alienate working class children from the educational system. They may develop an anti-school culture, involving misbehaviour or playing truant, as a way of dealing with their alienation and lack of educational success (Willis, 1977). This brings them into conflict with the school authorities and often with the police as their delinquency extends beyond the school setting into wider society.

6.3 Crime and Age

There are a number of theories which predict that crime will vary by age. Some even predict specific age variations, like the fact that crime will rise and peak in the late teens and early twenties before subsequently declining. Whilst these theories may not be able to fully explain the crime-age variation, or the exact shape of the crime-age profile, they do at least inform the way we think about crime and age.

Whilst they are young most individuals have no strong sense of self-identity; much of their behaviour is based on achieving short term desires. Delinquency in this sense is a way of getting ‘kicks’, having a laugh or relieving boredom. Strain theory predicts that this may be accentuated if youngsters feel that their opportunities of achieving these short term aims legally are blocked (Merton 1938). According to sub-cultural theory young people may develop their own subcultures as a way of dealing with the strain of blocked opportunities which may well encourage the illegal pursuit of short term desires (Cloward and Ohlin 1960, Cohen 1955). Additionally, peer pressure may increase delinquency in youth as youngsters are encouraged to prove themselves and show loyalty to their peers by partaking in delinquent acts.

At this stage, most youngsters feel little pressure to conform to societal norms. Because of this, social controls are unable to deter them from breaking the law. At the same time youths are protected, by their dependent status, from harsh punishment in the criminal justice system.

All these factors predict a higher involvement in public crime for young people. According to labelling theory (Becker 1960), this may lead to young people in general being labelled as delinquent, though many of them are not. Because young people may be more affected by labels that are given to them this may in itself encourage young people to conform to the deviant label that is attached to them (or give them less of an opportunity to escape such categorisation) and thus increase youth involvement in crime.

As youngsters grow up, they are influenced by a series of factors that discourage them from breaking the law. Maturation theory (see Farrington 1986) predicts that as individuals mature, they begin to think of much delinquent behaviour as childish. As they move from dependence to independence, leaving school and the parental home and entering the labour market, getting married and starting families of their own, young people begin to develop ties to society and attachments to social institutions such as the family, the labour market and the community. These factors coupled with the possibility of severe legal sanctions all encourage a lower crime rate, at least in public, as young people move towards adulthood.

Whilst many of these theories offer plausible explanations of the crime-age distribution, not all offer an account of why we might expect to see potential variation in the crime-age profiles of two youths of the same age. Thus, some can be thought of as pure age theories, explaining differences between age groups but shedding little light on within age group variation. For example, social controls and treatment by the criminal justice system do not differentially affect different groups of young people once age is taken into account.

As this Chapter is concerned with how crime-age profiles vary by education, theories which offer an account of this potential variation are of the most interest. For example, if opportunities depend on educational attainment, strain theory may predict that the less educated are more likely to be involved in crime than the more educated as they are more likely to experience blocked opportunities. Equally, if less educated youngsters are more easily influenced by their delinquent contemporaries, or if they have larger peer groups, peer group theories predict they are more likely to be involved in crime.

As far as this Chapter is concerned, maturation theory is perhaps the most useful theory. It predicts that we should see the crime-age profiles for the more and less educated groups peaking at different times as the two groups make the transition from childhood to adulthood at different ages depending on what age they left school. Maturation theory also predicts that we might expect the less educated group to be more involved in crime as they potentially find it more difficult to make the transition to adulthood. Thus, since they leave school earlier, the less educated group move to adulthood before those who stay at school, but this transition may be more difficult.

For example, a key element of adulthood involves finding employment. However, having invested in only basic human capital those with less education may have more difficulty securing a job with good remuneration and working conditions than those who stay on at school and invest in extra human capital.

It is clear that some theories not only help us to explain why the crime-age distribution peaks in the mid to late teens and early twenties and then declines, but may also suggest that we are likely to see potential differences in the crime-age profiles for different educational groups, for different societies, different time periods, different sections of society and for different crimes.

6.4 Empirical Work

Some empirical work supports the idea that the crime-age profiles may differ with observable characteristics. For example, Steffensmeier et al (1989), working with US data from Uniform Crime reports across three different periods and using a number of statistical measures, find variation in the distribution of crime and age across crime groups in 1980 (the peak age for property crimes being younger than for other crimes) and also across time between 1940 and 1980 (the offenders were older and more varied in age in 1940 than 1980). In Laub's (1983) study, using data which asks the victims the age of the perpetrator, differences in the crime-age profiles of those living in urban areas compared to non-urban areas, blacks compared to whites and males compared to females are discovered. Rowe and Tittle (1977) find that much of the relationship between crime and age is explained by other variables such as social integration, fear of sanctions, moral commitment and utility of crime when these variables were examined together. Kercher (1987) re-analyses the data used by Rowe and Tittle and finds that the relationship between age and crime is an indirect one, mediated through other explanatory variables such as moral commitment and having criminal associates.

However, other research contradicts these findings. Hirshi and Gottfredson (1983, 1985) argue that the crime-age distribution does not vary across time and space. They argue that different groups in society may differ in their levels of involvement in crime, but not in the way they vary with age. Thus, the number of crimes committed per person at any given age as a proportion of that age group should be the same for all groups. For Hirshi and Gottfredson, age has a direct influence on crime, which cannot be explained by other variables. This leads them to argue that existing theories cannot be used to explain crime, as variables predicted by these theories to have a causal impact on crime vary both temporally and spatially.

Hirshi and Gottfredson use data on indictable offences of theft and personal violence crimes in England and Wales in 1842 to 1844, total convictions in England in 1913, and, total arrests from the US Uniform Crime Reports in 1979 to show that crime-age profiles are invariant. However, the evidence used to support their theses is somewhat limited and Hirshi and Gottfredson provide no statistical tests to validate their argument.

Britt (1994) examines arrests for 7 different types of crime in the US for a number of years between 1952 and 1987. His findings support those of Hirshi and Gottfredson, that crime-age profiles are invariant across time and offence category.[4]

Tittle (1980) uses self-reported data and finds that the crime-age distribution is not affected by controls for sex, ethnicity, marital status, family background or labour market status. However, Tittle uses age bands 15-24, 25-44, 45-64, 65+ which would only pick out extreme differences in the crime-age profile for different offences. Also

[4] Although Greenberg (1994) examining arrests in the US between 1952 and 1957 found no trend over time in the crime-age distribution.

Tittle's definition of criminal involvement incorporates anyone who has committed a crime in the past five years, which is not likely to be an accurate measure for examining the crime-age profile.

Shavit and Rattner (1988) use self-reported data in the form of life histories of 2144 Jewish Israeli men born in 1954. Interviews were conducted with the men when they were 26-27 years old. The authors find a similar crime-age distribution across social groups and conclude that the distribution cannot be explained by age variations in other variables such as schooling. However, the research looks at all crimes combined, which may well mask differences between different crime categories. Moreover, by their own admission, some of the life course variables used in their research are fairly crude.

6.5 Data

The data used in this Chapter were collected by Market and Opinion Research International (MORI) for the Home Office in 1992/3. The data were originally used by Graham and Bowling (1995) in an examination of self-reported offending, to establish the correlates of criminal onset and desistence amongst 14 to 25 year olds in England and Wales.

The data are derived from a nationally representative sample of (893) 14-25 year olds in England and Wales, with a secondary sample of (823) 14-25 year olds in high crime areas, and booster samples of ethnic groups (808): Afro-Caribbeans, Indians and Pakistanis/Bangladeshi. In total 2529 young people were interviewed. The overall response rate was 69%, 70% for the national sample and 68% for both the high crime sample and ethnic booster. The response rate was lower in London than elsewhere.

The interviews began with face-to-face questions asking for socio-demographic and lifestyle information. Respondents were then asked to complete booklets asking questions on four areas: drug use, offending behaviour and more detailed questions on offending behaviour and police contact. This was followed by an interviewer assessment of background details such as the area where the respondent lived.

Because the survey collected self-reported data it is not affected by bias associated with the selection and processing of individuals by the criminal justice system.[5] One of the problems with much of the work done on the crime-age distribution is that it has used aggregated official statistics and thus may be more a reflection of police activity than any real trends in the crime-age distribution. However, as some of the discussion in Chapter 1 showed, there are also some problems associated with self-report surveys: respondents may conceal or exaggerate their involvement in crime, or may answer in a way that they think the interviewer wants them to. Moreover, because some of the information is being asked retrospectively, respondents may not remember accurately events that have happened in the past or may say they happened at a specific time which the researcher is asking about when in reality they happened before or after that date (Brantingham and Brantingham, 1984).

This survey contains no information on individuals who refused to take part in the survey. However, we do know that the non-response rate was higher in the poorly maintained areas[6] (Graham and Bowling, 1995). If the occupants of these areas are more or less likely to commit crimes than individuals who did take part in the survey an element of bias may be introduced into empirical work based on the sample.

[5] This is not to deny the possibility that such selection and processing has already taken place informally through labeling or stigmatization.

Additionally, the data exclude young people who live in institutions: hospitals; prisons or young offender institutions; residential care homes; army barracks; nurses' accommodation, and colleges and public schools. It also excludes the homeless. These groups only make up a tiny proportion of young people living in England and Wales, so whilst their exclusion may introduce additional bias into the sample, as it is possible that those youngsters in prison or living rough are likely to be (or to have been) more involved in crime (Carlen 1996, Hagan and McCarthy 1997), the numbers involved are so small this is unlikely to be the case.

Despite the potential problems, these data offer a unique source of information on individual crime at a national level not found elsewhere in the UK. But, because of the possible sample selection bias discussed above it may be better to think of the study as shedding light on the nature of crime-age profiles for the sample of young men studied as opposed to a nationally representative study.[7]

6.6 Descriptive Statistics

Table 6.1 shows that, of all respondents, 15% reported committing a property offence in the last year, 13% reported committing a violent offence and 11% said that they had committed a handling offence. These Figures vary by age, just under a sixth of 16 and 17 year olds and just over a fifth of 18-22 year olds reported committing a property offence in the last year, compared to only 7% of 23-25 year olds. 16% of 18-21 year olds said they had committed a handling offence in the last year, while only 5% of 22-25 year olds said they had committed the same kind of

[6] Derived from the interviewer's classification of the respondent's home and surrounding area.
[7] Although to try to ensure the sample was representative and to correct for sampling variance and any bias produced by the inclusion of the booster samples, both household and individual weights were used.

crimes. 17% of 16-17 year olds reported committing a violent offence in the last year, while just over 5% of 23-25 year olds said they had committed similar offences.

Table 6.1. Percentage of Males who Committed Offences in the last 12 Months

	Property offences		Handling offences		Violent offences	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
All	15.0	.357	10.6	.308	12.7	.333
16 - 17	14.7	.354	7.9	.271	16.9	.376
18 - 21	20.5	.404	16.0	.367	15.0	.357
22 - 25	7.0	.255	4.9	.217	5.3	.224

6.7 Methodology and Preliminary Data Analysis

This Chapter examines different age profiles for people with different educational attainment. However, for the age groups in these data the usual educational variable used, educational qualifications, is not suitable. It does not allow identification of those who genuinely leave the education system with the lowest qualifications (1 CSE grade 5 for example) from those who have left with 5 or more GCSEs. Nor is it possible to distinguish between different levels of vocational qualifications, which vary greatly in terms of standards. It is possible to identify those people who have no qualifications at all, but very few people leave the education system today with no qualifications. Moreover, the fact that many people are now gaining qualifications in later life cannot be ignored. For these reasons this Chapter looks at the distribution of crime and age for those who have left school compared to those who stay on after 16.[8]

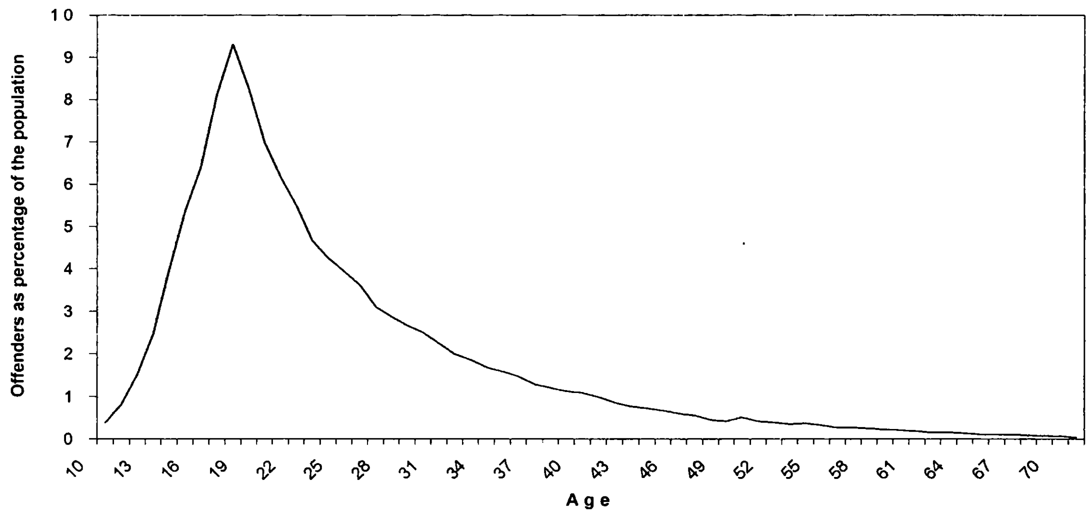
More specifically, this Chapter examines the probability that a youth who left school at 16 will commit an offence (as compared to not committing an offence) and compares this to the probability that a youth who stayed on at school will commit an

[8] This includes people in Further Education colleges as well as schools.

offence (as compared to not committing an offence). The parametric model that enables this comparison is a maximum likelihood probit[9] model (Gujarati 1995). This model is based on the assumption that the probability distribution in question (i.e. the probability of committing an offence) is normal and predicts probability Y=1 (i.e. a youth who left school at 16 [stayed on] committing an offence) compared to Y=0 (not committing an offence).

When thinking about the best way to model the crime-age distribution we first have to identify the most appropriate functional form. Figure 6.1, shows males found guilty or cautioned for indictable offences in 1997[10] (as a percentage of the population). We can see from this that there is a maximum peak in the data at age 18. And for the age range 16-25 the profile is approximately quadratic in shape.

Figure 6.1 The Crime-Age Profiles of Males aged 10-71, 1997



Source: Home Office

[9] The analysis was also carried out using a maximum likelihood logit model, which gave very similar results. Logit models are closely related to probits but are based on a logistic distribution rather than a normal distribution.
[10] This is different from the data I use which examines separate crime types.

Along with the quadratic, the functional forms considered in this Chapter are the linear, cubic and age dummy profiles, which can be seen in Figures 6.2A-6.2C. The statistical tests (shown in Appendix C) indicate that the linear profile is not appropriate as it predicts that crime declines with age. This is surprising given the findings of other studies. Of the non-linear functional forms both the quadratic and cubic follow similar patterns, with a maximum peak in the data. The inclusion of the age dummies produce a similar pattern, though they jump around a lot, which may be a reflection of sampling error rather than any real trends in the data as the number of those involved in crimes is quite small. Despite this, the age dummies display a similar crime relationship across age groups.

Using dummies may be thought a truer reflection of the data than other methods which impose a functional form to the data. Because of the small sample sizes involved in this analysis perhaps a better way to look at patterns in the data without imposing a functional form is to use a Nadaraya-Watson non-parametric regression estimator.[11] This is done in Figures 6.3A-6.3C, which show a very similar crime-age distribution to the quadratic even more so to the cubic profiles in Figures 6.2A-6.2C.

For violent crimes (Figures 6.2C and 6.3C), the relationship between crime and age appears to be linear, declining with age and producing no peak in the data for the ages examined. In part, this may reflect the lack of any of the most violent crimes in these data, such as rape and murder. Including such offences may create a peak in the data at a later age than observed here. However, in a sample of this size there would be too few of these crimes to produce meaningful analysis, even if they were included in the data.

Figure 6.2A Crime-Age Profiles for Property Crime

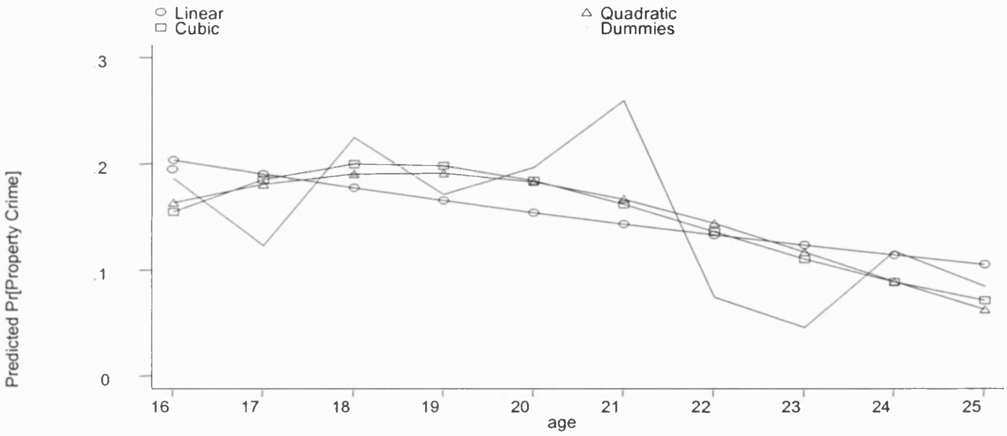


Figure 6.2B. Crime-Age Profiles for Handling Crime

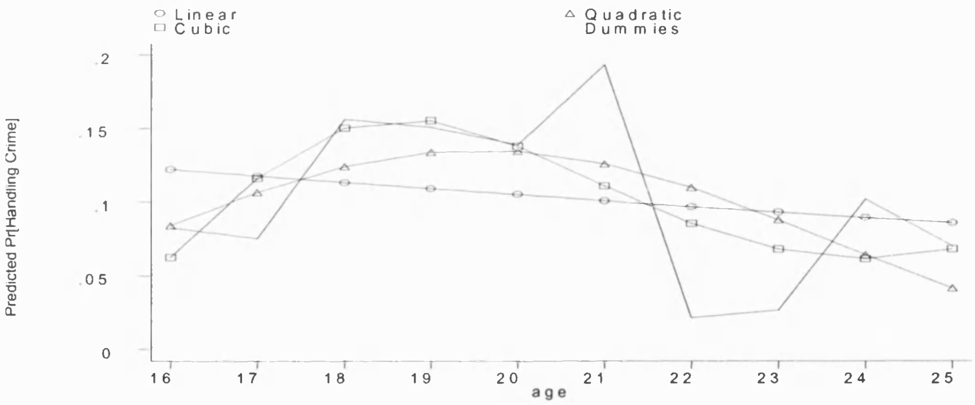


Figure 6.2C. Crime-Age Profiles for Violent Crime

[11] Here no assumption is made about the functional form of the crime-age distribution. Unlike probit regressions which assume a normal distribution and logistic regressions which assume a logistic distribution.

Figure 6.3A Crime-Age Profiles using Non-Parametric Methods for Property Crime

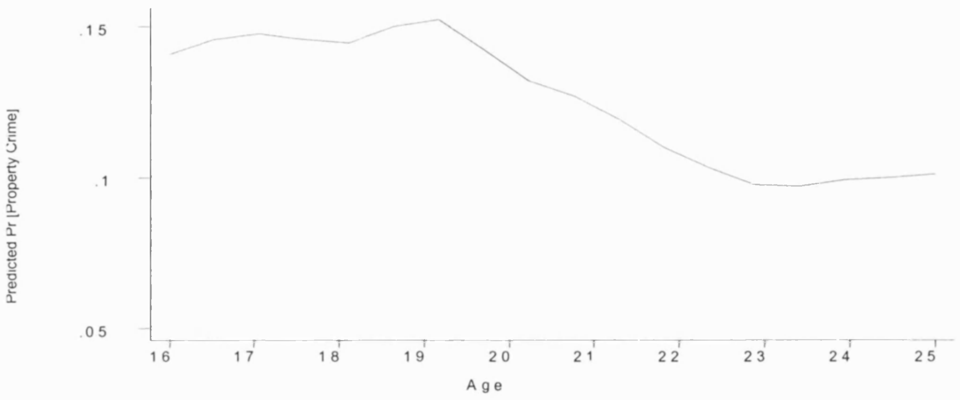


Figure 6.3B Crime-Age Profiles using Non-Parametric Methods for Handling Crime

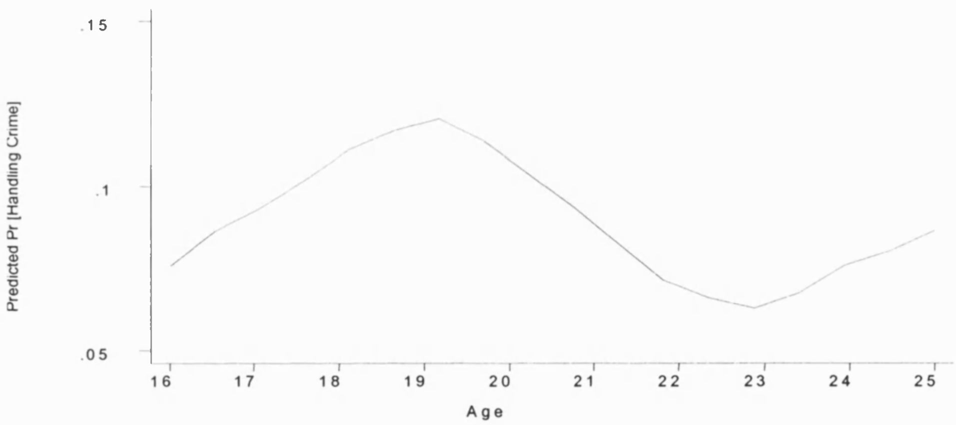
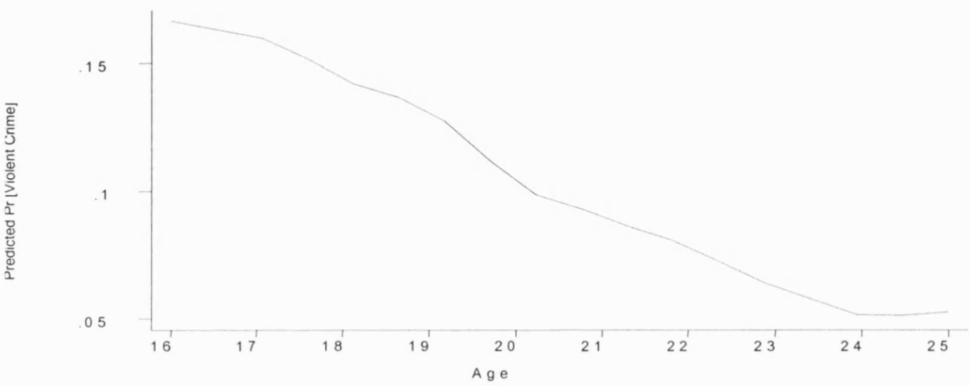


Figure 6.3C Crime-Age Profiles using Non-Parametric Methods for Violent Crime



Despite the slightly different pattern produced by violent crimes, to enable comparisons across crime categories, the inverse U quadratic crime-age profile is the preferred model for this Chapter.[12] Of the non-linear profiles, only the quadratic coefficient on the age variable is significant.[13] This may be because the data (curtailed at 25 year olds) has only 10 years of observations, which is not ideally suited to a functional form that allows for two or more turning points in the data.

6.8 Reverse Causality?

It may be thought that there are inherent problems with trying to make causal statements about schooling and crime. Is the lower involvement in crime by the more educated caused by the fact that these individuals have more education? Are the more educated individuals also those with higher ability anyway, who will be rewarded for their ability in later life with better jobs and so do not need to engage in crime? Or is it more the case that young people who are already involved in crime, or expect to become involved in crime in the future, decide not to invest in education, or are unable to invest in education because they are excluded or because they are less able?

Although it is rather difficult to answer all of these questions I have attempted to reduce any bias resulting from the potential problem of the endogeneity of education in a number of ways. Firstly, the focus is on criminal activity after individuals have made the decision about whether or not to stay on at school after the age of 16. Secondly, because education varies across the population in terms of observable factors such as school quality and parental education by using a nationally representative sample it is likely that there will be enough variation in the education

[12] Although a similar pattern is produced using both the cubic and age dummies.
[13] The same pattern was found when probits were replaced by logits. For property offences using logits the linear coefficient was -.568 and the standard error (3.38), the quadratic .056 (.179) and the cubic -.001 (.003).

variable to reduce any possible bias. Thirdly, controlling for other variables such as neighbourhood and family background will also reduce any potential bias.

Lochner's (1999) work in the US directly addresses the potential endogeneity of education with respect to crime. He argues that individuals who expect to spend time committing offences must expect to spend less time in the labour market, so therefore will invest less in their education. Thus, Lochner tests the causal effects of additional schooling on crime by looking at whether individuals who report illegal earnings spend less hours in legal employment. He finds that differences in hours worked between the groups is less than 4%, making it unlikely that observed variations in education are the result of labour market returns. It is, he concludes, 'safe to interpret our estimated effects of schooling on crime as causal: education reduces crime' (p30).

A final point is that it is possible to draw an analogy between the education and crime debate and the debate between education and earnings. Research in this field has found that any bias due to reverse causation is small and if anything is likely to understate the causal effect of education (Card 1999, Griliches 1977). Moreover, different methods that try to establish a causal relationship between schooling and earnings which are not associated with the problems of the endogeneity of an individual's education do not produce substantially different results (Card 1999).

6.9 Results

6.9.1 The basic model

If the age at which an individual leaves school is unrelated to criminal activity we would expect the crime-age profiles of the two groups to be essentially the same. We can see from Figures 6.4A-6.4C that this does not appear to be the case. For all three types of crime, the profiles for the two groups of young people are different. Furthermore, looking at the regression tables in Appendix C we can see that when we carry out a chi-square test, the profiles for property and handling crimes are significantly different for the two groups (at 10% significance level for property crimes, and 1% for handling crimes). For violent crimes, the profiles are not significantly different from one another.[14]

For both property and handling offences, the crime-age profiles of those who left school at 16 declines from a peak at the age of 16, while the profiles of those who stayed on rise gradually from age 16 to form a peak between the ages of 19-21, before declining at a slightly faster rate than the pre-age 16 increase. For violent offences, both groups of youngsters decline from a peak at age 16, but the decline is faster for those who stay on at school as apposed to those who leave school at age 16.

For property and handling offences, these patterns support the idea of maturation. Crime appears to peak when each group makes the transition to adulthood and the age at which an individual leaves school (or the period shortly after) can be used as a proxy for this transition. If this were the only difference in the offending patterns of the two groups, there would not be much cause for concern. However, for all offences, the level of crime committed by the less educated group is much higher at all ages than the crime committed by the more educated group. Moreover, for all three offences the profile for the more educated looks like crime is close to dying out by the age of 25. For the less educated, this is not the case. In fact there is no real decline in the crime rate from age 22 onwards for property crimes and handling crimes. For violent crimes the decline for the less educated is slower than for the more educated young people and so the gap widens with age.

[14] If we focus on 18-25 year olds the profiles are significantly different from one another.

Figure 6.4A Crime-Age Profiles by Education. Basic Model for Property Crime

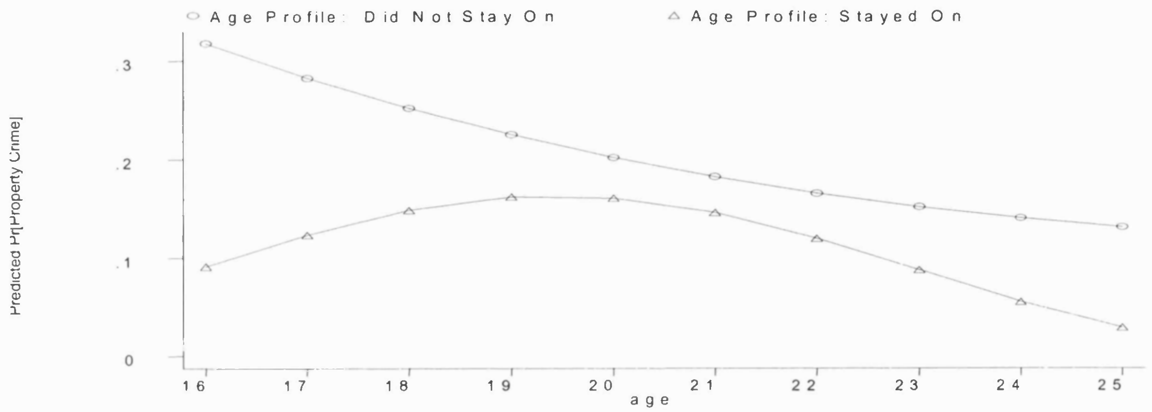


Figure 6.4B Crime-Age Profiles by Education. Basic Model for Handling Crime

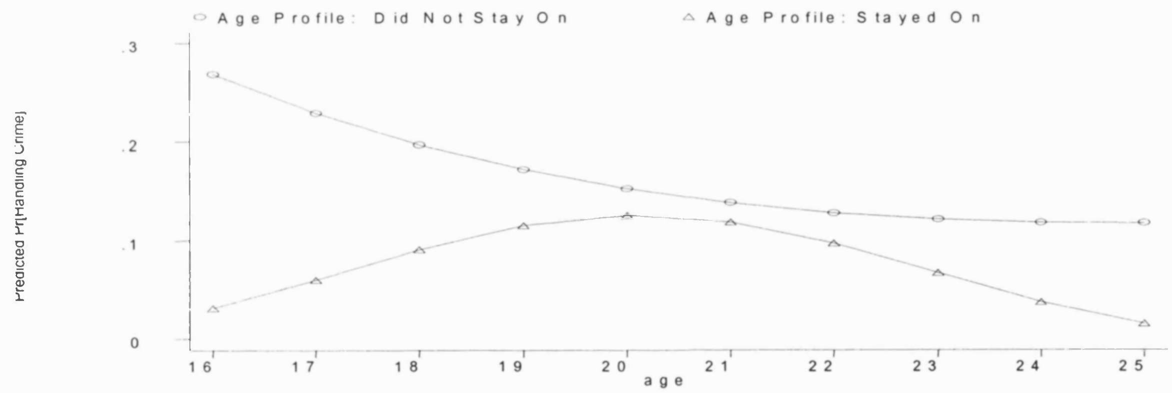
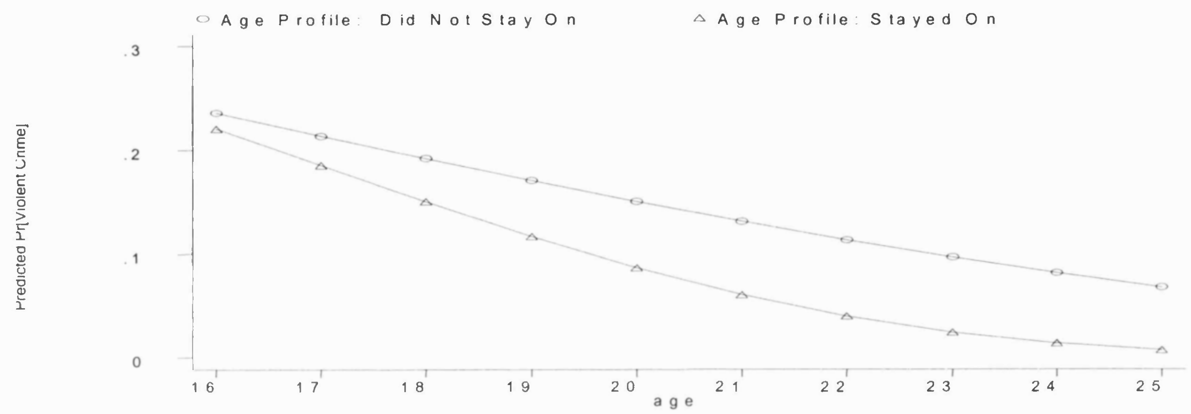


Figure 6.4C. Crime-Age Profiles by Education. Basic Model for Violent Crime



These results do not seem to support the invariance hypothesis. On the contrary, they indicate that the two groups of young people have significantly different crime-age distributions. Moreover, by the age of 25, whilst crime has declined to almost insignificant levels for the more educated people, it remains relatively high for the less educated, with little probability that it will decline to the level of the more educated group in the foreseeable future.

This finding has potentially important policy implications as crime and age are related to education which can be affected by the implementation of policy. However, from a policy perspective, it is not sufficient to highlight the difference in the crime-age profiles of these two groups. What is needed is an explanation of why the profiles are different. In order to do this, this Chapter now goes on to examine a whole range of variables that theory and past empirical work informs us may be able to explain the observed difference in the two profiles.

Thus, the procedure is to move away from the original model by progressively controlling for each set of new variables that may influence the crime-age distribution for the two groups, each time testing that the curves remain significantly different, and also testing for the joint significance of the additional variables. We would expect that if any of these variables are correlated with crime, age and education in an appropriate direction by accounting for a proportion of the difference in the crime-age distributions between the two groups we will see the two distributions move together. If the variables completely explain the difference in the profiles, then the gap will be completely reduced and the two groups will have the same crime-age profiles.

6.10 Explanatory variables

The data are rich with regard to explanatory variables so the focus is on variables related to neighbourhood/area, school, family, individual and the labour market.

6.10.1 Neighbourhood/area variables

The 1998 British Crime Survey identified locality to be an important indicator of risk of crime. Over half of all property crime and a third of all victims of property crime are found in a fifth of communities in England and Wales (Home Office Statistical Bulletin 21/98). Areas most at risk are inner city areas, areas with a high proportion of social housing and areas of high physical disorder. These are the same types of areas that are associated with offending. Rutter (1979) found delinquency to be much higher in disadvantaged areas at 36% compared to 19% in what he referred to as 'favoured areas'. This is supported by police force statistics, which reveal that between April 1999 and March 2000 Metropolitan Forces (Metropolitan, City of London, West Midlands, Merseyside, Greater Manchester, West Yorkshire, South Yorkshire and Northumbria) recorded rises in crime of over 7%, while the non-metropolitan forces recorded increases of less than 1%. The West Midlands saw the greatest increase of 16%, followed by the Metropolitan force which saw crime increase by 13%. On the other hand, in Lancashire crime decreased by around 8% (Home Office 2000).

With these findings in mind area/neighbourhood variables (ACORN groups[15] and whether individuals live in social housing) were introduced into the crime-age model. For property crime (Figure 6.5A) this does not alter the profile of the two groups very much at all. Indeed the two profiles do not look like they have shifted

[15] A Classification of Residential Neighbourhoods (ACORN) classifies households using demographic, and housing characteristics of the neighbourhood.

from the basic profiles in Figure 6.4A. This suggests that area/neighbourhood variables do not account for much of the variance in the crime-age profiles of the two groups of young people. The regression results (in Appendix C) show that with the inclusion of area/neighbouhood variables the chi-square test that the two profiles are different remains significant at the 10% level. Neighbourhood variables also have little effect on handling crimes (Figure 6.5B). The two profiles come together slightly for 20 and 21 year olds, but the profiles remain significantly different at the 1% level (see regressions results). For violent crimes, the inclusion of the neighbourhood/area variables (Figure 6.5C) moves the profile for the more educated above the less educated at age 16. After age 16 the profiles cross and become very similar in shape to the basic profile.

Figure 6.5A Crime-Age Profiles with Neighbourhood Variables for Property Crime

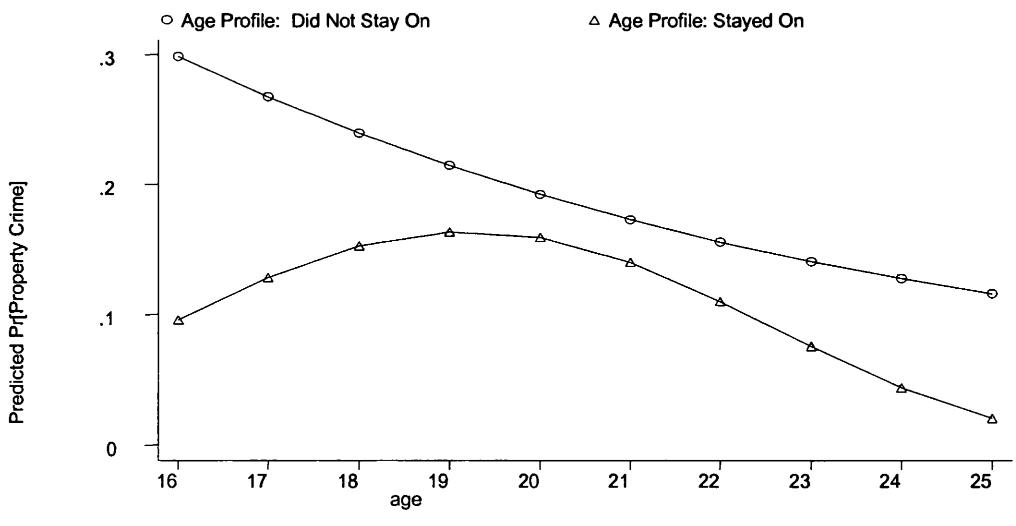


Figure 6.5B Crime-Age Profiles with Neighbourhood Variables for Handling Crime

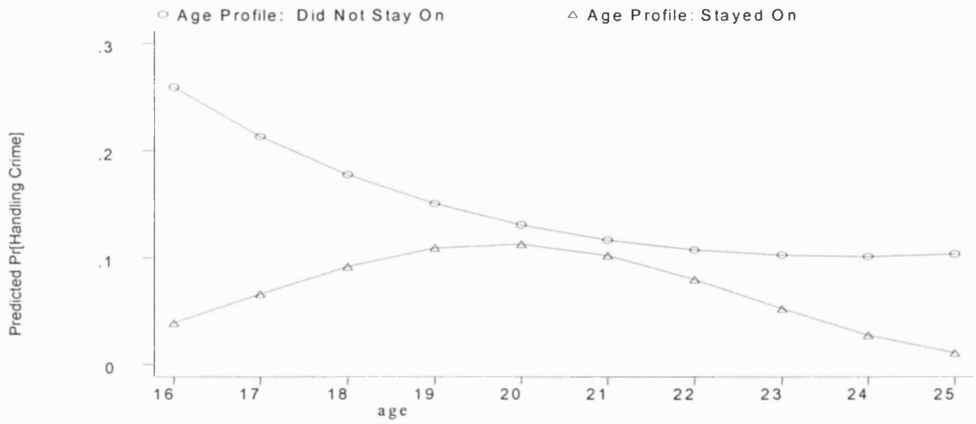
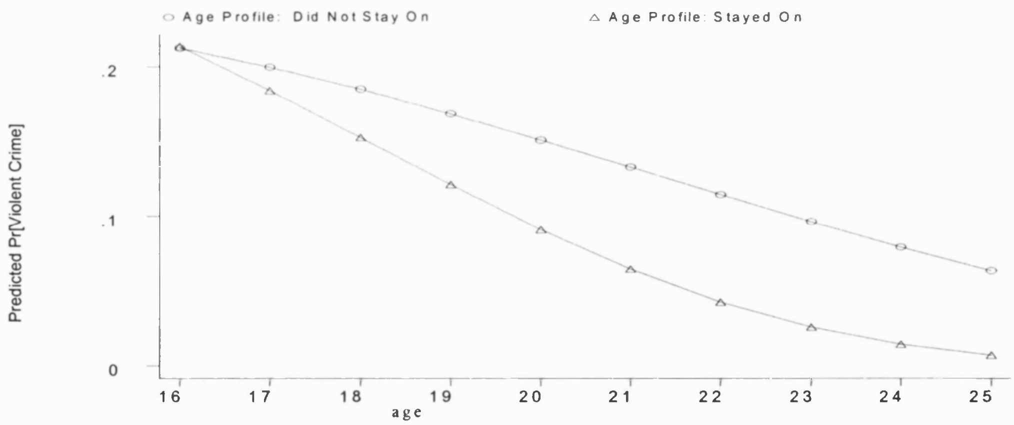


Figure 6.5C Crime-Age Profiles with Neighbourhood Variables for Violent Crime



6.10.2 School variables

In 1979, Rutter pointed out that 'schools may influence children's behaviour outside as well as inside the school' (p19) particularly in relation to delinquency. The age an individual leaves school (Thornberry et al 1985, Lochner 1999), their attendance (Rutter 1979, Nagin and Land 1993, Home Office 1998c), whether they have truanted (Graham and Bowling 1995) or been excluded (Home Office 1998c) and the qualifications they gain (ibid) are all differentially associated with offending.

Here truancy and exclusions are introduced as school variables into the model. For property crimes (Figure 6.6A), this lowers the profile of the less educated and raises the profile for the more educated. This causes the profiles to cross for 19 to 22 year olds, when the more educated group have a higher predicted probability of committing property offences than the less educated groups for these ages. Despite this, the two profiles still look different. This is confirmed in the regression results which show that with the introduction of school variables, the two profiles remain significantly different from one another at the 10% significance level. A very similar pattern is seen when school variables are introduced to the basic model for handling crimes (Figure 6.6B). The two profiles remain significantly different at the 1% level. For violent crimes, the introduction of school variables means that at the age of 16 the profile of the more educated is above the less educated where it remains, until the age of 19, when the two profiles cross and follow a similar decline (Figure 6.6C).

<u>Figure 6.6A Crime-Age Profiles with School Variables for Property Crime</u>

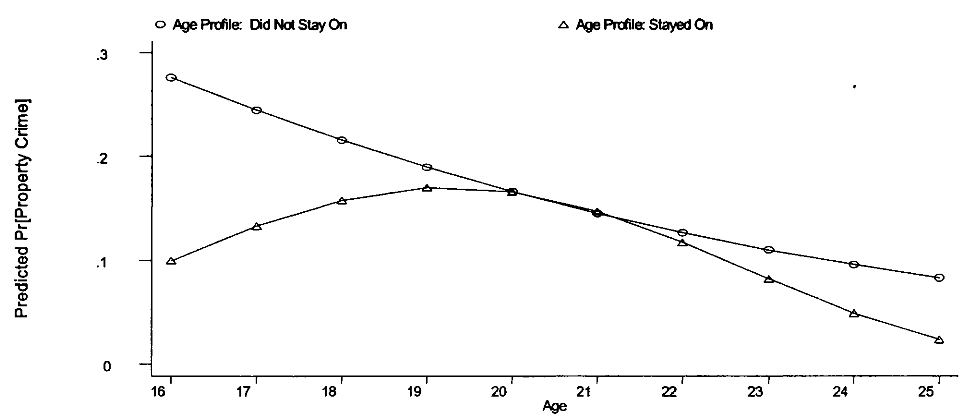


Figure 6.6B Crime-Age Profiles with School Variables for Handling Crime

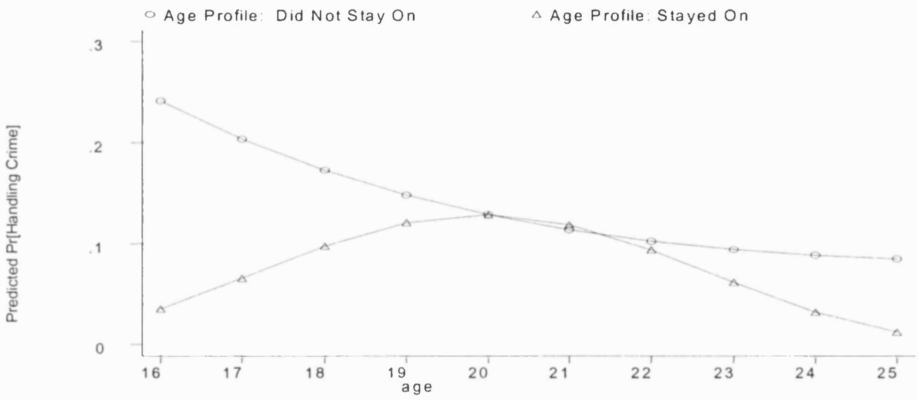
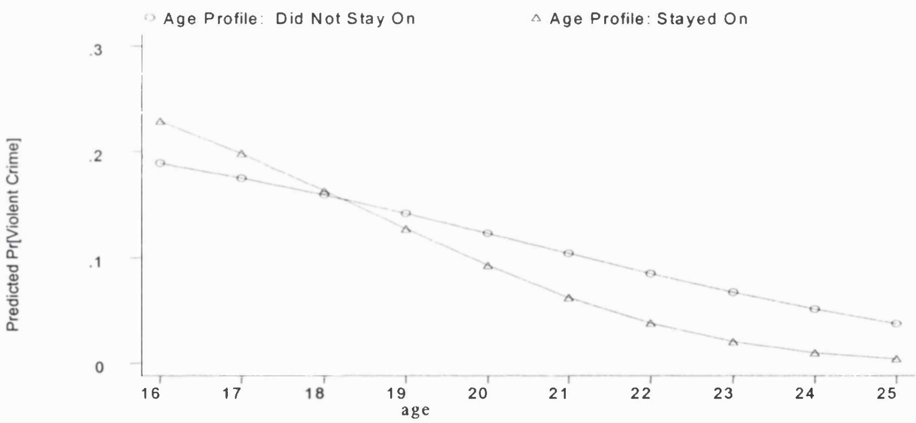


Figure 6.6C Crime-Age Profiles with School Variables for Violent Crime



6.10.3 Individual variables

Empirical work has shown that a number of individual characteristics are associated with offending. The first individual risk factor incorporated into the model is whether an individual is non-white. In 1993 around 7% of black men over the age of 18 and 12% of black men aged 25-34 were in prison in the US (Freeman 2000). In 1997 the prison population of England and Wales consisted of 18% non-white men, although non-whites only made up 6% of the entire population of England and Wales (Home Office 1998a). Another important individual characteristic related to offending is family commitment. Farrington (1995) finds marriage often encourages desistence from offending. This Chapter looks at the presence of children, which it could be argued, more accurately reflects family ties than marriage (see Graham and Bowling, 1995). Families of origin, as well as formation, have also been found to be linked to offending. Those youths who have good relationships with their parents are less likely to be involved in offending (Farrington, 1995), while those youths who have run away from home are more likely to be offenders (Freeman, 2000). This is concurrent with Farrington's work that finds that delinquents who were convicted by the age of 18 are more likely to be living away from home. These factors are taken into account here by controlling for whether an individual voluntarily lives in the parental home after the age of 16.

Inclusion of individual variables (being non-white[16], religious, having children, living with parents) affects the profiles of property crimes (Figure 7A) by lowering the profile for the less educated, which becomes almost linear. At the same time, the profile of the more educated is raised and between the ages of 20 and 21, the two profiles nearly meet. The profiles remain significantly different at the 5% level. A very similar pattern is seen in Figure 6.7B, which examines handling offences. The only exception is that the cross over between the two profiles happens between the ages of 20 and 22. Again, the regression results in Appendix C show the two profiles

[16] For all crime types non-white people have a lower probability of committing offences than whites. This may indicate that the higher rates of crimes committed by non-whites which appear in the official statistics may be more a result of selection and processing bias by the criminal justice system or it may indicate that non-whites under report their involvement in crime (Hindelang, Hirshi and Weiss 1981). To ensure that the regression is not biased in any way I also calculated the individual variable regression excluding the non-white dummy, which made no significant difference to the results at all. For acquisitive property crimes the test age_left school=age_stayed on, age2_left school=age2_stayed on moved from 7.11 to 5.47, the first significant at 5%, the second at 10%. The joint test on the individual variables was 21.24 with the non-white dummy included, and moves to 19.76 without it, both are significant at >1%. For handling crimes the age test goes from 13.59 to 9.90, both significant at >1%. And the individual variables test moves from 21.15 to 22.09, again both significant at >1%. The age test on violent offences increases from 3.22 to 3.26 once the non-white dummy is dropped. And the individual tests moves from 2.44 to 2.07.

remain significantly different at the 1% significance level. For violent crimes, the introduction of individual variables reduces the gap slightly for the youngest ages (Figure 6.7C). Otherwise the profiles are little altered by the inclusion of the individual variables.

Figure 6.7A Crime-Age Profiles with Individual Variables for Property Crime

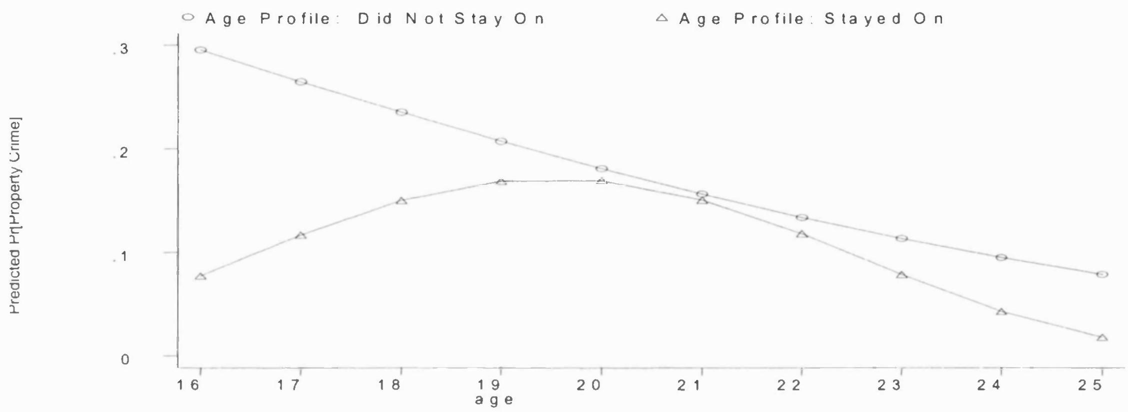


Figure 6.7B Crime-Age Profiles with Individual Variables for Handling Crime

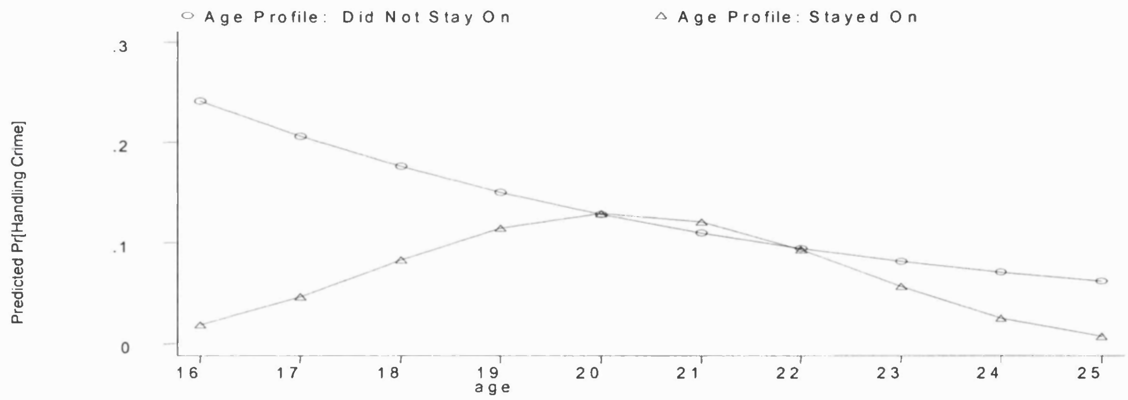
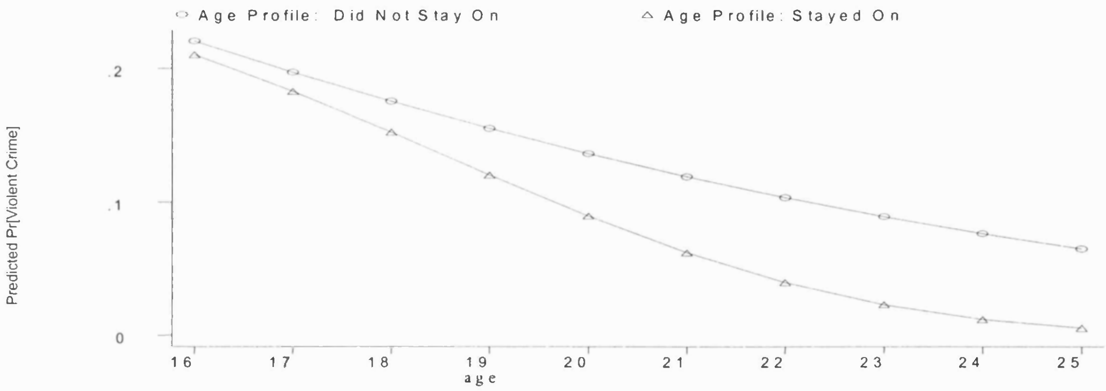


Figure 6.7C Crime-Age Profiles with Individual Variables – Violent Crime



6.10.4 Family variables

Freeman (2000) finds that many incarcerated young men have parents who were in low paid, blue collar jobs. This supports Farrington's (1996) work which finds that delinquents are likely to come from lower class families and delinquents who are convicted by age 18 are likely to come from low income families. Research has also found that delinquents are more likely to have convicted parents or delinquent older siblings (Farrington 1996, Nagin and Land 1993).

Both father's class[17] and whether an individuals family has had contact with the police are introduced into the model as family variables. When this is done for property crimes (Figure 6.8A) the profile of the less educated becomes more like the profile of the more educated. The gap remains considerable for the younger people, but by the age of 23 the profiles are exactly the same. Thus, family variables explain most of the gap for the older people. This is reflected by the fact that once family variables are introduced, the gap between the two profiles becomes insignificant.

[17] The importance of class was discussed in the section on education and offending.

When handling crimes are examined (Figure 6.8B), we find that even with the inclusion of family variables, there remains a considerable gap between the two profiles for the younger ages. However, by the age of 20 the two profiles begin to come together, meeting by the age of 22, then widening out slightly for the older ages. The two profiles remain significantly different at the 10% level.

For violent crimes (Figure 6.8C), the profile for the less educated remains above that of the more educated at all ages, even after the inclusion of family variables. The gap is widest at the age of 16. The two profiles move together at age 17, and by age 18 and 19 the profiles are almost the same, although after age 20 the gap does begin to widen out again.

Figure 6.8A Crime-Age Profiles with Family Variables for Property Crime

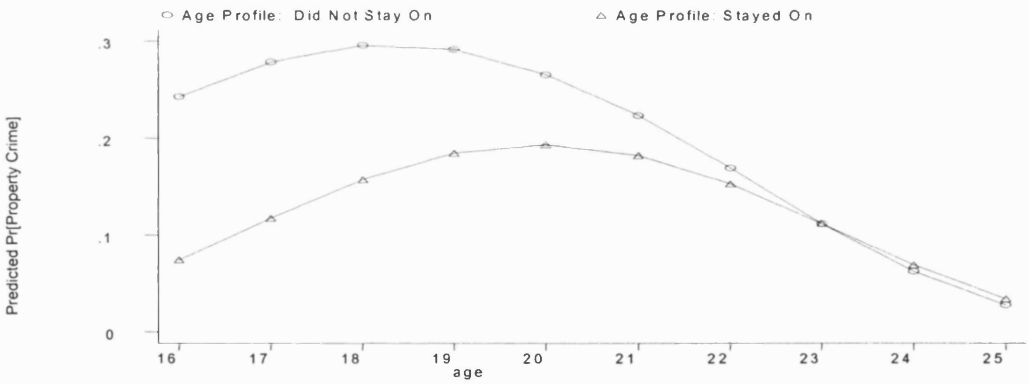


Figure 6.8B Crime-Age Profiles with Family Variables for Handling Crime

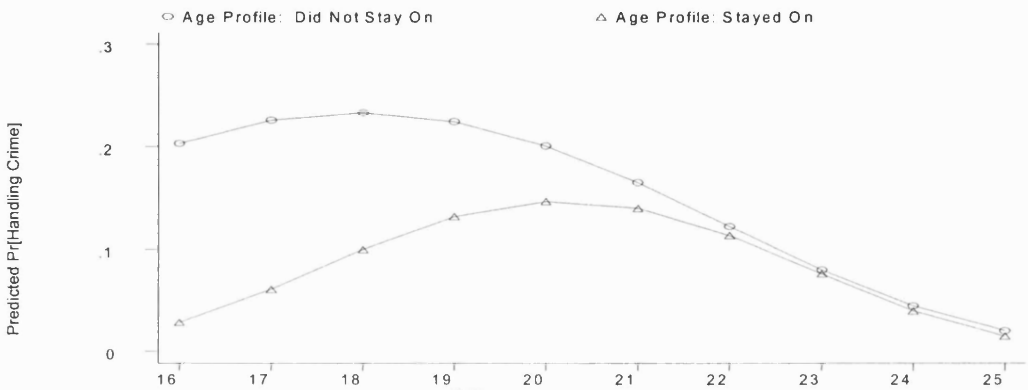
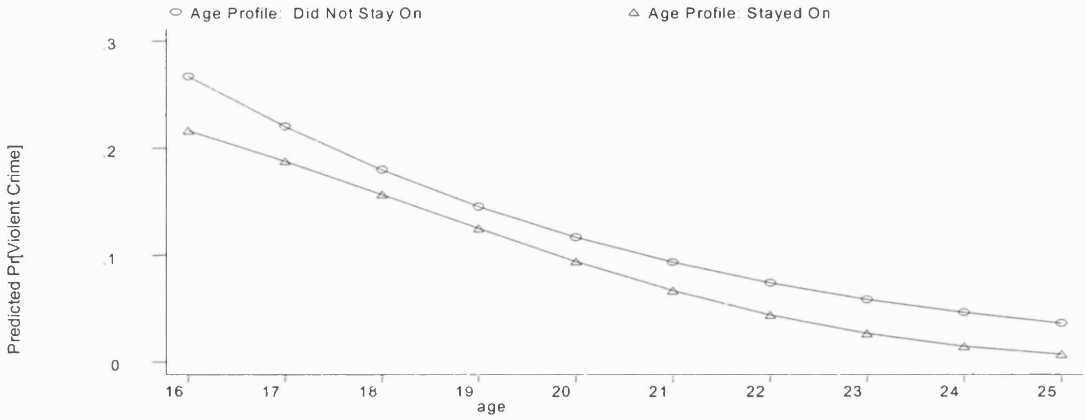


Figure 6.8C Crime-Age Profiles with Family Variables for Violent Crime



6.10.5 Labour market variables

There have been a number of studies that examine the labour market and crime (including previous Chapters of this thesis, for additional sources see reviews in Freeman 1983, 1999, Chiricos 1987, Box 1987). Although there is no consensus many studies find that, at least to some extent, crime is related to unemployment (Cook and Zarkin 1985, Land, McCall and Cohen 1990), inequality (Lee 1993) and wages (Machin and Meghir 2000, Gould, Weinberg and Mustard 2002). In this Chapter unemployment, full time employment and weekly income are added to the model as labour market variables. For property crime (Figure 6.9A) this inclusion slightly flattens the profile of the more educated for the younger ages, but has little impact on the profile of the less educated. Despite this, the two profiles are not significantly different once labour market variables are introduced to the model, as can be seen from the regression results in Appendix C.

For handling offences the profile of the more educated is again flattened with the inclusion of labour market variables to the basic model (Figure 6.9B). For the less educated, labour market variables cause the profile to decline quicker in the early years and then flatten out at a lower rate than the basic model. This suggests that for both groups, the probability of committing handling crimes is lower once labour market variables are controlled for. Despite this, the two profiles remain significantly different at the 10% level.

For violent crimes, the inclusion of labour market variables closes the gap between the two profiles at the age of 16, but does little else (Figure 6.9C). This indicates that labour market variables are more important determinants of property and handling offences than violent crimes.

Figure 6.9A Crime-Age Profiles with Labour Market Variables for Property Crime

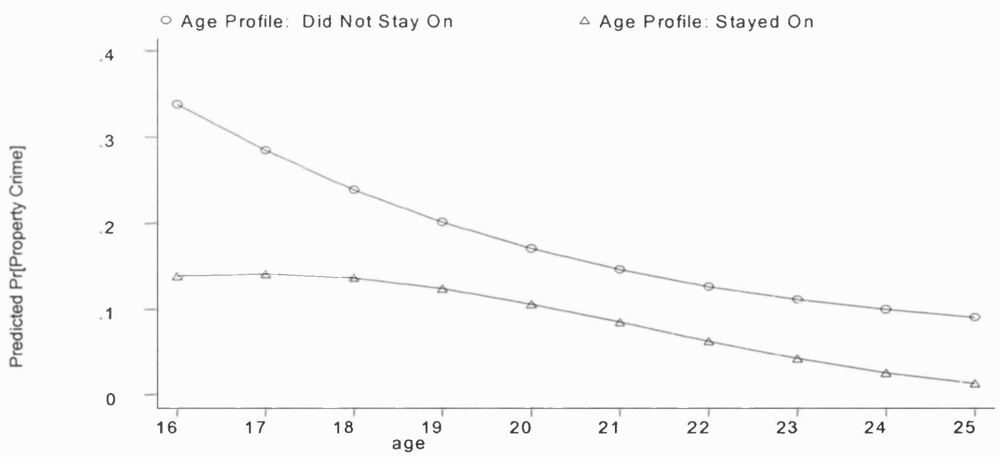


Figure 6.9B Crime-Age Profiles with Labour Market Variables for Handling Crime

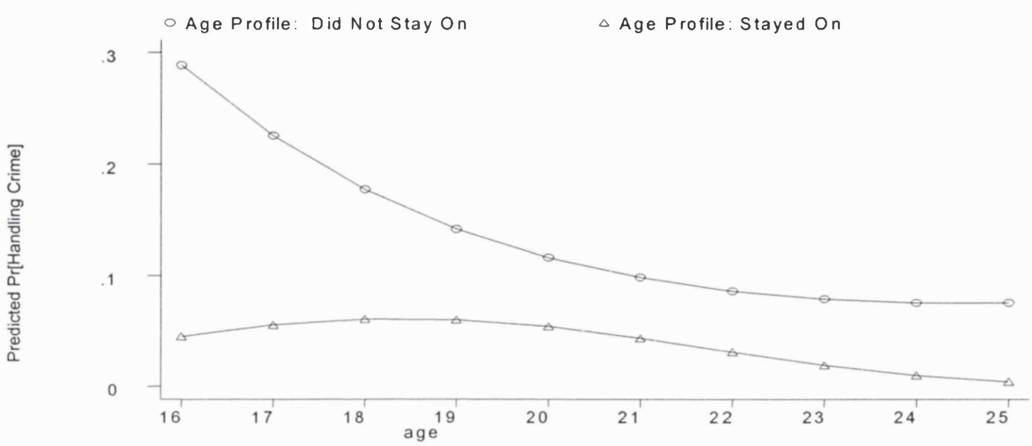
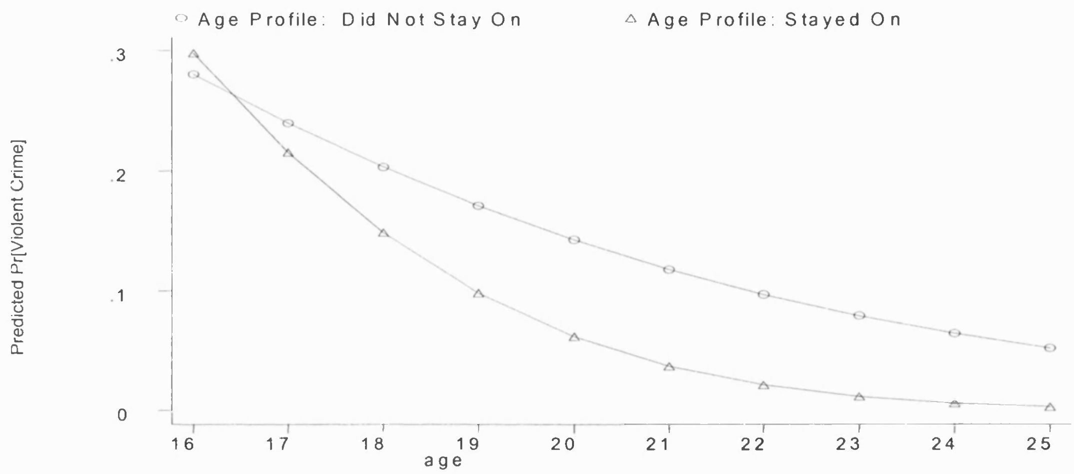


Figure 6.9C Crime-Age Profiles with Labour Market Variables for Violent Crime



6.10.6 All variables

Having examined the effect of introducing a number of different variables into the equation, we now need to consider what happens when we examine all the variables together.

When all these factors are taken into account, the crime-age profiles are indeed substantially altered. For property crimes (Figure 6.10A) there is essentially no difference between the profiles of the two educational groups at ages 16, 24 and 25. Here, differences in the other variables completely explain the gap in offending rates between those who stayed on at school and those who left at age 16. There remains only a slight gap between the two profiles from age 17 to 23. Interestingly, with all variables included a chi-square test indicates the two profiles are no longer statistically significantly different across all ages.

For handling offences, the two profiles remain different for the youngest ages despite the inclusion of all the variables (Figure 6.10B). However, at age 18 the two profiles begin to come together, by 20 the two profiles cross very slightly and by age

22 the two groups have the same profiles. This indicates that in the case of handling offences the inclusion of other variables accounts for the gap between the two profiles for the older groups, but not for the younger ages. Overall, the gap between the two profiles becomes insignificant with the inclusion of all variables.

Figure 6.10C shows that the inclusion of all variables into the violent crime model shifts the profile of the more educated above that of the less educated until the age of 21 when it falls beneath the less educated profile. Despite the crossing of the profiles, the two distributions look very similar[18].

Figure 6.10A Crime-Age Profiles with All Variables for Property Crime

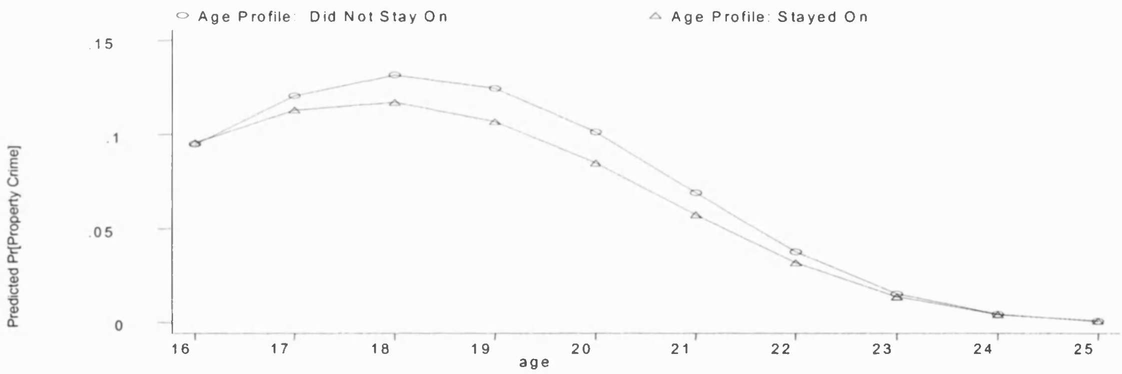
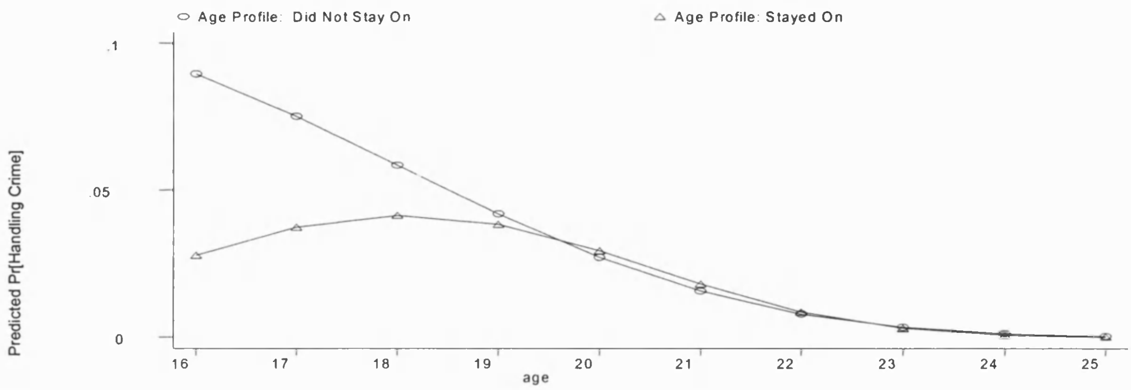
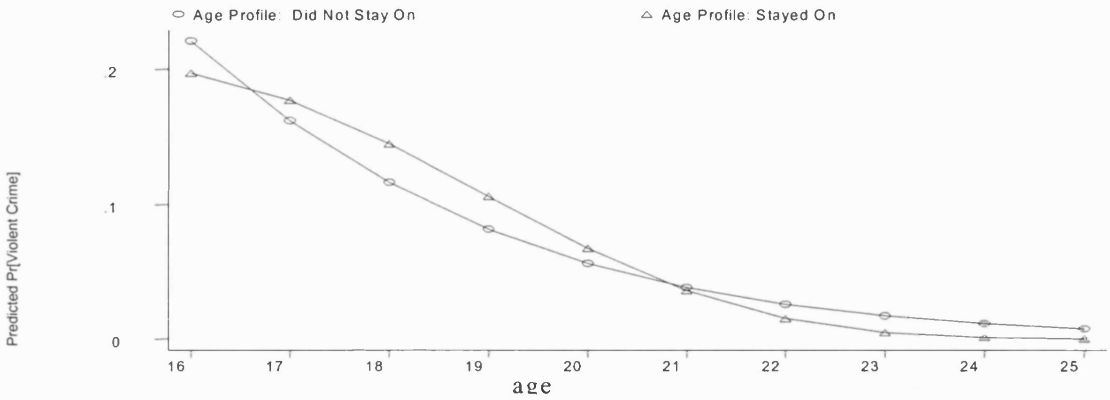


Figure 6.10B Crime-Age Profiles with All Variables for Handling Crime



[18] These findings were mirrored when this exercise was repeated using age dummies, linear and cubic forms. The crime-age profiles are on the whole significantly different from one another in the basic model. However, in the full model the difference between the profiles becomes insignificant.

Figure 6.10C Crime-Age Profiles with All Variables for Violent Crime



6.11 Examining the variables together

When all variables are included in the model, we are interested in which ones are more important. This can be considered in two different ways: The first way is to look at the individual explanatory contributions each group of variables make in explaining the gap between the two profiles. Table 6.2A shows that for property offences, the most important set of variables explaining the gap on average are: school variables which account for approximately 46% of the gap overall; family variables 26% of the gap, and; individual variables which account for 27%[19]. All the variables combined account for 90% of the gap overall, indicating that on average by combining the variables, most of the variation in the two profiles can be accounted for. But we can also see from table 6.2A that there are variations across ages. For example, individual variables explain very little of the gap for the younger ages (4% of the gap at age 16), but between the ages of 20 and 22 individual variables account

[19] These were also the variables that accounted for the largest proportion of the gap between the two profiles when this exercise was repeated using age dummies, cubic and linear functional forms.

for most of the gap. This perhaps highlights the movement away from the parental home and towards setting up new families and having children in the early twenties.

Table 6.2A Proportion of the Gap in the Crime-Age Profiles Accounted for by the Inclusion of Additional Variables for Property Offences

Age	16	17	18	19	20	21	22	23	24	25	Mean
Gap	**.226**	**.159**	**.103**	**.063**	**.043**	**.036**	**.046**	**.064**	**.085**	**.102**	**.092**
% explained by area	10.2	11.9	15.5	17.5	17.1	8.3	0	0	1.2	6.9	**9.0%**
% explained by school vars.	21.7	30.2	44.7	69.8	100.0	105.6	97.8	56.3	44.7	42.2	**45.7%**
% explained by family vars.	25.2	-1.3	-34.0	-68.3	-75.6	-16.7	65.2	100.0	122.4	105.9	**26.1%**
% explained by individual vars.	4.0	6.9	17.5	39.7	70.7	83.3	65.2	45.3	38.8	40.2	**27.2%**
% explained by labour market vars.	11.9	10.1	0	-22.2	-58.5	-69.4	-37.0	-7.8	14.1	23.5	**-1.2%**
% explained by all variables	104.4	96.9	82.5	60.3	39.0	50.0	80.4	95.3	101.2	100.0	**90.2%**

For handling offences (Table 6.2B) the most important sets of variables in accounting for the gap between the two profiles are: school variables, which on average explain around 33% of the variation in the two profiles; family variables (24%), and; individual variables (30%).[20] All variables combined, on average, account for 86% of the gap, slightly less than the property crimes. Again we see variations by age, both school and individual variables account for a much greater proportion of the gap between the ages of 20 to 22 than any other age.

[20] These were also the variables that explained the largest proportion of the gap using the age dummies, the cubic and linear functional forms.

Table 6.2B Proportion of the Gap in the Crime-Age Profiles Accounted for by the Inclusion of Additional Variables for Handling Offences

Age	16	17	18	19	20	21	22	23	24	25	Mean
Gap	**.237**	**.169**	**.106**	**.057**	**.027**	**.019**	**.031**	**.054**	**.081**	**.102**	**.088**
% explained by area	7.2	13.0	19.8	26.3	33.3	21.1	9.7	5.5	9.9	8.8	**12.5**
% explained by school vars.	13.1	18.3	29.2	52.6	100.0	126.3	129.0	40.7	29.6	29.4	**33.0 %**
% explained by family vars.	26.2	2.4	-25.5	-63.2	-100.0	-31.6	74.2	92.6	93.8	95.1	**23.9 %**
% explained by individual vars.	7.2	5.9	12.3	38.6	103.7	157.9	93.5	53.7	43.2	46.1	**29.5%**
% explained by labour market vars.	-3.0	-1.2	-9.4	-43.9	-129.6	-184.2	-77.4	-11.1	19.8	30.4	**-11.4%**
% explained by all variables	78.5	78.1	79.2	82.5	88.9	94.7	96.8	98.1	100.0	99.8	**86.4%**

In the case of violent crimes (Table 6.2C) the variables that by far account for the largest proportion of the gap between the two profiles are school variables, which on average account for 70% of the gap. Again this varies by age, school variables are more important for explaining the gap for the youngest ages (16 to 19), than for the older groups. Like property offences and handling offences, family variables and individual variables also account for large proportions of the gap between the two profiles[21], 44% and 19% respectively. Family variables account for more of the gap between the ages of 19 and 21, while individual variables account for more of the gap for 17 and 18 year olds.

Table 6.2C Proportion of the Gap in the Crime-Age Profiles Accounted for by the Inclusion of Additional Variables for Violent Offences

Age	16	17	18	19	20	21	22	23	24	25	Mean
Gap	**.015**	**.028**	**.041**	**.054**	**.064**	**.071**	**.074**	**.073**	**.068**	**.061**	**.054**
% explained by area	106.7	42.9	22.0	13.0	6.3	4.2	4.1	4.1	4.4	8.2	**10.4%**
% explained by school vars.	366.7	178.6	109.8	74.1	53.1	42.3	70.3	35.6	38.2	44.3	**69.6%**
% explained by family vars.	-233.3	-14.3	43.9	61.1	65.6	62.0	59.5	56.2	52.9	50.8	**44.4%**
% explained by individual vars.	33.3	50.0	43.9	35.2	28.1	19.7	14.9	9.6	5.9	3.3	**18.5%**
% explained by labour market vars.	220.0	14.3	-31.7	-35.2	-26.6	14.1	-1.4	6.8	13.2	19.7	**-1.9%**
% explained by all variables	193.3	185.7	153.7	120.4	96.9	83.1	77.0	78.1	83.8	86.9	**100.9%**

[21] See above.

6.12 Examining the Full Model

The second way to look at all the variables together is to examine which variables remain statistically significant in the full model (column 7 in the regression Tables in the Appendix C). Only the variables that remain statistically significant at the end can account for the gap between the profiles. For property offences, the quadratic age profile remains significant, as does whether an individual lives in the parental home. Those living in the parental home are 8 percentage points less likely to commit crimes than others. Those with family members who have had contact with the police are 19 percentage points more likely to commit offences. Those who have truanted are 14 percentage points more likely to commit property crimes.

For handling crimes, those individuals who live in the parental home are 5 percentage points less likely to commit offences Those with families who have had contact with the police are 20 percentage points more likely to commit offences, as are those who have truanted from school.

The Table for violent offences shows those who live in the parental home are 6 percentage points less likely to commit offences; those with fathers in SES V[22] are 11 percentage points more likely to commit violent crimes; those whose family have had contact with the police are 16 percentage points more likely more likely to commit offences; those who have truanted 11 percentage points more likely; and, those who live in social housing 7 percentage points more likely to commit violent offences.

[22] State pensioners or widows (no other earners), casual or lowest grade workers, or long term unemployed.

6.13 Frequency

It is possible that using a variable that records whether an individual committed a crime in the last year ignores the fact that some people may have committed only one crime, while others may have committed a large number. This may potentially be important if the frequency of criminal activity, not just whether an individual breaks the law, but how many times they do so is differentially related to age. We can see what difference taking the frequency of criminal offences into account makes to the basic crime-age profiles in Figures 6.11A-6.11C.[23]

For property crimes the profiles produced by the frequency count variable in the poisson regression[24] (Figure 6.11A) differ little from the profiles produced using the binary variable in the probit regression (Figure 6.4A). For handling crimes the profiles are slightly altered (Figure 6.11B) with the profile of the more educated rising above that of the less educated between the ages of 19 and 22. This is similar to the pattern produced when school variables were added to the basic probit model (Figure 6.6B). Taking into account the frequency with which violent crimes are committed (Figure 6.11C), the profiles for violent crimes appear to be marginally different from the original profiles. The profile of the less educated declines more rapidly, while the profile of the more educated becomes more of an inverse U shape with a peak at age 18 and a long tail off from age 22 onwards.[25]

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[23] To do this we use a poisson maximum likelihood regression which regresses the dependent variable on independent variables, where the dependent variable is a non-negative count variable, in this case, the frequency of criminal offences in the last year. No assumption is made about the functional form of the distribution.
[24] See above and the discussion in Appendix B.
[25] Chi-square tests (age_left school=age_stayed on and age2_left school=age2_stayed on) using the poisson model were significant at >1% level for all three types of crimes.

Figure 6.11A Crime-Age Profiles by Education using Poisson Regressions – Property Crime

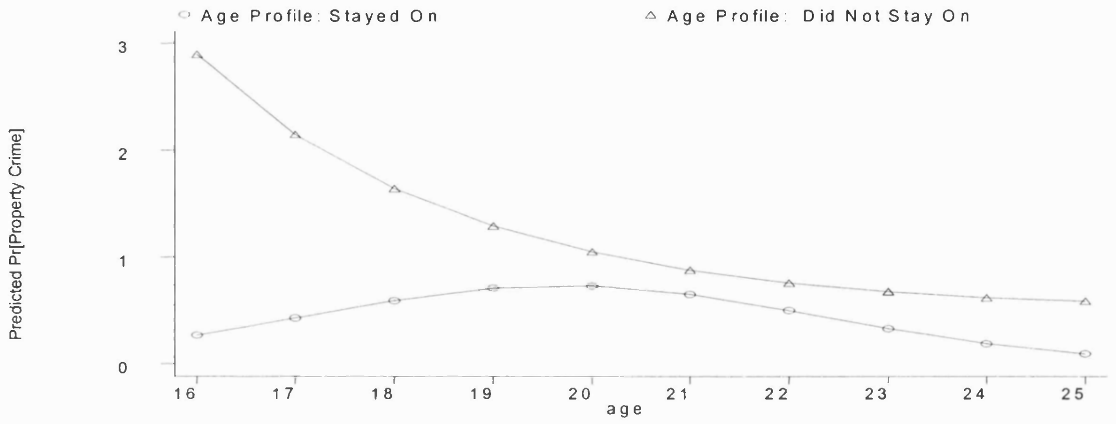


Figure 6.11B Crime-Age Profiles by Education using Poisson Regressions – Handling Crime

Figure 6.11C Crime-Age Profiles by Education using Poisson Regressions – Violent Crime

There are some problems associated with using the frequency of crimes committed in the last year, rather than just whether or not an individual had committed a crime. The main problem is that a single extreme observation could possibly distort the profiles. Moreover, in this study, 60% of those who had committed a property crime in the last year did so on only 1 or 2 occasions; 27% had committed more than 5 crimes; and only 10% of all those who had committed a property crime in the last year had done so more than 10 times. 61% of those who had committed a handling offence in the last year had done so only once or twice; 24% had done so on more than 5 occasions; and only 5% had done so more than 10 times. These patterns are similar to those produced by violent offences, 50% of those who had committed a violent offence in the last year had done so just once or twice, while only 19% had done so more than 10 times.

The fact that most individuals only commit a small number of offences confirms the idea that most crimes are committed by a small group of individuals. Of all property crimes that were committed in the last year, 18% were committed by only 3 people, 26% by 6 people, and 34% by 10 individuals. 18% of handling offences were committed by 4 people and 48% by 13 people. Of the violent crimes committed, 11% were carried out by 1 individual, 32% by 4 and 54% by 10 individuals.

Despite this, the profiles produced by the count variable are similar to those produced using the binary variable. Therefore, I can be reasonably confident that I have adopted an accurate measure of the crime-age distribution, even though I am not measuring frequency in the empirical models presented earlier in this Chapter.

6.14 Concluding Remarks

This Chapter examines the crime-age profiles of two groups of young males in England and Wales in 1992: those who have more education and those who have less. It then goes on to try to account for observed differences in the two profiles using a number of other variables which may be related to crime and age: neighbourhood/area, school, individual, family and labour market. Although in this Chapter a binary variable (whether an individual committed a crime in the last year) is used it also looked at the basic crime-age profiles produced taking account of the frequency with which young people committed crime in the last year.

The results show that the crime-age profiles for the less educated (those who left school at 16) seem to be different from the profile for the more educated group (those who stayed in education past the compulsory leaving age). Whilst the probability of the more educated group committing offences had been reduced to negligible levels by the age of 25, the profile for the less educated group showed little sign of decline from around the age of 22. By age 25, the latter group had a much higher probability of committing all three types of offences examined here than the more educated group.

Once other variables were introduced into the equation, the gap between the two profiles was reduced. In some cases, for particular ages or offences, the gap was completely removed. Overall the most important sets of variables in accounting for the gap in the profiles for all three crime types were school, family and individual variables. These variables differentially accounted for more or less of the gap at particular ages. The individual variables which remained significant in the full model were: whether individuals live in the parental home (negative for all offences); whether their family had previous contact with the police (positive for all offences);

whether the individual played truant from school (positive for all offences); whether the individual's father was SES V (positive for violent offences), and; whether an individual lived in social housing (positive for violent offences). These are the variables that bring the profiles together in the full model. They are also the variables which act as individual determinants of crime, regardless of age.

This Chapter has shown that age, although correlated with crime, is also correlated with other variables such as schooling, individual and family characteristics, which are differentially associated with the probability of young people of the same age committing crimes. Once we take into account the fact that the two groups vary in terms of other observable characteristics (such as whether they truanted or were excluded from school, where they live, who they live with and what they do), we see a reduction in the gap between the two groups and the profiles are brought together.

This research suggests a number of possible policy implications for someone who is interested in bringing the youth crime rate down. The first, which is probably the most obvious and easy to target, is to encourage youths to stay on at school, which would, in the context of this research, facilitate a jump across education profiles. The recent introduction of the Educational Maintenance Allowance[26] for children staying on at school may go some of the way to encourage children, particularly those from lower income families to stay in education (Dearden et al 2001). Unfortunately, the data used here are not appropriate to elaborate on this idea in terms of educational qualifications, but it would seem that this is an area worth investigating in future research. What research (quantitative and qualitative) needs to establish, is whether it

[26] An allowance of up to £30-£40 paid to the young person during term time if their annual family income is less than £30,000.

is the acquisition of qualifications or merely the act of staying on at school that achieves this protective factor against crime.

Alternatively, some policies designed to affect the variables that close the gap in the crime-age profile between the less and the more educated may have the potential to reduce crime. This would include policies to reduce truanting such as the publication of truancy league tables and the provision of facilities for less academic children to maintain their interest in the education system. The recent emphasis placed on reducing child poverty by the Labour government, such as the 'Sure Start' programme, is also likely to help reduce differences between children by improving conditions for the poorest children in a number of key areas such as health, social and emotional development, children's ability to learn, and family and community bonds. These measures are likely to equip and motivate children better for education as well as reducing the financial burden placed on families where children remain living in the parental home and continue in education past the age of 16. However, these are likely to be much more long term policy measures that may only have the potential to affect future generations of school leavers.

Through a combination of policies aimed at improving conditions in a number of areas, it is likely that differences in criminal profiles shown in this Chapter can be reduced over time. The implementation of such policies generates a role for future research to evaluate their success on a number of important outcomes including crime and education.

7. Conclusion

7.1 The Contributions of this Thesis

The focus of the research presented in this PhD was to examine the relationship between crime and the labour market. Although this is by no means a new research agenda, the work presented herein makes a number of original contributions to the area, both substantively and methodologically.

7.1.1 Substantive Contribution

Despite the large literature that exists within the field of crime and the labour market, the existing evidence points to a general lack of consensus as to which labour market variables are most strongly related to crime. By examining shifts that have occurred in the labour market and the effect these have had on crime, this thesis set out to provide new evidence on the most robust labour market determinants of crime.

The findings of this thesis are, that of the labour market variables considered, wages are the most consistent and robust predictor of crime. Property crime is found to be higher in areas where wage inequality is higher (Chapter 2) and where wages at the bottom end of the distribution are lower (Chapter 3). Perhaps the most compelling evidence for the existence of a link between property crime and low wages is found in Chapter 4, where the existence of a crime-wage link is tested by looking at a situation where people on the margins of criminal participation receive a wage increase. This Chapter shows that the introduction of the National Minimum Wage to the UK labour market in April 1999 affected some areas more than others depending on the initial proportion of people in the area paid less than the minimum before the Minimum Wage was introduced. Those areas most affected saw relative reductions in crime compared to other areas. Moreover, the relationship between property crime and low wages was shown to be stronger for young males and males working in low-skilled occupations. This is not surprising given the expectation that such people are among the most marginalized in the workforce.

While Chapter 4 identifies a link between crime and low wages by focusing on the protective factor of increasing the wages of those at the bottom of the wage distribution, Chapter 5 identifies a process that decreases wages at the bottom of the wage structure and thus increases crime. Chapter 5 provides evidence showing that increased female labour force participation tends to reduce male wages at the bottom end of the distribution, and this has a knock-on effect, which leads to a rise in crime. Again, this effect is shown to be stronger when considering males in low skilled occupations.

The fact that low wages seem to be a critical determinant of property crime indicates that perhaps motivation is the driving factor associated with crime. Thus, increasing wages reduces crime because it reduces the motivation for crime. This supports other work (Chiricos 1987) that identifies a negative motivational effect as the most important factor in explaining crime.

Explaining violent crime in terms of wages proved more difficult. Violent crime was found to be positively related to average wages in Chapter 2, yet Chapter 3 failed to uncover a statistically significant relationship, while Chapter 5 shows the introduction of the Minimum Wage to have a similar crime reducing effect on violent crime as property crime (albeit one that is much less statistically precise). The lack of consistency in identifying the wage determinants (or indeed, as will be shown, any determinants) of violent crime is not surprising given the relative infrequency with which violent crimes appear in the criminal statistics. Indeed, in 2001/2002 less than 15% of all notifiable offences were violent crimes (Home Office 2002).

Like much of the existing literature the relationship between unemployment and crime is fragile at best and much less robust than the relationship between crime and wages. Evidence presented in Chapter 2 shows a positive relationship between unemployment and both property and violent crime when analysed using cross-sectional data. However, this type of analysis is shown to be statistically and conceptually weak, in particular results produced from cross-section data are likely to suffer from omitted variable bias. When using the methodologically more appealing longitudinal data, the effect of unemployment on both property and violent crime is shown to be statistically insignificant. This is congruent with evidence from Chapter 4, which fails to uncover a statistically significant effect of unemployment on either property or violent crime.

However, Chapter 3 identifies unemployment as being negatively related to both property and violent crime, although only the relationship with property crime is statistically significant. Thus, in areas where unemployment is higher, crime is lower. This makes sense if we think that people who are unemployed are less likely to go out, making them less likely to be victims of violent crime and also less likely to be victims of property crime, as their presence in the home will increase the guardianship of their property. However, I am reluctant to attach a great weight to this result given the conflicting and contradictory evidence on the relationship between crime and unemployment in other Chapters of this thesis.

While the labour market determinants of crime were the key focus of this thesis a number of other demographic or socio-economic variables were found to be related to crime. For example, a number of measures of deterrence were shown to be related to measures of crime. The numbers of police officers are found to be negatively related to property crime (Chapters 2 and 5) and violent crime (Chapter 2). The proportion of individuals found guilty is also shown to have a negative effect on property crime (Chapter 2). Evidence on the effect of the crime clear-up rate is more contradictory. Chapter 4 finds the crime clear-up to be negatively related to both property and vehicle crime, but not violent crime, while Chapter 3 fails to find a statistically significant effect of crime clear-ups on any crime type.

The most robust evidence on the importance of demographic and background factors is provided in Chapter 6. This shows that education is an extremely important predictor of youth crime and delinquency. Youths who leave school at 16 are shown to have, on average, higher levels of all types of crime that those who stay on past the compulsory school leaving age. Other factors identified in this Chapter as having a significant effect on youth crime are: whether individuals lives in the parental home (negative for all offences); whether their family had previous contact with the police (positive for all offences); whether the individual had played truant from school (positive for all offences); whether the individual's father was SES V (positive for violent offences), and; whether an individual lives in social housing (positive for violent offences).

In summary, this research identifies wages, in particular low wages, as the most robust labour market determinant of crime. However, labour market variables are not the only ones to affect crime. Evidence presented here indicates a range of deterrence and demographic variables also have an impact on crime. Demographic and lifestyle variables are particularly important in accounting for youth crime.

In addition to identifying which determinants are most important for crime, this thesis also offers evidence concerning data and methodological issues, a discussion of which is now turned to.

7.1.2 Methodological Contribution

In the past much of the work on the labour market determinants of crime in the UK has relied on economy wide time series data. This current work improves on that by using area level data at various levels of aggregation, as well as individual level data, to look for relationships that may be obscured in the more aggregate data. It also uses new methodological tools, like looking for quasi-experimental situations that allow one to more accurately look at the key hypotheses of interest.

The strengths of using individual level data have been illustrated in Chapter 6. Individual level data such as the Youth Lifestyles Survey, offer a rich depth of information in terms of both crime and delinquency, and also background variables relating to demographic, socio-economic and lifestyle factors. This makes it possible to both elaborate on the relationship between crime and its determinants for individuals, and also to uncover the more subjective characteristics associated with criminal behaviour such as family criminal associations.

However, individual level data should not be seen as some kind of methodological panacea. It does have limitations. As pointed out in Chapter 1, the relatively small sample size and the cross-sectional nature of the data provided by many self-report studies, such as that used in Chapter 6, do raise issues of representativeness. Moreover, as Chapter 2 showed, models using cross-sectional data are more likely to suffer from omitted variable bias (or unobserved heterogeneity) than other studies, which may cause results to be biased. Chapter 2 also pointed out that crime is heavily persistent over time and that the failure to be able to account for this persistence by using data measured at only one point of time may mean that some of the factors which help to explain crime are ignored.

Although often criticised for their failings, this research has shown that whilst the official statistics do have limitations, they also provide a rich source of data with which to analyse the relationship between crime and the labour market, not found elsewhere in the UK. Their strength lie in the ability they give the researcher to construct longitudinal data with which it is possible to follow the same units or areas over time. There are a number of methodological advantages of using this kind of data. For example, under certain conditions, they allow the researcher to examine changes in the trends and patterns of crime, despite the existence of the 'dark figure' of unreported and unrecorded crime.

Moreover, as Chapter 3 identified, there are likely to be a number of factors which affect crime that we are unable to measure. Using area level data measured over time makes it possible to control for characteristics which differ across police force area, but are constant over time through the use of an area fixed effects model. In addition those characteristics which vary over time, but are constant across areas (such as the macro economic shocks which hit the economy as a whole), can also be controlled for by including a measure of each time period in the model.

Another methodological advantage of these area level data measured across time is that they allow the incorporation of lagged measures of variables. This is extremely important because as Chapter 2 illustrated (and as discussed above), both property crime and violent crime are strongly persistent over time. This enables one to say something about dynamic, and not just static, processes.

In terms of addressing hypotheses, examining changes over time allows the researcher to ask the methodological question that corresponds best to theory: What happens to crime across areas if the hypothesised determinants of crime change? This makes it easier to establish causality.

In the natural sciences causality is routinely established through experiment, where a group of people are randomly assigned into two groups. For example, in medical trials one group receives a new drug, the other a placebo. Both groups are monitored and if the first group have a change of condition compared to the second group, this change can be attributed to the new drug.

Experimental data in the social sciences are very rare. Quasi-experimental data (which themselves are rare), offer the best opportunity for social scientists to establish the causal affect of a particular determinant (Achen 1986, Schutt 2001). Chapter 4 showed that such a situation was offered by the introduction of the National Minimum Wage in April 1999 to the UK labour market. By utilising the fact that areas differ in the proportion of people paid beneath the Minimum Wage before it was introduced and using this as a quasi-natural experiment, Chapter 4 carried out a before and after analysis of the crime rate. The results show that areas with a higher proportion of people paid less than the minimum (i.e. those areas most affected by the Minimum Wage introduction) saw greater crime reductions relative to areas less affected. The only factor which varied across these areas was the extent to which they were affected by the introduction of the Minimum Wage. Thus, differences in criminal outcomes can clearly be attributed to the Minimum Wage increasing the wages of the low paid.

A further methodological strength of the quasi-experimental nature of the data used in Chapter 4 is that the Minimum Wage is an exogenous independent variable. One of the problems with previous work that looks at the relationship between crime and low wages is that these two variables can be thought of as being jointly determined. Low wages can affect crime, but crime can in turn affect the level of wages an individual receives. However, Chapter 4 avoids this problem by using the Minimum Wage as a type of instrumental variable for low wages.

7.2 Placing the Findings into Policy Context

One of the strengths of the work presented in this thesis is that it is based on nationally representative data.[1] This means that the results produced should be representative of society as a whole. This is important for any criminologist interested in linking quantitative research to criminal policy.

This research produces a number of possible policy suggestions, the first set of which are aimed at reducing crime by targeting the determinants of crime as identified in this thesis; the second group relate to the need to improve the quality of the existing crime data in the UK.

[1] Even with the small sample size of the Youth Lifestyle Survey used in Chapter 6, these data should be representative of 16-25 year olds.

7.2.1 *The Determinants of Crime*

As discussed above, the most robust and consistent labour market determinant of crime is shown to be wages, in particular low wages and wage inequality. Thus, anyone interested in reducing crime should look to reduce wage inequality and to raise the wages of those at the bottom of the wage distribution. In doing so, one should however, be careful to set the findings in their proper context.

The results presented in Chapter 4 show the positive effect the introduction of the Minimum Wage had on reducing crime. As yet, we do not have enough data to examine whether this is a one-off effect or whether the effect will be longer lasting. Although perhaps rather obvious, the likelihood the effect will be longer lasting will be higher if the levels at which the minimum is set continue to be reviewed regularly and to keep up with the level of inflation.[2]

Given the importance of raising the wages of those at the bottom, perhaps the UK could learn something from 'The Living Wage Movement' which has been adopted in many areas in the US. The Living Wage Campaigns seek to pass local ordinances requiring private businesses that benefit from public money to pay their workers a living wage (see Pollin and Luce 1998). Unlike the Minimum Wage, which is set and controlled centrally, the living wage is organised locally by coalitions of community, union, and religious leaders. This means that living wages can be set differently from place to place, often taking into account differences in living costs across these areas. Moreover, many

[2] For example, the UK Minimum Wage was raised to £4.10 in October 2001 for adults and £3.50 for younger people.

living wage coalitions are proposing other community standards in addition to a wage requirement, such as health benefits, vacation days and community hiring goals.

The importance of increasing wages for those at the bottom of the wage distribution (as demonstrated in this thesis) supports changes that have been made to means tested benefits. For example, a policy change seen in recent years which is likely play an important role in helping those with low wages is the Working Families Tax Credit that was phased in between 1998 and April 2000. This is an extension of the old Family Credit but is more generous in terms of income support and the rate at which support is reduced as family income rises.

Other policies aimed at encouraging low wage workers to gain more education may not only have the potential to increase the earnings power of the low paid but also improve the state of overcrowding in the low skilled occupations, by allowing them to compete for better jobs. Thus, this evidence would suggest that recent moves to allocate additional resources to 'life long learning' schemes after the publication of the Moser Report (1999) may help to alleviate the problem by improving the basic skill levels of those who are disadvantaged in the labour market.[3]

The importance of education in reducing crime is also identified in Chapter 6, from which a number of policy measures that may help in reducing youth crime present themselves. The first is to encourage youths to stay on at school. As more and more youths obtain educational qualifications, the stigma of having less education grows. Moreover, the increasing wage returns to education means that those with less education

[3] Although there is a dilemma expressed by Willis (1977) that if everyone were well qualified, no-one would be well qualified, and, moreover, there would be fewer people to fill the unrewarding positions.

are likely to end up in low paid employment, which as the rest of the thesis has shown, is itself a strong determinant of crime.

As discussed in Chapter 6 the recent introduction of the Educational Maintenance Allowance (EMA) for children staying on at school may go some of the way to encourage children, particularly those from lower income families to stay in education. Indeed, the evaluation of the EMA reports very positive results (Dearden et al 2001). As it is usually the less academically able children from the poorer backgrounds who leave school, policies to improve facilities for less academic children and to maintain their interest in the education system may go some way to encouraging these types of children to stay in the education system. The recent emphasis placed on reducing child poverty by the Labour government, such as 'Sure Start', is also likely to help reduce differences between children by improving conditions for the poorest children in a number of key areas such as health, social and emotional development, children's ability to learn, and family and community bonds. These measures are likely to equip and motivate children better for education as well as reduce the financial burden placed on families where children remain living in the parental home and continuing in education past the age of 16.

There are a great number of suggestions for policies or support for existing policies discussed above, all of which may be effective in reducing crime. However, many of these are long term policy measures that may only have the potential to affect future levels of crime.

7.2.2 Crime Data

The second set of policy recommendations which stem from evidence presented in this thesis concerns the systematic and consistent collection and provision of good quality crime data. It is only with good quality data that researchers are able to carry out robust examinations of the factors that determine crime.

Evidence presented in this thesis support the argument that what is needed is the collection of data which incorporates some kind of longitudinal design. Indeed, one of the most powerful findings to result from this research is the methodological advantage associated with the use of longitudinal data. Ideally, we would like to follow the same people over time, but where this is not possible data following consistently defined areas allows the construction of area level longitudinal data.

One of the key advantages of using official statistics is that they are available across areas and over time. In the future, when data collected at the smaller area levels (such as Crime and Disorder Reduction Partnership areas used in Chapter 3) are available over longer periods of time, the official statistics will provide an even richer source of area data.

A clear recommendation from this research is to allow the BCS to release area identifiers.[4] At present, the Home Office remains reluctant to do this for fear that particular individuals may be recognised. This argument appears weak against the evidence presented here for the need to examine crime across areas. Perhaps researchers could be entrusted with the area identifiers, and forced to sign an anonymity disclaimer.

[4] This would not strictly be new but rather a return to previous practice. As has been noted throughout this thesis the BCS released area code in the early years of the survey and a number of researchers have taken advantage of this (see Hale et al 1994, Osborn et al 1992 or Trickett et al 1995). However, the area codes in the early data sets have subsequently been removed.

This would allow the construction of longitudinal victimisation data, which could be compared to the official statistics.

However, a problem that is brought to light by the need for data consistently measured over time and area, is that both the official statistics (measured both at police force area and Crime and Disorder Reduction Partnership level) and the victimisation data collected by the BCS are based on area boundaries that are not consistently defined. Evidence provided by this thesis strongly supports the recommendation for keeping area boundaries consistent over time to allow the construction of longitudinal data measured over area and time.

Another policy suggestion which could be made from the evidence presented in this thesis is to incorporate some kind of experimental design into the data. Although experiments are generally frowned upon in the arena of the social sciences for ethical (as well as financial) reasons, the evidence presented here has highlighted the methodological advantages of work that uses experimental or quasi-experimental data.

While it is generally thought unfair (on 'ethical' grounds) to randomly assign individuals into control and treatment groups, because this means that one group is privileged over the other in the short term, doing so may produce better quality research that would benefit all groups in the long run. While it may never be possible to have a fully experimental design, current government initiatives such as Sure Start or some regional initiatives may offer quasi-experimental opportunities in the future in much the same way as the Minimum Wage introduction (used in Chapter 4), where they have a differential effect across areas.

While the evidence presented in this thesis points to these types of design as providing the best data, there are still ways that existing data could be improved upon even where it is not possible to incorporate a longitudinal or experimental element. For example, carrying out surveys regularly will allow researchers to take pooled cross-sections to look at differences in crime over time. Since 2001, the BCS has started to sample continuously (Home Office 2001) and evidence presented in this thesis suggests this is a good move, particularly in the future when this regular data will be available for a longer period of time.

Another way to improve the data is to ensure some consistency across surveys. The depth and richness of the data from the Youth Lifestyle Survey that was shown in Chapter 6 could be put to greater use if it is carried out again in the future.[5] Asking the same question or group of core questions across different surveys or using the same survey carried out in different time periods will allow comparisons to be made between different surveys.

Data could also be improved by trying to increase the representativeness of samples. Surveys should endeavour to sample a large enough population to ensure the data they collect are representative of the entire population, or at least a particular population of interest. In particular, special effort should be made to contact hard to reach groups such as the homeless and 'off record' youths.

Surveys are very costly and it is easy to make suggestions which would improve the quality of data but which could never be implemented because of the huge expense likely to be incurred. However, many of the suggestions above involve reforming existing data sources such as the BCS. Other methods may include adding questions on crime to

[5] Two surveys have been carried out to date, the first in 1992/3, the second in 1998/9.

existing surveys such as the Labour Force Survey which, as discussed in this thesis, is a nationally representative survey of around 60,000 households carried out on a quarterly basis.[6]

In terms of finances, it should be borne in mind that between 2000 and 2001 the government spent some 13 billion pounds on the criminal justice system. The bulk of this was spent on policing (61% of the total) and prisons (which accounted for an additional 15%). If better crime data were collected, researchers might be able to more accurately pinpoint the causes of crime. Criminal policy, in turn, may be better able to accurately target the causes of crime and thus may have more success in reducing crime. In the long run this could reduce the expenditure needed to maintain the police force and prison system.

7.3 Potential Limitations

Whilst this thesis has made a number of contributions there are some potential limitations to the work presented herein, which need to be considered. The first cautionary note is related to the methodology utilised throughout much of this thesis, namely fixed effects models to analyse longitudinal data. The strengths of using such a technique have been repeatedly given in previous Chapters and the advantages over cross section and time series analysis are clear. However, some of the strengths of fixed effects models also produce weaknesses. For example, one of the advantages of this methodology is that the model is able to control for unobserved factors that may effect crime, which other types of methodologies (particularly those associated with cross

[6]Other possibilities include using the General Household Survey which already asks about burglary to extend its range of crime questions. Or the British Household Panel Survey which already contains a young persons supplement asking about delinquency.

sections) cannot. However, while such factors can be controlled for they cannot be identified nor estimated. Moreover, while many factors are likely to be either constant across areas or time, there may still be some other factors which do not fit this criteria, and are thus not included in the model.

Another cautionary note relates to issues surrounding the 'ecological fallacy'. When interpreting the findings of this research it must be borne in mind that chapters using area level longitudinal data inform us only of relationships that work at the area level, while individual level data (Chapter 6) only inform the reader of individual risk factors. And even individual level data are unable to elaborate on how risk factors operate for particular individuals, for this, qualitative interviews with particular individuals would be needed.

A final point relating to potential issues or weaknesses with the work presented in this thesis relates to the interaction of empirical investigation and theory. While this work draws heavily from a wide range of theories to build hypotheses, construct empirical models and help interpret certain findings it remains unable to provide evidence as to which of the sociological and criminological theories are preferable. Indeed, many of the theories offer similar predictions for relationships between crime and the labour market. One issue with trying to provide evidence with which to differentiate between theories is that some theories are not created for being tested (Gibbs and Martin 1966), while a number of others offer few, if any, distinctive predictions by which they can be tested against other theories.

Moreover, in order to differentiate between theories the data would need to include variables which could act as proxies for specific aspects of different theories.

While this is not impossible (see for Box and Hale 1984 for example) it is often very difficult to find suitable proxy variables with which to actually test the predictive strengths of one or a number of different theories. While failure to provide evidence as to which is the most appropriate theory does not pose a particular problem for this work (as the main focus is to offer a quantitative empirical examination of the relationship between crime and the labour market drawing on theory rather than a more theoretically oriented thesis) its existence should be acknowledged nevertheless.

7.4 Future Directions

This research has produced evidence relating both to the substantive debates concerning factors most associated with crime and technical concerns surrounding the appropriate data and methodological tools with which to examine these relationships. However, as well as answering questions, the work presented here raises questions and issues which should be addressed in future research.

Many of these future projects depend on data becoming available over time. For example, Chapter 3 showed the advantages of using the smaller area data available at Crime and Disorder Reduction Partnership level to look at how the relationship between crime and the labour market works at the more localised level. However, as yet data at this level are not available over very long periods of time. When these data do become available, this will make it possible to look at the importance of dynamic effects or long run changes in crime over time.

Another question which deserves future attention when more data become available is whether the Minimum Wage effect on crime identified in this thesis produces a one-off reduction in crime or whether the effects are longer lasting. In future, it will also be possible to examine whether additional increases in the level of the Minimum Wage also have the potential to reduce crime.

If the British Crime Survey ever releases its area codes, this will open up the possibility for future research to examine whether some of the results shown in this thesis hold true for victimisation data. If the results produced from the BCS are congruent with those described here, this will add additional weight to the overall findings. This is true not only of the BCS, but any other type of data used to examine these same issues, both qualitative and quantitative. If two or more different studies using different data and different techniques reach the same conclusions, it is harder to ignore or dismiss the findings.

The final area of future research brought to light by this current study is the possibility of evaluating the effect of policy initiatives aimed at reducing crime. Chapter 4 showed that a policy, not directly aimed at reducing crime, could nevertheless have an indirect effect on crime. Systematic evaluation of policies that have the potential to influence crime would seem to be a very important research agenda for the future.

8. Appendices

Appendix A: Data Appendix

Chapter 2: Looking for A Relationship Between Crime and the Labour Market: Some Exploratory Research

Police Force Areas

There are 43 police force areas in England and Wales. Most correspond to counties or an aggregation of counties. These can be seen clearly from the Table below.

Police Force Areas of England and Wales

Police Force Area	County
Greater Manchester	Greater Manchester
Merseyside	Merseyside
Cheshire	Cheshire
Cumbria	Cumbria
Lancashire	Lancashire
Cleveland	Cleveland
Durham	Durham
Northumbria	Northumberland, Tyne and Wear
South Yorkshire	South Yorkshire
West Yorkshire	West Yorkshire
Humberside	Humberside
North Yorkshire	North Yorkshire
West Midlands	West Midlands
Staffordshire	Staffordshire
Warwickshire	Warwickshire
West Mercia	Hereford, Worcester, Shropshire.
Derbyshire	Derbyshire
Leicestershire	Leicestershire
Lincolnshire	Lincolnshire
Northamptonshire	Northamptonshire
Nottinghamshire	Nottinghamshire
Cambridgeshire	Cambridgeshire
Norfolk	Norfolk
Suffolk	Suffolk
City of London and Metropolitan	London
Bedfordshire	Bedfordshire
Essex	Essex
Hampshire	Hampshire
Hertfordshire	Hertfordshire
Kent	Kent
Surrey	Surrey
Sussex	East Sussex, West Sussex, Isle of Wight
Thames Valley	Berkshire, Buckinghamshire, Oxfordshire.
Avon and Somerset	Avon, Somerset.
Devon and Cornwall	Devon, Cornwall.
Dorset	Dorset

Gloucestershire	Gloucestershire
Wiltshire	Wiltshire
Dyfed Powys	Dyfed, Powys.
Gwent	Gwent
North Wales	Clwyd, Gwynedd.
South Wales	Glamorgan, South Glamorgan, West Glamorgan.

The data are analysed using 41 police force areas. The Metropolitan and City of London police forces have been amalgamated because the low residential population in the City of London produces artificially high crime rates. Also South Wales and Gwent have been analysed together because of boundary changes that took place in 1996 which mean that these areas can only be examined consistently over time together.

Crime Variables

The crime data are crimes reported to and recorded by the police and are produced by the Home Office as an annual publication Criminal Statistics. They can also be found as statistical bulletins on the Home Office web page (www.homeoffice.gov.uk/rds/). Because of the different evolution of different types of crime this Chapter looks at total, property, vehicle and violent offences separately.

As discussed in Chapter 1 notifiable offences are unlikely to be a totally accurate picture of the true level of crime because not all crimes are reported to the police and of those that are, not all are recorded by them. However, increased pressure on both the public to report crimes (because of insurance requirements) and the police to record crime trends in notifiable offences closely mirror trends in victimisation reported in the British Crime Survey (which is generally thought to capture the 'dark figure' of crime more accurately). Moreover, findings from the British Crime Survey suggest that most crimes that are not recorded are mostly trivial offences. Nevertheless, if reporting or recording varies in some systematic way across the police force areas this Chapter examines this is a form of measurement error (see Appendix B), the existence of which may produce bias in the results. However, generally we are less concerned about measurement error in the dependent variable.

Property Crime and Violent Crime by police force area – 1992 and 1998

(Crime/population)

	Property Crime		Violent Crime	
Police Force Area	**1992**	**1998**	**1992**	**1998**
Avon and Somerset	10.0	6.7	.36	.44
Bedfordshire	8.6	5.1	.35	.44
Cambridgeshire	7.8	5.9	.41	.44
Cheshire	6.3	4.2	.29	.37
Cleveland	11.7	8.5	.47	.47
Cumbria	7.0	4.4	.40	.62
Derbyshire	7.0	5.5	.42	.45
Devon and Cornwall	5.9	4.0	.26	.28
Dorset	6.0	4.6	.23	.22
Durham	8.0	5.0	.40	.31
Dyfed-Powys	4.1	2.1	.47	.44
Essex	5.9	3.8	.29	.30
Gloucester	9.3	6.0	.30	.28
Greater Manchester	11.5	8.8	.39	.86
Gwent and South Wales	8.5	6.1	.47	.60
Hampshire	6.9	4.4	.31	.36
Hertfordshire	5.3	3.6	.22	.28
Humberside	11.3	10.1	.56	.58
Kent	7.8	5.0	.37	.43
Lancashire	6.9	5.3	.23	.26
Leicestershire	8.4	5.9	.39	.56
Lincolnshire	6.2	4.6	.37	.36
London	9.0	6.5	.51	.54
Merseyside	7.6	6.0	.49	.60
Norfolk	7.1	4.5	.24	.37
North Wales	5.6	3.7	.40	.36
North Yorkshire	6.2	4.7	.27	.26
Northamptonshire	7.2	6.3	.42	.42
Northumbria	11.1	6.3	.44	.37
Nottinghamshire	12.1	8.2	.81	.66
South Yorkshire	8.2	7.0	.38	.28
Staffordshire	7.1	5.4	.52	.64
Suffolk	5.1	3.4	.32	.32
Surrey	5.4	3.1	.26	.31
Sussex	6.7	5.1	.22	.42
Thames Valley	7.6	5.5	.24	.30
Warwickshire	7.3	5.1	.26	.29
West Mercia	5.6	4.3	.31	.21
West Midlands	9.6	7.2	.44	.44
West Yorkshire	11.4	8.2	.46	.43
Wiltshire	5.3	3.7	.44	.34

Labour Market Variables

Despite the body of work that exists within the area of crime and the labour market there is no consensus as to which labour market measure has the greatest impact on crime. In Chapter 2, which largely involved exploratory research the effect of both unemployment and wages on crime were examined. All labour market variables were constructed from the Labour Force Survey and the New Earnings Survey. The unemployment measure is ILO unemployed, and was constructed as those unemployed/the active population (from the LFS). The wage measures used (from the NES) are the median wage in the area, the 25th and 75th percentile of the wage distribution and a measure of wage inequality (75th – 25th percentile).

Unemployment by police force area 1992 and 1998

Police Force Area	1992	1998
Avon and Somerset	9.2	4.6
Bedfordshire	9.5	5.0
Cambridgeshire	8.9	3.8
Cheshire	8.0	5.6
Cleveland	14.4	10.2
Cumbria	7.8	6.5
Derbyshire	9.1	5.0
Devon and Cornwall	10.3	6.2
Dorset	10.7	4.7
Durham	10.4	7.9
Dyfed-Powys	9.3	7.4
Essex	9.9	5.2
Gloucester	8.1	3.7
Greater Manchester	11.7	6.5
Gwent and South Wales	11.1	7.5
Hampshire	9.0	4.2
Hertfordshire	7.9	3.5
Humberside	10.0	7.3
Kent	8.2	6.2
Lancashire	8.4	5.2
Leicestershire	9.6	4.6
Lincolnshire	6.9	5.3
London	13.0	8.0
Merseyside	13.9	11.6
Norfolk	9.0	6.1
North Wales	8.6	7.2
North Yorkshire	6.1	3.7
Northamptonshire	8.0	4.0
Northumbria	13.3	9.0
Nottinghamshire	10.1	6.7
South Yorkshire	13.3	9.2
Staffordshire	9.6	5.7
Suffolk	6.8	4.9
Surrey	7.0	2.9
Sussex	9.7	4.8
Thames Valley	8.1	3.4
Warwickshire	9.9	3.7
West Mercia	8.6	4.8
West Midlands	12.8	7.2
West Yorkshire	9.0	6.9
Wiltshire	7.9	3.2

Median Wages and Wage Inequality by police force area – 1992 and 1998

	Median Wages		Wage Inequality	
Police Force Area	**1992**	**1998**	**1992**	**1998**
Avon and Somerset	5.83	7.16	4.06	5.45
Bedfordshire	6.15	7.41	4.25	5.54
Cambridgeshire	5.79	7.27	3.83	5.11
Cheshire	5.81	7.06	4.38	5.67
Cleveland	5.72	6.39	4.08	5.32
Cumbria	5.52	6.36	3.95	4.91
Derbyshire	5.54	6.62	3.64	4.55
Devon and Cornwall	5.00	5.90	3.35	4.12
Dorset	5.35	6.54	3.77	5.21
Durham	5.20	6.30	3.53	4.68
Dyfed-Powys	5.09	6.50	3.67	5.08
Essex	5.81	6.86	4.04	4.95
Gloucester	5.75	7.11	3.90	4.97
Greater Manchester	5.61	6.85	3.98	5.03
Gwent and South Wales	5.47	6.70	3.77	5.01
Hampshire	5.89	7.17	4.38	5.59
Hertfordshire	6.58	8.00	4.93	6.44
Humberside	5.21	6.50	3.66	4.98
Kent	5.76	6.81	3.89	5.18
Lancashire	5.36	6.61	3.75	4.74
Leicestershire	5.24	6.63	3.28	4.63
Lincolnshire	4.95	5.98	3.35	4.03
London	7.85	9.39	5.40	7.57
Merseyside	5.61	6.71	3.86	5.15
Norfolk	5.32	6.24	3.18	4.33
North Wales	5.42	6.24	3.77	4.57
North Yorkshire	5.01	6.16	3.03	4.62
Northamptonshire	5.53	6.98	3.44	4.51
Northumbria	5.42	6.58	3.46	4.73
Nottinghamshire	5.42	6.36	3.97	4.74
South Yorkshire	5.54	6.45	3.68	4.91
Staffordshire	5.02	6.50	3.05	4.38
Suffolk	5.37	6.05	3.55	3.81
Surrey	6.65	8.44	4.77	7.14
Sussex	5.76	6.95	4.02	5.47
Thames Valley	6.53	8.05	4.85	6.09
Warwickshire	5.65	7.40	3.97	5.51
West Mercia	5.10	6.41	3.37	4.28
West Midlands	5.80	7.09	3.87	5.18
West Yorkshire	5.40	6.55	3.57	4.94
Wiltshire	6.01	7.04	4.49	4.99

Criminal Justice System Data

Although this thesis is mainly interested in the relationship between crime and the labour market it is also important to look at the effect of deterrence. This makes it not only possible to compare the effect of the labour and deterrence on crime. But also if deterrence is related to crime failing to include it in the model will mean that the model will be under specified and will suffer from omitted variable bias (see Appendix B for further discussion of bias). The variables used to capture deterrence effects in Chapter 2, (the number of people found guilty, the numbers placed in immediate custody, the average sentence length (for all crime as well as crime specific measures) and the number of police officers) were provided by the Home Office.

Proportion Found guilty of property and violent offences by police force area – 1992 and 1998
(per 100 of the population)

	Property Crime		Violent Crime	
Police Force Area	**1992**	**1998**	**1992**	**1998**
Avon and Somerset	.32	.29	.14	.14
Bedfordshire	.32	.29	.13	.16
Cambridgeshire	.31	.25	.14	.16
Cheshire	.38	.33	.16	.23
Cleveland	.58	.60	.29	.18
Cumbria	.51	.39	.25	.35
Derbyshire	.32	.26	.19	.20
Devon and Cornwall	.29	.26	.14	.17
Dorset	.32	.28	.10	.12
Durham	.39	.34	.23	.32
Dyfed-Powys	.32	.29	.20	.33
Essex	.32	.28	.11	.16
Gloucester	.33	.28	.15	.15
Greater Manchester	.55	.68	.22	.26
Gwent and South Wales	.26	.21	.13	.16
Hampshire	.33	.32	.12	.22
Hertfordshire	.28	.24	.12	.13
Humberside	.43	.40	.24	.25
Kent	.25	.38	.09	.18
Lancashire	.50	.52	.26	.31
Leicestershire	.33	.36	.17	.22
Lincolnshire	.34	.34	.16	.22
London	.44	.36	.17	.16
Merseyside	.54	.47	.18	.20
Norfolk	.37	.28	.15	.25
North Wales	.36	.32	.23	.28
North Yorkshire	.35	.28	.19	.24
Northamptonshire	.31	.32	.19	.20
Northumbria	.49	.50	.22	.29
Nottinghamshire	.54	.38	.26	.26
South Yorkshire	.48	.46	.17	.17
Staffordshire	.32	.31	.18	.22
Suffolk	.34	.26	.17	.15
Surrey	.28	.17	.11	.12
Sussex	.32	.25	.12	.12
Thames Valley	.31	.25	.10	.11
Warwickshire	.27	.24	.11	.18

West Mercia	.31	.24	.16	.16
West Midlands	.45	.43	.20	.22
West Yorkshire	.56	.58	.21	.21
Wiltshire	.29	.28	.19	.20

<u>Proportion jailed for property and violent offences by police force area – 1992 and 1998</u>
(per 100 of the populaton)

	Property Crime		Violent Crime	
Police Force Area	**1992**	**1998**	**1992**	**1998**
Avon and Somerset	.032	.057	.011	.017
Bedfordshire	.045	.087	.015	.038
Cambridgeshire	.038	.048	.011	.022
Cheshire	.054	.082	.019	.036
Cleveland	.066	.116	.016	.026
Cumbria	.054	.067	.019	.031
Derbyshire	.042	.063	.021	.037
Devon and Cornwall	.039	.048	.015	.025
Dorset	.027	.054	.008	.027
Durham	.054	.069	.015	.030
Dyfed-Powys	.026	.042	.012	.022
Essex	.033	.065	.011	.035
Gloucester	.027	.047	.008	.013
Greater Manchester	.088	.126	.024	.041
Gwent and South Wales	.029	.040	.012	.021
Hampshire	.027	.045	.011	.030
Hertfordshire	.030	.037	.010	.022
Humberside	.057	.088	.019	.034
Kent	.038	.067	.011	.025
Lancashire	.068	.117	.018	.036
Leicestershire	.045	.065	.018	.039
Lincolnshire	.032	.053	.013	.022
London	.057	.088	.023	.037
Merseyside	.061	.099	.017	.037
Norfolk	.041	.045	.012	.025
North Wales	.039	.057	.015	.034
North Yorkshire	.035	.063	.010	.023
Northamptonshire	.040	.062	.017	.027
Northumbria	.059	.083	.019	.032
Nottinghamshire	.065	.082	.031	.057
South Yorkshire	.049	.093	.016	.034
Staffordshire	.043	.069	.020	.026
Suffolk	.031	.045	.014	.023
Surrey	.023	.028	.008	.015
Sussex	.036	.052	.012	.023
Thames Valley	.026	.033	.009	.014
Warwickshire	.036	.057	.014	.024
West Mercia	.043	.049	.013	.024
West Midlands	.057	.093	.023	.034
West Yorkshire	.050	.010	.017	.031
Wiltshire	.025	.039	.011	.018

Average Sentence length for property crimes and violent crimes by police force area – 1992 and 1998
(in months)

	Property Crime		Violent Crime	
Police Force Area	**1992**	**1998**	**1992**	**1998**
Avon and Somerset	7.54	8.70	19.40	21.28
Bedfordshire	7.43	7.48	22.35	18.66
Cambridgeshire	10.55	10.03	28.77	17.85
Cheshire	9.57	8.92	19.95	19.27
Cleveland	10.14	10.75	22.34	24.57
Cumbria	7.99	8.59	24.19	12.75
Derbyshire	9.83	9.53	20.87	14.13
Devon and Cornwall	7.26	8.01	19.93	18.66
Dorset	7.24	8.00	22.63	16.77
Durham	9.00	10.50	22.42	17.78
Dyfed-Powys	8.14	9.72	26.29	15.40
Essex	10.07	7.06	27.86	14.72
Gloucester	9.09	9.58	28.47	17.95
Greater Manchester	6.88	7.83	21.88	21.39
Gwent and South Wales	9.00	8.61	22.08	18.13
Hampshire	9.73	8.51	20.89	15.71
Hertfordshire	9.53	9.50	25.22	19.81
Humberside	9.38	10.41	23.59	17.44
Kent	7.88	8.35	28.09	18.91
Lancashire	7.81	8.12	19.12	17.20
Leicestershire	8.80	9.95	25.88	16.77
Lincolnshire	8.36	8.94	16.55	19.92
London	9.52	9.76	26.43	19.35
Merseyside	7.53	7.50	25.01	22.06
Norfolk	9.92	7.54	23.54	13.07
North Wales	9.31	8.45	17.79	16.81
North Yorkshire	8.47	9.17	25.91	16.14
Northamptonshire	9.75	9.99	23.20	20.31
Northumbria	9.12	9.44	23.81	24.92
Nottinghamshire	8.62	12.61	17.93	15.82
South Yorkshire	8.52	9.51	23.66	18.04
Staffordshire	8.98	9.59	16.74	15.71
Suffolk	9.90	7.37	23.67	16.61
Surrey	8.93	10.46	27.83	16.28
Sussex	9.32	8.89	26.30	20.58
Thames Valley	8.91	9.99	24.65	19.13
Warwickshire	9.68	11.62	17.97	20.35
West Mercia	10.74	12.13	23.42	20.65
West Midlands	8.70	10.14	23.68	21.72
West Yorkshire	8.88	9.60	4.43	22.18
Wiltshire	7.55	8.39	18.68	18.20

Number of police officers by police force area – 1992 and 1998

Police Force Area	1992	1998
Avon and Somerset	3061	2999
Bedfordshire	1121	1041
Cambridgeshire	1237	1274
Cheshire	1901	2071
Cleveland	1501	1416
Cumbria	1196	1133
Derbyshire	1810	1759
Devon and Cornwall	2915	2887
Dorset	1318	1298
Durham	1376	1575
Dyfed-Powys	957	1026
Essex	2917	2900
Gloucester	1148	1109
Greater Manchester	7055	6810
Gwent and South Wales	4161	4230
Hampshire	3285	3486
Hertfordshire	1688	1728
Humberside	2033	1981
Kent	3106	3208
Lancashire	3205	3245
Leicestershire	1830	1993
Lincolnshire	1191	1140
London	27934*	26734
Merseyside	4653	4211
Norfolk	1426	1394
North Wales	1356	1415
North Yorkshire	1408	1337
Northamptonshire	1203	1143
Northumbria	3583	3840
Nottinghamshire	2321	2236
South Yorkshire	3000	3168
Staffordshire	2169	2238
Suffolk	1236	1192
Surrey	1657	1665
Sussex	2979	2847
Thames Valley	3763	3766
Warwickshire	980	909
West Mercia	2060	1998
West Midlands	6960	7320
West Yorkshire	5067	4982
Wiltshire	1167	1085

* 1993

Population Variables

Population is obviously an important factor when talking about crime. Crime varies greatly across differently populated areas. For example, crime is much higher in urban compared to rural areas and higher still in the metropolitan areas (Home Office, 2000). Indeed, to make crimes comparable across areas we must use population as the denominator in crime rates (i.e. number of crimes/population). Even then rates are higher in the more heavily populated areas. Potential explanations for this are not difficult to conceive. More highly populated areas have a higher supply of potential crime targets, more people, more properties and more goods. In an area with a higher population any particular individual will be more anonymous, potentially making it easier to commit and crime without detection. It is also possible that areas with more people provide greater opportunities to form networks and associations which may be beneficial to crime. The population data for Chapter 2 comes from the Home Office.

Population numbers by police force area – 1992 to 1998

Police Force Area	1992	1998
Avon and Somerset	1440866	1488575
Bedfordshire	536560	556628
Cambridgeshire	677689	719767
Cheshire	966878	984280
Cleveland	560013	556344
Cumbria	490193	492884
Derbyshire	947317	970087
Devon and Cornwall	1520457	1558758
Dorset	664232	691215
Durham	607056	607770
Dyfed-Powys	470405	479368
Essex	1484089	1533255
Gloucester	541330	557257
Greater Manchester	2573497	2577434
Gwent and South Wales	1773811	1796506
Hampshire	1713049	1770947
Hertfordshire	846209	878368
Humberside	881423	883117
Kent	1538254	1574561
Lancashire	1413522	1426839
Leicestershire	902340	928716
Lincolnshire	596847	623130
London	7391139	7688699
Merseyside	1445653	1409371
Norfolk	762926	790275
North Wales	654323	657450
North Yorkshire	723051	742404
Northamptonshire	590157	615796
Northumbria	1441619	1425486
Nottinghamshire	1025287	1031587
South Yorkshire	1304328	1304136
Staffordshire	1051835	1061280
Suffolk	648003	671095
Surrey	769901	786729

Sussex	1433163	1499028
Thames Valley	1990879	2098760
Warwickshire	491941	506713
West Mercia	1103206	1136332
West Midlands	2630540	2628196
West Yorkshire	2093532	2113252
Wiltshire	579367	605511

Demographic Variables

Because crime varies so greatly by ethnicity and education, both these variables were included in the models in Chapter 2. Constructed from the LFS, the ethnicity variable was defined as the proportion of people in the area who identified themselves as non-white/all those who answered the ethnicity question. The educational variable was also constructed from the LFS and defined as the number 16 to 19 years olds in the area who are in full time education as a proportion of all 16 to 19 year olds in the area.

Ethnicity and education by police force area – 1992 and 1998

	Proportion Non-White		**Proportion of 16 to 19 year olds in Full Time Education**	
Police Force Area	**1992**	**1998**	**1992**	**1998**
Avon and Somerset	2.1	1.6	49.8	63.0
Bedfordshire	8.5	9.2	51.6	57.2
Cambridgeshire	3.0	3.6	53.9	53.7
Cheshire	0.7	0.7	55.2	63.1
Cleveland	1.3	1.9	41.4	49.6
Cumbria	*	*	40.7	55.1
Derbyshire	2.3	2.5	45.9	52.5
Devon and Cornwall	0.1	0.5	46.7	57.6
Dorset	0.6	0.5	53.2	53.2
Durham	0.3	0.8	41.3	47.3
Dyfed-Powys	0.6	1.2	53.0	74.5
Essex	1.2	1.8	46.7	59.8
Gloucester	1.7	0.6	52.0	59.5
Greater Manchester	5.1	6.0	45.1	53.1
Gwent and South Wales	1.6	1.4	50.6	60.7
Hampshire	1.7	1.8	55.4	60.3
Hertfordshire	3.5	4.2	57.1	62.7
Humberside	3.5	4.2	43.5	49.6
Kent	2.4	1.7	52.8	54.4
Lancashire	3.9	4.4	46.7	55.1
Leicestershire	10.7	8.5	55.4	59.9
Lincolnshire	0.8	1.0	44.4	57.4
London	18.7	22.1	56.8	66.5
Merseyside	1.4	1.7	51.5	54.2
Norfolk	1.0	0.5	37.7	55.1
North Wales	0.4	0.7	52.3	57.7
North Yorkshire	0.7	1.3	50.5	61.1
Northamptonshire	2.4	2.1	47.9	65.0
Northumbria	1.0	1.8	41.0	54.0

Nottinghamshire	3.1	3.0	40.9	53.9
South Yorkshire	2.3	2.4	38.7	44.6
Staffordshire	2.1	1.9	48.8	53.1
Suffolk	1.5	1.2	48.8	42.6
Surrey	2.2	4.0	61.4	72.5
Sussex	1.4	1.5	55.1	61.8
Thames Valley	5.4	4.4	57.4	56.9
Warwickshire	3.7	3.2	51.6	60.1
West Mercia	1.2	1.3	44.3	59.9
West Midlands	8.7	10.7	49.0	54.1
West Yorkshire	6.2	7.9	46.0	50.3
Wiltshire	1.4	1.2	53.9	57.5

* Too Few Observations

Chapter 3: Spatial Patterns of Crime: Can Labour Market Variables Account for Them?

Crime Variables

The crime data are crimes reported to and recorded by the police at Crime and Disorder Reduction Partnership, which correspond to Local Authorities. They can be found as statistical bulletins on the Home Office web page (www.homeoffice.gov.uk/rds). Because of the different evolution of different types of crime this Chapter looks property and violent offences separately.

Labour Market Variables

Despite the body of work that exists within the area of crime and the labour market there is no consensus as to which labour market measure has the greatest impact on crime. In Chapter 3, the effect of both unemployment and income on crime were examined. The unemployment measure is ILO unemployed, and was constructed as those unemployed/the active population from the Labour Force Survey. The income measures used come from the income data collected in 1999 by the marketing company CACI (formerly known as California Analysis Centre Inc) from a survey question which asks "What is your approximate family income per year?" CACI calculate income data at post code sector for around 4 million observations. For Chapter 3 the post code sector data were aggregated to Local Authority level. The data contain a measure of the mean level of income in each area as well as a measure of the distribution of income in that area measured by standard deviations away from the mean.

Deterrence

The variables used to capture deterrence effects in this Chapter are crime specific clear up rates which were obtained from Home Office Publication "Crime in England and Wales" which can be obtained from the web site: www.homeoffice.gov.uk/rds.

Population Variables

Because areas vary greatly in terms of their population numbers a spatial analysis of crime must incorporate controls for population size. The population data for Chapter 3 comes from the Home Office and are produced in the same publication as the crime and deterrence numbers.

Demographic Variables

Crime not only varies by population size but also the make up of the population in different areas. Therefore, Chapter 3 includes a measure of the population in the area who are male (defined as the number of males as a proportion of the entire population in the area); people under the age of 25 (as a proportion of the entire population); the 16-19 year olds in full time education (as a proportion of all 16 to 19 year olds) and the number of non-whites in the area (as a proportion of the entire population). All of these variables were constructed from the Labour Force Survey. Also included in the data were a measure of social housing in the area (measured as the number of social housing properties as a proportion of all property types); the number of lone parents (as a proportion of all family types) and the number of people claiming lone parent income support (as a proportion of the entire population). These variables were constructed from the Family Resources Survey (FRS) which is a quarterly survey of around 26,000 households per year, carried out by the Office of National Statistics and the National Centre for Social Research for the Department of Work and Pensions (originally the Department of Social Security).

Chapter 4: Crime and the Minimum Wage: A Quasi-Natural Experiment

Minimum Wage Variable

The police force areas are delineated into four areas depending on the proportion of the population in each area who earned less than the Minimum Wage before its introduction. The groups are given below:

Least Low Pay Areas (where less than 7.5% of workers are paid beneath the minimum):

- Essex
- Northamptonshire
- Hampshire

- Wiltshire
- Sussex
- London
- Surrey
- Thames Valley
- Hertfordshire
- Warwickshire

Second Least Low Pay Areas (where between 7.5% and 10.2% of workers are paid beneath the minimum):

- Gloucestershire
- Avon and Somerset
- West Yorkshire
- West Midlands
- Dorset
- Cambridgeshire
- Cheshire
- Bedfordshire
- Kent
- North Yorkshire

Second Most Low Pay Areas (where between 10.2% and 11.7% of workers are paid beneath the minimum):

- West Mercia
- Suffolk
- Derbyshire
- Staffordshire
- Greater Manchester
- Lancashire
- North Wales
- Merseyside
- Gwent and South Wales
- Leicestershire

Most Low Pay Areas (where over 11.7% of workers are paid beneath the minimum):

- Humberside
- Dyfed-Powys
- Lincolnshire
- Devon and Cornwall
- Durham
- Northumbria
- Norfolk
- Nottinghamshire
- Cleveland
- Cumbria
- South Yorkshire

Percentage of Workers Paid less than the Minimum prior to the Introduction of the National Minimum Wage by Police Force Area

Police Force Area	April 1998-March 1999
Avon and Somerset	8.5
Bedfordshire	7.4
Cambridgeshire	9.1
Cheshire	10.1
Cleveland	16.6
Cumbria	13.4
Derbyshire	11.1
Devon and Cornwall	16.3
Dorset	9.5
Durham	13.1
Dyfed-Powys	15.7
Essex	6.5
Gloucester	7.9
Greater Manchester	10.2
Gwent and South Wales	11.4
Hampshire	6.7
Hertfordshire	5.1
Humberside	13.9
Kent	9.7
Lancashire	11.4
Leicestershire	10.2
Lincolnshire	13.3
London	5.0
Merseyside	10.8
Norfolk	13.4
North Wales	10.6
North Yorkshire	9.4
Northamptonshire	6.2
Northumbria	14.3
Nottinghamshire	12.4
South Yorkshire	11.7
Staffordshire	10.6
Suffolk	11.3
Surrey	4.6
Sussex	6.5
Thames Valley	5.2
Warwickshire	6.2
West Mercia	10.8
West Midlands	10.0
West Yorkshire	9.4
Wiltshire	7.2

Other measures of Low Pay

Not all low paid individuals are involved in crime. Indeed, evidence suggests that those on the margins of crime are more likely to be males, young males in particular, and those in the lowest skilled occupations working for the lowest pay. For these reasons the measure of low pay is refined to focus on these groups. Low skilled males are defined as males working in occupations where the average pay is beneath the 25th percentile pay for all males. The young males pay measure is defined as the initial low pay proportion for males under the age of 25 only, while the wage bill measure is defined as how far the wage bill would need to be raised to take all people initially beneath the minimum up to the Minimum Wage.

The Initial Percentage in each Low Pay Category prior to the Introduction of the Minimum Wage

Police Force Area	Low Skilled Males	Young Males	Wage Bill Measure
Avon and Somerset	6.8	7.5	0.83
Bedfordshire	5.6	12.3	0.83
Cambridgeshire	7.5	9.1	0.96
Cheshire	9.0	9.2	1.00
Cleveland	13.3	23.1	1.72
Cumbria	11.1	27.9	1.40
Derbyshire	9.2	17.9	1.19
Devon and Cornwall	13.8	27.0	1.76
Dorset	8.2	7.3	0.95
Durham	10.7	21.2	1.31
Dyfed-Powys	13.4	21.7	1.59
Essex	5.8	4.4	0.59
Gloucester	6.5	7.8	0.73
Greater Manchester	8.3	22.4	1.05
Gwent and South Wales	9.7	10.2	1.10
Hampshire	5.2	16.4	0.64
Hertfordshire	4.1	15.4	0.40
Humberside	11.6	18.1	1.34
Kent	8.8	10.8	0.82
Lancashire	9.5	21.1	1.14
Leicestershire	8.7	24.2	0.95
Lincolnshire	11.3	21.7	1.33
London	4.1	7.2	0.43
Merseyside	8.4	17.8	1.18
Norfolk	11.0	18.3	1.42
North Wales	9.3	15.2	1.03
North Yorkshire	7.6	12.9	0.83
Northamptonshire	5.3	7.2	0.50
Northumbria	11.6	27.5	1.45
Nottinghamshire	10.4	16.4	1.17
South Yorkshire	10.2	18.5	1.27
Staffordshire	8.9	13.6	1.01
Suffolk	9.0	18.1	1.15
Surrey	3.8	7.0	0.39
Sussex	5.7	7.2	0.53
Thames Valley	4.3	6.7	0.46
Warwickshire	5.1	11.8	0.58
West Mercia	9.6	13.7	1.09
West Midlands	8.8	10.8	0.97
West Yorkshire	7.5	18.8	0.96
Wiltshire	5.7	9.3	0.69

Crime Variables

The crime data are crimes reported to and recorded by the police and are produced by the Home Office as an annual publication Criminal Statistics. They can also be found as statistical bulletins on the Home Office web page (www.homeoffice.gov.uk/rds/). Because of the different evolution of different types of crime this Chapter looks at total, property, vehicle and violent offences separately.

Total Crime (per 1000 of the population)

Police Force Area	April 1998-March 1999	April 1999-March 2000
Avon and Somerset	104.7	102.6
Bedfordshire	92.2	100.7
Cambridgeshire	100.6	102.8
Cheshire	67.4	66.8
Cleveland	119.8	116.5
Cumbria	82.2	77.1
Derbyshire	89.6	90.8
Devon and Cornwall	73.1	72.9
Dorset	80.1	79.4
Durham	83.2	80.6
Dyfed-Powys	52.5	50.6
Essex	64.9	69.6
Gloucester	89.4	94.5
Greater Manchester	141.0	146.7
Gwent and South Wales	109.4	105.7
Hampshire	75.1	79.1
Hertfordshire	58.8	62.9
Humberside	149.0	138.4
Kent	84.4	81.5
Lancashire	83.8	77.2
Leicestershire	104.4	105.7
Lincolnshire	79.1	78.2
London	127.5	143.6
Merseyside	97.2	102.3
Norfolk	75.3	78.3
North Wales	67.2	68.3
North Yorkshire	76.9	74.5
Northamptonshire	111.6	104.4
Northumbria	105.4	99.1
Nottinghamshire	132.7	134.3
South Yorkshire	102.4	101.3
Staffordshire	87.6	94.2
Suffolk	61.0	66.3
Surrey	55.7	60.7
Sussex	91.3	95.6
Thames Valley	89.4	97.2
Warwickshire	78.7	78.9
West Mercia	74.6	77.4
West Midlands	119.8	139.0
West Yorkshire	131.4	124.9
Wiltshire	66.8	67.3

Changes in Total, Property, Vehicle and Violent Crime – Average across all Police Force Areas
(Per 1000 of the population)

	April 1998-March 1999	April 1999-March 2000
Total Crime	91.1	92.4
Property Crime	57.2	55.9
Vehicle Crime	26.5	26.0
Violent Crime	8.3	9.3

Deterrence

The likelihood of detection and the severity of punishment are factors along with labour markets and demographics which are likely to be related to crime. Here the crime clear-up rates are used to gauge differences in deterrence. However, as it is only a very short period of time being examined, it is unlikely that there will have been substantial shifts in crime clear-up rates.

Proportion of Crimes Cleared Up

Police Force Area	April 1998-March 1999	April 1999-March 2000
Avon and Somerset	.24	.22
Bedfordshire	.33	.25
Cambridgeshire	.29	.25
Cheshire	.37	.31
Cleveland	.23	.22
Cumbria	.44	.39
Derbyshire	.31	.28
Devon and Cornwall	.36	.35
Dorset	.31	.26
Durham	.33	.32
Dyfed-Powys	.69	.65
Essex	.29	.30
Gloucester	.31	.30
Greater Manchester	.25	.23
Gwent and South Wales	.44	.38
Hampshire	.35	.32
Hertfordshire	.34	.27
Humberside	.22	.19
Kent	.34	.33
Lancashire	.34	.29
Leicestershire	.34	.30
Lincolnshire	.40	.28
London	.22	.16
Merseyside	.31	.26
Norfolk	.37	.30
North Wales	.43	.36
North Yorkshire	.33	.31
Northamptonshire	.33	.33
Northumbria	.30	.31
Nottinghamshire	.25	.21
South Yorkshire	.32	.25
Staffordshire	.32	.22
Suffolk	.41	.36
Surrey	.40	.32
Sussex	.25	.25
Thames Valley	.25	.20
Warwickshire	.26	.22
West Mercia	.34	.29
West Midlands	.30	.27
West Yorkshire	.27	.25
Wiltshire	.38	.33

Unemployment

When the Minimum Wage was first introduced, there were concerns that it would effectively price workers out of jobs, thereby increasing the number of unemployed who may then turn to crime. For this reason, it is important to control for changes in unemployment that may have occurred differentially across areas, in case we are biasing the coefficient on the low pay proportion by neglecting another route in which crime may be affected by the labour market.

Unemployment Rate by Police Force Area

Police Force Area	April 1998-March 1999	April 1999-March 2000
Avon and Somerset	4.3	3.8
Bedfordshire	4.5	4.7
Cambridgeshire	3.4	4.2
Cheshire	5.2	3.9
Cleveland	9.7	11.4
Cumbria	6.1	5.9
Derbyshire	4.6	4.6
Devon and Cornwall	5.9	5.8
Dorset	4.1	4.0
Durham	7.4	6.0
Dyfed-Powys	7.4	7.2
Essex	4.9	4.1
Gloucester	3.6	2.7
Greater Manchester	6.1	6.0
Gwent and South Wales	6.6	7.1
Hampshire	3.7	3.8
Hertfordshire	2.9	3.4
Humberside	8.2	8.5
Kent	5.4	4.8
Lancashire	4.8	4.3
Leicestershire	4.4	5.4
Lincolnshire	4.8	4.7
London	7.5	7.1
Merseyside	10.7	8.7
Norfolk	5.6	4.1
North Wales	6.9	5.3
North Yorkshire	3.4	3.3
Northamptonshire	3.4	3.5
Northumbria	8.6	9.5
Nottinghamshire	6.0	5.9
South Yorkshire	8.3	6.6
Staffordshire	5.5	4.9
Suffolk	4.3	3.9
Surrey	2.6	2.1
Sussex	4.4	4.2
Thames Valley	3.2	3.0
Warwickshire	3.6	4.0
West Mercia	4.7	4.9
West Midlands	7.8	8.2
West Yorkshire	6.5	5.2
Wiltshire	2.9	2.5

Demographic Variables

The models in Chapter 4 also control for changes in a number of demographic variables which theory and past empirical work inform us may be related to crime and which may be occurring over the time period of examination. However, once again, as the period under examination is relatively short, we are unlikely to see large shifts in the demographic structure of areas. All demographic variables are constructed from the Labour Force Survey.

The first demographic variable examined is the mean age in the area, which is important as age is such a strong demographic predictor of crime (see Chapter 6). Changes in the proportion of young males (males under the age of 25) in the area are also controlled for because a high volume of crime is carried out by young males. The analysis also controls for the proportion of females in the area, because the Minimum Wage does affect females more than males as they tend to be lower paid. In terms of the minimum wage effect the models also controls for the proportion of people in the area working in the public sector. This is important as public sector jobs are unlikely to pay beneath the Minimum Wage, even before its introduction. The final variable controlled for is the proportion of people in the area who have no qualifications. Those people who fall into this category are not only likely to be in the low paid jobs but are also disproportionately involved in crime.

Demographic Variables – Mean across all Police Force Areas

	April 1998-March 1999	**April 1999-March 2000**
Age	39.26	39.33
Percentage Young Male	7.0	7.0
Percentage Female	47.4	47.4
Percentage with no Qualifications	16.6	15.7
Percentage Public Sector Jobs	22.3	22.5

Chapter 5: Rising Crime and Improvements in the Socio-Economic Position of Women: Are they Related?

Notifiable Offences

These are crimes reported to and recorded by the police and are produced by the Home Office as an annual publication Criminal Statistics. They can also be found as statistical bulletins on the Home Office web page (www.homeoffice.gov.uk/rds/).

Mean Crime Rates 1975-1997

Year	Property Crime Rate	Total Crime Rate
1975	.0282	.0303
1976	.0283	.0306
1977	.0328	.0352
1978	.0317	.0342
1979	.0310	.0335
1980	.0326	.0352
1981	.0361	.0388
1982	.0398	.0427
1983	.0395	.0425
1984	.0421	.0451
1985	.0433	.0465
1986	.0460	.0494
1987	.0470	.0501
1988	.0441	.0482
1989	.0456	.0501
1990	.0549	.0596
1991	.0642	.0691
1992	.0677	.0730
1993	.0664	.0718
1994	.0620	.0677
1995	.0587	.0643
1996	.0562	.0624
1997	.0501	.0563

Crime Rates Changes by Police Force Area 1975-1997

Police Force Area	1975		1997	
	Property Crime Rate	Total Crime Rate	Property Crime Rate	Total Crime Rate
Avon and Somerset	.0242	.0255	.0617	.0699
Bedfordshire	.0278	.0301	.0512	.0593
Cambridgeshire	.0333	.0354	.0528	.0586
Cheshire	.0200	.0214	.0347	.0394
Cleveland	.0325	.0351	.0715	.0777
Cumbria	.0233	.0250	.0392	.0456
Derbyshire	.0230	.0255	.0434	.0499
Devon and Cornwall	.0207	.0225	.0364	.0414
Dorset	.0285	.0301	.0397	.0434
Durham	.0238	.0264	.0433	.0473
Dyfed-Powys	.0150	.0163	.0170	.0222
Essex	.0225	.0241	.0330	.0366
Gloucester	.0207	.0222	.0558	.0595
Greater Manchester	.0371	.0392	.0692	.0777
Gwent and South Wales	.0622	.0666	.1068	.1229
Hampshire	.0278	.0297	.0399	.0454
Hertfordshire	.0232	.0245	.0294	.0322
Humberside	.0316	.0348	.0771	.0859
Kent	.0216	.0231	.0452	.0509
Lancashire	.0224	.0240	.0486	.0525
Leicestershire	.0206	.0225	.0518	.0592
Lincolnshire	.0185	.0205	.0396	.0453
London	.0971	.1022	.1289	.1536
Merseyside	.0485	.0514	.0523	.0601
Norfolk	.0197	.0209	.0395	.0441
North Wales	.0250	.0272	.0304	.0352
North Yorkshire	.0206	.0223	.0419	.0458

Northamptonshire	.0237	.0259	.0504	.0565
Northumbria	.0396	.0419	.0542	.0587
Nottinghamshire	.0449	.0499	.0609	.0789
South Yorkshire	.0252	.0279	.0607	.0655
Staffordshire	.0177	.0199	.0467	.0544
Suffolk	.0183	.0199	.0291	.0335
Surrey	.0155	.0168	.0214	.0243
Sussex	.0240	.0261	.0443	.0494
Thames Valley	.0243	.0260	.0490	.0532
Warwickshire	.0173	.0187	.0430	.0462
West Mercia	.0167	.0182	.0390	.0427
West Midlands	.0322	.343	.0637	.0705
West Yorkshire	.0377	.0406	.0699	.0758
Wiltshire	.0272	.0291	.0328	.0377

Convictions Data:

The main focus of Chapter 5 is the impact of increased female labour supply on male criminal activities. Notifiable offences, where the perpetrator is not known, contain crimes committed by both males and females. While this is unlikely to pose a substantial problem as women commit relatively few crimes (and the share of crimes committed by females has remained relatively constant over time) the inclusion of even a small number of crimes committed by women may produce bias in the results (see Appendix B for more details). To focus solely on crimes committed by males, this Chapter also utilises male convictions, that is the number of males found guilty of property crimes (theft and handling, burglary and fraud and forgery) in both Crown (where crimes are mainly indictable offences (which roughly correspond with notifiable offences) and Magistrates Courts (which usually deal with more minor indictable offences, summary and non-summary (including driving) offences.

Numbers found guilty in England and Wales between 1975 and 1997
(as percentage of the population in parenthesis)

	Total Found Guilty at Magistrates Courts		**Total Found Guilty at Crown Courts**		**Found Guilty of Property Crime at Magistrates Courts**		**Found Guilty of Property Crime at Crown Courts**	
	Male	Female	Male	Female	Male	Female	Male	Female
1975	293279	56615	48846	3741	224660	51424	29520	2549
1976	298507	60763	51717	4450	225902	53928	32014	3237
1977	308278	63228	52514	4710	234699	56106	33697	3412
1987	315457	62931	50919	4663	238280	56997	32272	3355
1979	302859	58416	46335	4325	217873	51617	27978	3056
1980	333013	62357	53560	5415	235254	54431	32992	3905
1981	340379	60062	57547	5393	241688	52464	36215	3913
1982	343784	60622	61962	5432	244592	52717	39742	4016
1983	330196	56580	66790	6072	226807	48763	43121	4661
1984	319105	53496	68309	6355	223367	46142	43621	4616
1985	307547	52032	74961	7007	213222	44632	47069	5038
1986	258813	43498	72904	6540	176694	37052	44172	4408

1987	257112	40584	79321	6933	168127	34235	46620	4636
1988	253747	38834	83769	7227	152572	31217	45848	4752
1989	217647	35999	76072	6978	128292	28295	39285	4376
1990	222401	37011	76265	6998	129093	28600	37735	4295
1991	222109	35403	71350	6532	132798	27414	36608	3980
1992	213457	33915	69464	6092	127566	25979	34848	3646
1993	209205	32695	58968	5102	124299	24228	28045	2811
1994	212734	34426	60505	5105	122535	25048	27786	2594
1995	200933	31864	62425	5578	115435	23195	27315	2702
1996	200310	32166	60752	5898	113690	23012	23745	2522
1997	212231	35696	64255	6544	114680	24758	25026	2685

Changes in Conviction Rates for Property Crimes by Police Force Area 1975-1997
(As percentage of population)

Police Force Area	**1975**	**1997**
Avon and Somerset	.90	.44
Bedfordshire	1.00	.46
Cambridgeshire	.92	.42
Cheshire	.96	.55
Cleveland	1.72	.94
Cumbria	1.04	.75
Derbyshire	.74	.43
Devon and Cornwall	.89	.43
Dorset	.80	.41
Durham	1.01	.56
Dyfed-Powys	.58	.50
Essex	.73	.42
Gloucester	.83	.43
Greater Manchester	1.58	.75
Gwent and South Wales	1.44	.65
Hampshire	.93	.50
Hertfordshire	.74	.28
Humberside	1.29	.65
Kent	.72	.53
Lancashire	1.29	.85
Leicestershire	.75	.49
Lincolnshire	.77	.54
London	1.28	.57
Merseyside	1.50	.72
Norfolk	.68	.44
North Wales	1.09	.52
North Yorkshire	.88	.51
Northamptonshire	1.01	.44
Northumbria	1.35	.75
Nottinghamshire	1.22	.65
South Yorkshire	1.08	.61
Staffordshire	.82	.46
Suffolk	.74	.44
Surrey	.44	.22
Sussex	.79	.46
Thames Valley	.75	.32
Warwickshire	.71	.47
West Mercia	.71	.40
West Midlands	1.04	.59
West Yorkshire	1.34	.69
Wiltshire	.69	.35
Mean - All Police Force Areas	.97	.53

Number of Police Officers

In Chapter 5 the number of police officers is calculated from the occupation codes available in the NES. Prior to 1991 the NES soc code for police officers is 248, from 1991 onwards it becomes 610.

As a sample the NES will not include all police officers, but it is nationally representative, so the number of police officers are taken over the number of all who report an occupation in the NES, to give the share of police officers in areas, this measure should allow consistent comparison of police presence across police force areas.

There is a potential problem that the number of police officers may be an endogenous measure, in other words there is the possibility that the number of police officers is correlated with crime. However, it is not obvious which way the bias would go in this case. It may be the case that areas with more police have a lower crime rate producing a negative bias. Equally it may be the case that areas with a larger crime problem respond to this by hiring more police officers in which case the bias will be in the opposite direction (see Appendix B for further discussion of bias). However, Levitt (1997) examined the issue of causation with regard to police officers and found that the relationship between the number of police had an effect on crime rather than the other way around.

Changes in the share of Police Officers by Police Force Area 1975-1997
(As a percentage of all occupations)

Police Force Area	1975	1997
Avon and Somerset	.27	.88
Bedfordshire	.37	.90
Cambridgeshire	.07	.37
Cheshire	.04	.70
Cleveland	.27	.72
Cumbria	.33	1.26
Derbyshire	.51	.62
Devon and Cornwall	.68	.88
Dorset	.62	.50
Durham	.56	.81
Dyfed-Powys	.29	1.06
Essex	.47	.79
Gloucester	.66	.42
Greater Manchester	.53	.81
Gwent and South Wales	.54	1.16
Hampshire	.77	.76
Hertfordshire	.43	.46
Humberside	.39	.81
Kent	.64	1.38
Lancashire	.82	1.19
Leicestershire	.39	1.18
Lincolnshire	.75	.89
London	.73	1.20

Merseyside	.54	1.40
Norfolk	.35	.76
North Wales	.46	1.01
North Yorkshire	.81	.88
Northamptonshire	.68	.52
Northumbria	.41	.81
Nottinghamshire	.64	.84
South Yorkshire	.62	.77
Staffordshire	.64	.74
Suffolk	.43	.56
Surrey	.42	.63
Sussex	.53	.75
Thames Valley	.57	.82
Warwickshire	.54	.54
West Mercia	.55	.98
West Midlands	.16	.91
West Yorkshire	.46	.68
Wiltshire	1.21	.93
Mean - All Police Force Areas	.52	.84

Female Labour Supply

The female labour supply variable is taken from the NES as the total number of females in work over everyone in work.

Changes in Female Labour Supply by Police Force Area 1975-1997

Police Force Area	1975	1997
Avon and Somerset	34.8	46.5
Bedfordshire	34.0	43.7
Cambridgeshire	32.4	46.4
Cheshire	32.9	46.3
Cleveland	32.5	43.9
Cumbria	34.4	49.3
Derbyshire	33.3	40.7
Devon and Cornwall	35.5	50.8
Dorset	37.6	49.8
Durham	34.9	45.6
Dyfed-Powys	34.1	45.1
Essex	36.2	48.2
Gloucester	33.8	46.5
Greater Manchester	39.1	48.2
Gwent and South Wales	34.0	46.8
Hampshire	37.2	47.1
Hertfordshire	38.2	48.2
Humberside	31.7	45.2
Kent	36.9	49.2
Lancashire	36.2	44.2
Leicestershire	34.4	44.5
Lincolnshire	34.0	48.7
London	38.3	45.8
Merseyside	37.7	51.5
Norfolk	34.2	45.5
North Wales	29.3	44.0
North Yorkshire	36.3	46.1
Northamptonshire	35.7	45.0
Northumbria	37.6	48.4

Nottinghamshire	35.9	46.1
South Yorkshire	32.9	47.2
Staffordshire	37.7	45.6
Suffolk	33.4	45.5
Surrey	39.4	49.1
Sussex	40.2	49.8
Thames Valley	36.8	47.1
Warwickshire	35.0	43.8
West Mercia	37.9	47.6
West Midlands	35.0	45.9
West Yorkshire	38.2	47.7
Wiltshire	34.4	46.2
Mean - All Police Force Areas	35.5	46.7

Female Labour Supply in Low Skilled Occupations

Low skilled occupations were defined as (1) those occupations where the average male wage was beneath the 25th percentile of the male wage distribution for all occupations in the year 1975; and, (2) occupations where the average male wage in beneath the 50th percentile of the male wage distribution for all occupations in 1975 and where at least 50% of the workforce were male in the initial period.

These measures were calculated using occupation and earnings data from the NES. The share of females in these occupations was calculated simply as the number of women in these occupations over the all people in the occupations. Due to changes in the way occupations were recorded in the NES from 1991 onwards it was not possible to exactly match the occupations identified as the low skilled in 1975 all the way through to 1997. Where exact matches were not possible low skilled occupations were matched with similar occupations in later years to make consistent comparisons possible, where this was not possible occupations identified as low skilled in the initial period, which could not be matched to the same or similar occupations in the later periods were dropped from the initial low skilled group.

Changes in the share of Females in Low Skilled Occupations – 25th Percentile

Police Force Area	**1975**	**1997**
Avon and Somerset	65.8	70.1
Bedfordshire	64.4	73.3
Cambridgeshire	59.4	67.2
Cheshire	62.1	74.6
Cleveland	71.0	76.7
Cumbria	65.6	74.9
Derbyshire	69.0	69.4
Devon and Cornwall	57.2	69.5
Dorset	63.8	67.8
Durham	74.2	71.4
Dyfed-Powys	60.1	67.9
Essex	63.3	70.2
Gloucester	62.7	66.3
Greater Manchester	69.8	69.3
Gwent and South Wales	68.4	69.8

Hampshire	69.3	72.7
Hertfordshire	66.3	71.0
Humberside	61.1	68.5
Kent	67.8	69.6
Lancashire	66.7	69.9
Leicestershire	64.8	70.6
Lincolnshire	54.6	64.9
London	58.1	59.8
Merseyside	67.8	69.9
Norfolk	54.6	68.0
North Wales	58.4	70.0
North Yorkshire	62.3	66.1
Northamptonshire	67.5	71.3
Northumbria	70.6	66.8
Nottinghamshire	68.1	72.2
South Yorkshire	73.8	75.6
Staffordshire	70.0	75.3
Suffolk	57.6	66.1
Surrey	62.2	66.7
Sussex	62.4	65.3
Thames Valley	66.7	71.9
Warwickshire	67.4	69.5
West Mercia	64.0	70.8
West Midlands	70.0	73.2
West Yorkshire	68.8	70.1
Wiltshire	62.5	70.1
Mean - All Police Force Areas	64.9	69.9

Changes in the share of Females in Low Skilled Occupations – 50th Percentile

Police Force Area	1975	1997
Avon and Somerset	12.1	14.6
Bedfordshire	8.8	12.7
Cambridgeshire	10.6	13.3
Cheshire	8.8	14.3
Cleveland	9.4	14.8
Cumbria	9.5	15.8
Derbyshire	9.6	10.8
Devon and Cornwall	11.5	15.6
Dorset	12.6	18.8
Durham	10.5	12.1
Dyfed-Powys	10.3	14.9
Essex	10.4	16.4
Gloucester	11.4	15.2
Greater Manchester	11.8	13.4
Gwent and South Wales	11.1	15.1
Hampshire	12.5	15.1
Hertfordshire	11.3	16.4
Humberside	9.6	13.9
Kent	12.0	15.4
Lancashire	13.8	14.0
Leicestershire	10.5	12.9
Lincolnshire	9.7	15.0
London	11.9	12.0
Merseyside	11.7	14.4
Norfolk	9.9	14.8
North Wales	10.6	12.4
North Yorkshire	12.9	14.8
Northamptonshire	9.4	13.4
Northumbria	12.9	12.7

Nottinghamshire	10.7	13.9
South Yorkshire	9.6	15.8
Staffordshire	10.1	12.8
Suffolk	12.6	16.2
Surrey	13.9	15.6
Sussex	13.1	15.4
Thames Valley	12.2	12.7
Warwickshire	11.4	12.2
West Mercia	12.7	13.8
West Midlands	11.9	15.1
West Yorkshire	12.4	17.2
Wiltshire	11.2	12.4
All Police Force Areas	11.2	14.3

Population

The population data used in Chapter 5 come from the Home Office.

Population Change across Police Force Area between 1975-1997

Police Force Area	1975	1997
Avon and Somerset	1319700	1478300
Bedfordshire	487900	552300
Cambridgeshire	553000	712200
Cheshire	911900	982100
Cleveland	65600	555800
Cumbria	474600	492100
Derbyshire	889500	965500
Devon and Cornwall	1340400	1551500
Dorset	571700	687500
Durham	610900	608300
Dyfed-Powys	423700	477900
Essex	1415500	1595300
Gloucester	487700	559300
Greater Manchester	2700200	2571900
Gwent and South Wales	870450	896500
Hampshire	1558100	1762500
Hertfordshire	937300	1024800
Humberside	847900	884700
Kent	1443800	1566000
Lancashire	1373700	1425100
Leicestershire	835100	929000
Lincolnshire	521900	619400
London	3554500	3561000
Merseyside	1588900	1413400
Norfolk	657400	783000
North Wales	599700	656000
North Yorkshire	652000	737700
Northamptonshire	501100	610300
Northumbria	1473300	1430100
Nottinghamshire	980400	1032200
South Yorkshire	1317800	1304500
Staffordshire	992800	1060300
Suffolk	571000	666600
Surrey	1001600	1057100
Sussex	1277100	1487300
Thames Valley	1697100	2085800
Warwickshire	470400	503600
West Mercia	945000	1147700

West Midlands	2767700	2630600
West Yorkshire	2082100	2110100
Wiltshire	509900	599400

Age

The age variable in Chapter 5 was constructed from the NES and defined as the number of individuals in the area under the age of 25 over all individuals in the area.

Changes in the Proportion of Young People across Police Force Areas between 1975 and 1997

Police Force Area	**1975**	**1997**
Avon and Somerset	18.7	11.4
Bedfordshire	16.9	12.0
Cambridgeshire	20.0	13.5
Cheshire	19.5	12.3
Cleveland	19.9	13.2
Cumbria	19.5	13.7
Derbyshire	18.1	11.4
Devon and Cornwall	19.4	12.0
Dorset	17.1	15.6
Durham	20.5	11.0
Dyfed-Powys	17.2	15.0
Essex	18.1	14.6
Gloucester	18.8	11.9
Greater Manchester	19.6	12.6
Gwent and South Wales	19.6	14.1
Hampshire	19.0	13.0
Hertfordshire	17.9	13.1
Humberside	19.7	12.5
Kent	19.9	13.4
Lancashire	18.9	12.6
Leicestershire	20.7	12.7
Lincolnshire	21.2	12.6
London	18.2	14.0
Merseyside	19.9	11.5
Norfolk	20.6	12.3
North Wales	16.3	13.0
North Yorkshire	19.5	12.8
Northamptonshire	19.7	13.3
Northumbria	21.2	11.9
Nottinghamshire	18.9	11.0
South Yorkshire	20.1	12.9
Staffordshire	18.3	12.5
Suffolk	21.0	14.3
Surrey	17.3	13.8
Sussex	18.0	13.7
Thames Valley	18.6	13.5
Warwickshire	19.6	12.1
West Mercia	20.1	12.6
West Midlands	18.5	13.0
West Yorkshire	19.2	14.7
Wiltshire	22.0	13.9
Mean - All Police Force Areas	19.2	12.9

Chapter 6: ***Age Differences in Crime: Are they Explained by Education?***

Property Crimes:
- Damaging or destroying, on purpose or recklessly, something belonging to somebody else.
- Writing or spraying graffiti on walls, buses, train seats, shelters etc.
- Stolen money from a gas or electricity meter, public telephone box, vending machine, video game, or fruit machine.
- Stealing from a shop, supermarket or department store.
- Stolen anything in school worth more than £5.
- Stolen anything from the place where you work worth more than £5.
- Taken a bicycle with out the owner's permission.
- Taken a motorcycle or moped with out the owner's permission.
- Taken away a car with out the owner's permission.
- Stealing something out of or from a car.
- Pick pocketing something from somebody.
- Snatching (from a person) a purse, bag or something else.
- Sneaken or broken into a private garden, a house or building intending to steal something (not abandoned or ruined buildings).
- Stolen anything worth more than £5, not already mentioned (e.g. Hospital, youth club, sports centre, pub etc).
- Buying, selling or holding onto something you know or believe at the time has been stolen.
- Selling a cheque book, credit card, cash point card belonging to you or someone else so that they can steal money from a bank account.
- Using a cheque book, credit card, cash point card which you know or believe at the time has been stolen to get money out of a bank account.
- Claiming on an insurance policy, an expenses form, a tax return or social security benefit form that you know to be incorrect in order to make money.

Handling Crimes:
- Buying, selling or holding onto something you know or believe at the time has been stolen.
- Selling a cheque book, credit card, cash point card belonging to you or someone else so that they can steal money from a bank account.
- Using a cheque book, credit card, cash point card which you know or believe at the time has been stolen to get money out of a bank account.
- Claiming on an insurance policy, an expenses form, a tax return or social security benefit form that you know to be incorrect in order to make money.

Violent Crimes:
- Carrying a weapon, such as a knife, stick etc, to defend yourself or attack other people.
- Threatening somebody with a weapon or beating them up, in order to get money or other valuables from them.
- Participating in fighting or disorder in a group in a public place (e.g. Football ground, railway station, riot, demonstration or in the streets).
- Beating up somebody not belonging to your immediate family, to such an extent that you think or know that medical help or a doctor is needed.
- Beating up somebody belonging to your immediate family, to such an extent that you think or know that medical help or a doctor is needed.
- Hurting someone with a knife, stick or other weapon.

Percentage of Males who committed an offence in the last 12 months

	Property Offences		Handling Offences		Violent Offences	
	Stayed on post 16	**Left School**	**Stayed on post 16**	**Left School**	**Stayed on post 16**	**Left School**
All Ages	13.4 (.385)	18.0 (.341)	8.5 (.279)	14.8 (.355)	10.0 (.300)	18.0 (.384)
16-17	12.1 (.327)	22.2 (.418)	4.1 (.199)	19.4 (.398)	14.7 (.355)	23.4 (.427)
18-21	19.3 (.396)	22.7 (.421)	14.8 (.356)	18.3 (.388)	11.1 (.315)	22.0 (.416)
22-25	5.4 (.226)	9.5 (.294)	3.2 (.177)	7.5 (.265)	2.2 (.146)	9.6 (.296)

Education Variable

This was a dummy variable coded 0 if the young person had stayed on at school after the compulsory school leaving age of 16 and 1 if they had left aged 16 or earlier.

Neighbourhood/area variables

The ACORN Group was a set of dummy variables coded 1 for the particular ACORN group the property belonged in, 0 otherwise. This was constructed from the interviewer's assessment of the house and local area the house was located in. The ACORN codes were: Affluent/prosperous; Affluent professional metropolitan; Middle class comfortable; Skilled working class; New home, material comfort; White collar, working affluent ethnic; Older people; Council better off; Council high unemployment, poorest; Multi-ethnic low income.

The social housing variable was a dummy variable coded 1 if the property was rented from the council or Housing Association, 0 otherwise. The question that identifies this is: Does this household own this accommodation or is it rented? The options given are: owned or mortgage, owned by parents, owned by spouse/partner, rented from private landlord, rented form council, rented from housing association, other, don't know.

School Variables

The measure of truancy was constructed as a dummy variable from two questions. The first: Have you ever played truant from school for a whole day without permission? Those that responded yes were additionally asked: About how often do you play truant from school? The truancy dummy is coded 1 for those whose responded '1 week a term or more', 0 otherwise.

The exclusion variable was a dummy variable coded 1 if the respondent said they had ever been suspended or excluded, 0 otherwise. The questions asked were: Have you ever been temporarily suspended from school or not? Have you ever been expelled from school or not?

Individual Variables

The variable measuring whether a young person is white or not came from a question: How would you describe your race or ethnic origin? It was constructed as a dummy variable 0 if the respondent was white, 1 otherwise.

Whether a young person had any children was measured by a dummy variable coded 1 if the respondent had children, 0 otherwise. The question asked was: Do you have any children, or are you responsible as a parent for any children?

A measure of religiosity was constructed as a 0, 1 dummy coded 1 if the young person identified themselves as having a religion when asked: What, if any, is your religion or church? 0 otherwise.

Whether a respondent is living with their parents came from the question: I would now like to ask you some questions about members of your household, that is people who normally live here and with whom you share a living room or normally share at least one meal a day. How many are there and what relationship to the respondent?

Family Variables

The variable measuring father's class was constructed from the following question: What is the Government Class of your father's job (last job)? The options were: I Higher managerial, administrative or professional; II Intermediate managerial, administrative or professional; III NM Supervisory or clerical, junior managerial, administrative or professional; III M Skilled manual worker; IV Semi and unskilled worker; V State pensioners or widows (no other earners), casual or lowest grade workers, or long term unemployed. From these options a dummy variable was constructed with a value of 1 for group V and 0 otherwise.

Family contact with the police was measured with a dummy variable which took the value of 1 if the respondent's family (i.e. parent or sibling) had previous contact with the police, 0 otherwise. The question posed is: Has anyone you know ever been in trouble with the police for committing a criminal offence? Who? Who else?

Labour Market Variables

The employment variables measuring unemployment and full employment are both dummy variables coded 1 if the respondent identifies themselves as either of these (0 if not) when asked: Which of these things on this card best describe what you are currently doing? The options are: at school, at sixth form college, at university, on a youth training scheme, working full time, working part time, unemployed, doing something else, don't know.

Weekly income is a banded measure constructed from answers to the question: how much money, after tax and national insurance, do you receive each week? The bands are: £1-10, £11-20, £21-30, £31-40, £41-50, £51-70,£71-90, £91-110, £111-130, £131-150, £151-200. Dummy variables were coded such that they took the value of 1 if the weekly earning fell within that particular bracket, 0 otherwise.

Appendix B: Methodology Appendix

Why Logs rather than Levels?

Because areas vary greatly in size and the amount of crime they experience if we were just looking at changes across areas in levels we would see the largest increase in the biggest areas. So that London would always have a much larger rise than Surrey for example. Instead we look at the proportionate change, by taking the natural log of variables. Taking the log of a variable means that the coefficient can be read as a percentage effect, for example in a very simple model where log(crime)= β log(wages) a coefficient of β is produced. This can be interpreted as the percentage effect on crime produced by a 1% increase in wages.

Omitted Variable Bias

Omitted variable bias results from excluding a variable from a model that actually belongs in it (i.e. one that has an effect on crime). For example, in the following model:

$$y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \varepsilon$$

If X_2 is left out of the model for any reason, the model will be under specified. And we will end up with a model that looks like this:

$$y = \alpha + \beta_1 X_1 + \varepsilon$$

In this case X_2, because it is not included explicitly in the model, but nevertheless is associated with *y*, is included in the error term ε. If X_1 and X_2 are correlated the error term is now correlated with the right hand side of the model and this causes the model to be biased. The direction of the bias depends on: two things. Firstly, how correlated X_1 and X_2 are. And secondly, on the effect X_2 has on *y* (measured by β_2). This is shown in the table below:

	Correlation between X_1 and $X_2 > 0$	Correlation between X_1 and $X_2 < 0$
$\beta_2 > 0$	Positive bias	Negative bias
$\beta_2 < 0$	Negative bias	Positive bias

(Source: Wooldridge, 1999, page 90)

Controlling for cluster samples

The data used in this Chapter is aggregated to police force level. If we think that anything that has been omitted from the model, for example, things we think may be related to crime but cannot measure (such as peer group effects) the model may suffer from heteroskedasticity if these variables vary across areas (i.e. the variance of the error term (where the omitted variable will appear in the model) will not be constant but will vary across areas).

This will result in the models producing incorrect test statistics. To try to correct for this potential problem the regressions analyses are all carried out with robust test statistics which means the test statistics produced by this method are valid even if the model suffers from heteroskedasticity.

Measurement Error

It is not always possible to collect all the data we would like. For example, most surveys do not interview everyone, they interview a sample of people. Where people are asked their wages the data contains what they report their wages as which may be different from their actual wages. Another example, already discussed with the crime data is that it only contains crime reported to and recorded by the police, this will not cover all crimes. In these cases our variable is an imprecise measure and the model will suffer from measurement error.

Measurement error then is the difference between the measured value and the true value of a variable. In the dependent variable *e=y-y**, where y* is the true value of *y*. The model we want to estimate is:

$$y^* = \alpha + \beta X + \varepsilon$$

But instead we have to estimate:

$$y = \alpha + \beta X + \varepsilon + e$$

So now the error term in the model contains two components, ε the normal error term and e the measurement error. When the measurement error is in the dependent variable y replaces y^* and as long as the measurement error in y is not systematically related to any of the independent variables (for example, in a model of crime on wages if low wage people are less likely to report crime the error term will be correlated with the wages measure on the right hand side of the equation) the model will not be biased.

Measurement error in the independent variables is much more a cause for concern. Here $e=X-X^*$ where X* is the true value of X. In this case (with no measurement error in the dependent variable) the equation becomes:

$$y = \alpha + \beta X + (\varepsilon - \beta e)$$

Here the X which is contaminated with measurement error must be correlated with the error term because it becomes part of it. The covariance between X and e is no longer 0, but depends on the measurement error in X. This leads to inconsistent estimates. In particular this produces attenuation bias where the estimate of β will always be closer to 0 than the true β.

Measurement error, even in an independent variable, need not be too much of a problem. It depends on the size of the measurement error. This in turn depends on the variance of X^* relative to the variance of the measurement error. When the variance of X^* is large relative to the variance of the measurement error any inconsistency in the results will be small.

What is a Quasi-Natural Experiment?

One way to determine the causal effect that something has on something else is to carry out an experiment. These are more often seen in the natural sciences. For example, when a drug company tests a new medicine a number of people take part in the experiment. Allocated randomly into two groups, people in group A (the treatment group) receive the new drug, while group B (the control group) are given a placebo. This allows the scientists to do a before and after study of the effect of the new drug, comparing the treatment to the control group. Such experiments rarely take place in the realm of social science (largely because of cost and ethical concerns over why one group should benefit from a particular treatment and not another group).

Studying the impact of the Minimum Wage across areas offers a quasi-natural experiment. Although, not a perfect natural experiment, the fact that areas differ in the proportion of their population paid less than the Minimum Wage means that when the Minimum Wage is introduced it will have a larger effect in some areas than others. This offers a quasi-treatment group (areas where the Minimum Wage has a greater effect) and control group (areas with fewer low paid workers where the Minimum Wage has less of an impact). This allows a before and after analysis with comparisons across the differentially effected areas.

One of the huge advantages of data such as these is that it facilitates clarification of the issue of causality. Many researchers (who do not specialize in quantitative methods) often have a problem understanding causality with non-experimental data analysed using regression techniques to establish ceteris paribus (see discussion below). The quasi-experimental nature of this data, using before and after analysis with differentially effected groups helps to show the causal effect of the Minimum Wage on crime.

The Minimum Wage as an Exogenous Variable

Although Chapter 4 focuses on the Minimum Wage, this is really just a different way of looking at the relationship between crime and low wages. A problem with examining low wages in relation to crime is that wages are an endogenous measure. That is, the relationship can work either way round. While low wages are likely to have an effect on crime, it is also true that those who commit crime are likely to receive lower wages. However, Chapter 4 attempts to overcome this problem by using the Minimum Wage as a type of instrumental variable for low wages.

Probit Regression

When the dependent variable can only take on two values (either a young person commits a crime or they do not), it is known as a limited dependent variable. While an ordinary least squares model can deal with these type of dependent variables by using linear probabilities models, there are a number of problems associated with this methodology. Firstly, they sometimes give probabilities less than 0 or greater than 1. Secondly, a probability cannot be linearly related to the independent variables at all given values (i.e. the partial effect of an independent variable (measured in levels) is constant). Thirdly, linear probability models necessarily contains heteroskedasticity, which although does not cause bias, does lead to incorrect standard errors. Instead, Chapter 6 uses a maximum likelihood estimation probit model. This model is based on the assumption that the probability distribution in question (i.e. the probability of committing an offence) is normal and predicts probability Y=1 (i.e. a youth who left school at 16 [stayed on] committing an offence) compared to Y=0 (not committing an offence).

Nonlinear Functional Forms – the Quadratic

The evidence presented in Chapter 6 suggests crime rises with age, peaking in the mid to late teens and then subsequently declining. This suggests that there exists a nonlinear relationship between the dependent variable (crime) and independent variable (age). To capture this quadratics are added to the age variable so that the model includes both age and age^2. When age and age^2 are both included in the model we need to examine both to find the effect of age on crime (as you cannot examine the effect of one while holding the other constant). Thus, the effect of age on crime is measured by:

$$\beta_1 age + \beta_2 age^2$$

In most of the specifications in this Chapter the coefficient on age is positive, while the coefficient on age^2 is negative. As has been shown, this produces a parabolic shape and implies that age has a diminishing effect on crime. Prior to and including the point where the effect of age on crime is zero age has a positive effect on crime, after this, age has a negative effect on crime. The turning point is given by:

$$\text{Turning point} = -\beta_1 age/(2\beta_2 age^2)$$

Poisson Regressions

Where the dependent variable is a count variable (i.e. when the variable of interest is not just whether an individual has committed a crime or not, but how many times he or she has done so) Chapter 6 uses a poisson maximum likelihood model (Greene 2000). A count variable cannot be normally distributed. Instead the count variable forms a poisson distribution, which is determined by the mean of the variable. Based on this distribution the poisson regression makes in possible to find probabilities at any given value of the independent variables.

Appendix C: Regression Results Appendix

Chapter 3: Spatial Patterns of Crime: Can Labour Market Variables Account for Them?

Property crime regressions

	(1) Basic Model (with Demographics)	(2) Labour Market Variables	(3) Labour Market (inequality)	(4) Clear Up Rate	(5) Full Model
Proportion Male	.033*** (.033) [.002]				.027*** (.007) [.001]
Proportion under 25	.979*** (.326) [.052]				.834*** (.289) [.044]
Proportion of 16-19 year olds in Full Time Education	-.130*** (.053) [-.007]				-.131*** (.051) [-.007]
Proportion non-white	.163 (.106) [.009]				.146 (.118) [.008]
Proportion Social Housing	.398*** (.092) [.021]				.095 (.112) [.005]
Proportion Lone Parents	1.90*** (.324) [.101]				.992*** (.423) [.052]
Population	.000*** (.000) [.000]				.000** (.000) [.000]
Area Size	-.000*** (.000) [.000]				-.000*** (.000) [.000]
Lone Parent Income Support		14.73*** (1.87) [.813]	14.72*** (1.86) [812]		8.39*** (2.27) [.440]
ILO Unemployment		-.325 (.495) [-.018]	-.343 (.484) [-.019]		-.940** (.440) [-.049]
Bottom End of the Income Distribution		-.417*** (.122) [-.023]			
Top End of the Income Distribution		.439*** (.143) [.024]			
Income Inequality			.412*** (.122) [.023]		.283** (.120) [.015]
Property Crime Clear up Rate				2.18** (.889) [.137]	.354 (.566) [.019]
Obs	**374**	**374**	**374**	**374**	**374**
R-squared	**.565**	**.484**	**.483**	**.587**	**.611**

With robust standard errors
[ ] Marginal Effects

Violent crime regressions

	(1) Basic Model (with Demographics)	(2) Labour Market Variables	(3) Labour Market (inequality)	(4) Clear Up Rate	(5) Full Model
Proportion Male	.045*** (.009) [.001]				.058** (.027) [.002]
Proportion under 25	.603* (.602) [.018]				.379 (.283) [.011]
Proportion of 16-19 year olds in Full Time Education	.021 (067) [.001]				.023 (.060) [.001]
Proportion non-white	.875*** (.128) [.026]				.802*** (.138) [.024]
Proportion Social Housing	.567*** (.115) [.017]				.163 (.133) [.005]
Proportion Lone Parents	1.32*** (.431) [.040]				.042 (.373) [.001]
Population	.000 (.000) [.000]				(.000) [.000]
Area Size	.000 (.000) [.000]				.000 (.000)
Lone Parent Income Support		19.05*** (2.40) [.577]	19.09*** (2.67) [.582]		11.37*** (2.80) [.335]
ILO Unemployment		.938** (.452) [.028]	.706 (.458) [.022]		-.585 (.439) [-.017]
Bottom End of the Income Distribution		-.208 (.168) [-.006]			
Top End of the Income Distribution		.541** (.241) [.016]			
Income Inequality			.149 (.182) [.005]		.261 (.175) [.008]
Violent Crime Clear Up Rate				1.70 (1.10) [.065]	-.100 (.136) [-.003]
Obs	**374**	**374**	**374**	**374**	**374**
R-squared	**.660**	**.635**	**.601**	**.014**	**.713**

With robust standard errors
[ ] Marginal Effects

Regressions of Changes in Log(Crime Rates)on the Initial Low Pay Proportion Across Police Force Areas in the Years Before and After Minimum Wage Introduction

	(1)	(2)	(3)
Change in Log(Total Crime Rate)			
Proportion Paid Beneath Minimum Wage in Year Before Introduction	-1.235*** (.268)	-.961*** (.223)	-.987*** (.235)
Change in Clear Up Rate		-.140* (.071)	-.145* (.074)
Change in Log(Unemployment Rate)			.073 (.076)
Change in Average Age		.020 (.024)	.029 (.027)
Proportion of Young Males		-.977 (1.62)	-.961 (1.67)
Proportion with no Qualifications		.271 (.643)	.205 (.629)
Proportion Female		.002 (1.18)	-.187 (1.26)
Proportion Public Sector Jobs		.011 (.583)	-.088 (.604)
Demographic Controls	No	Yes	Yes
R-Squared	.400	.520	.535
Change in Log(Property Crime Rate)			
Proportion Paid Beneath Minimum Wage in Year Before Introduction	-1.236*** (.337)	-.894 *** (.235)	-.910*** (.239)
Change in Clear Up Rate		-.257*** (.076)	-.260*** (.078)
Change in Log(Unemployment Rate)			.045 (.071)
Change in Average Age		.012 (.022)	.017 (.024)
Proportion of Young Males		-.387 (1.27)	-.381 (1.31)
Proportion with no Qualifications		.370 (.649)	.331 (.641)
Proportion Female		.192 (1.09)	.074 (.573)
Proportion Public Sector Jobs		-.643 (.561)	-.707 (.573)
Demographic Controls	No	Yes	Yes
R-Squared	.400	.572	.578
Change in Log(Vehicle Crime Rate)			
Proportion Paid Beneath Minimum Wage in Year Before Introduction	-1.166*** (.253)	-1.012*** (.282)	-1.002*** (.283)
Change in Clear Up Rate		-.157* (.091)	-.156* (.092)
Change in Log(Unemployment Rate)			-.029 (.101)
Change in Average Age		.017 (.029)	.014 (.030)
Proportion of Young Males		-.289 (1.73)	-.293 (1.72)
Proportion with no Qualifications		-.006	.020

		(1.05)	(1.04)
Proportion Female		1.10 (1.47)	1.18 (1.53)
Proportion Public Sector Jobs		-.947 (.667)	-.905 (.668)
Demographic Controls	No	Yes	Yes
R-Squared	.292	.378	.380
Change in Log(Violent Crime Rate)			
Proportion Paid Beneath Minimum Wage in Year Before Introduction	-1.079*** (.281)	-1.005** (.471)	-1.053** (.520)
Change in Clear Up Rate		-.003 (.126)	-.012 (.133)
Change in Log(Unemployment Rate)			.141 (.064)
Change in Average Age		.085 (.051)	.103 (.064)
Proportion of Young Males		-2.68 (3.49)	-2.67 (3.78)
Proportion with no Qualifications		-.502 (1.49)	-.624 (1.54)
Proportion Female		-1.26 (2.81)	-1.64 (3.22)
Proportion Public Sector Jobs		1.31 (1.25)	1.11 (1.36)
Demographic Controls	No	Yes	Yes
R-Squared	.121	.261	.285

Notes: Coefficients (heteroskedastic consistent standard errors) reported. The sample size in all regressions is 41 police force areas. All regressions weighted by area population. The demographic controls entered were – change in average age, change in the population share of young (<25) men, change in population share with no educational qualifications, change in proportion female, change in share of public sector jobs.

Using Other Measures of Low Pay

	(1)	(2)	(3)
	Low Skill Males Low Pay Measure	Young Males Low Pay Measure	Wage Bill Share Measure
Change in Log(Total Crime Rate)			
Proportion Paid Beneath Minimum Wage in Year Before Introduction in Period Surrounding Introduction	-.882*** (.315)	-.387** (.179)	-6.660 (2.291)
Change in Clear Up Rate	.-.195*** (.056)	-.217*** (.055)	-.202*** (.056)
Change in Log(Unemployment Rate)	.102 (.053)	.106** (.054)	.103 (.054)
Change in Average Age	.032 (.017)	.032 (.018)	.032* (.017)
Proportion of Young Males	-.354 (1.25)	-.231 (1.28)	-.397 (1.25)
Proportion with no Qualifications	-.107 (.401)	-.297 (.423)	-.188 (.407)
Proportion Female	-.029 (.750)	.239 (.761)	.007 (.748)
Proportion Public Sector Jobs	.193 (.554)	-.005 (.624)	.152 (.561)
R-Squared	.432	.423	.431

Change in Log(Property Crime Rate)			
Proportion Paid Beneath Minimum Wage in Year Before Introduction in Period Surrounding Introduction	-.969*** (.301)	-.439*** (.142)	-6.920 (2.267)
Change in Clear Up Rate	-.205*** (.040)	-.234*** (.046)	-.217*** (.042)
Change in Log(Unemployment Rate)	.037 (.036)	.040 (.035)	.035 (.036)
Change in Average Age	.034** (.013)	.034** (.014)	.033** (.014)
Proportion of Young Males	.630 (.760)	.777 (.764)	.592 (.765)
Proportion with no Qualifications	.226 (.343)	.051 (.353)	.159 (.350)
Proportion Female	.228 (.633)	.548 (.642)	.276 (.641)
Proportion Public Sector Jobs	-.312 (.362)	-.511 (.385)	-.365 (.368)
R-Squared	.592	.571	.578
Change in Log(Vehicle Crime Rate)			
Proportion Paid Beneath Minimum Wage in Year Before Introduction in Period Surrounding Introduction	-.798** (.367)	-.311* (.177)	-5.941** (2.683)
Change in Clear Up Rate	.-.282*** (.060)	-.302*** (.058)	-.293*** (.059)
Change in Log(Unemployment Rate)	.012 (.054)	.015 (.053)	.010 (.054)
Change in Average Age	.026 (.019)	.027 (.019)	.026 (.019)
Proportion of Young Males	.266 (1.00)	.351 (1.00)	.243 (1.00)
Proportion with no Qualifications	-.027 (.495)	-.162 (.504)	-.084 (.500)
Proportion Female	.944 (.962)	1.15 (.997)	.995 (.970)
Proportion Public Sector Jobs	-.350 (.527)	-.481 (.541)	-.412 (.538)
R-Squared	.556	.547	.550
Change in Log(Violent Rate)			
Proportion Paid Beneath Minimum Wage in Year Before Introduction in Period Surrounding Introduction	-1.292* (.776)	-.813** (.313)	-9.071* (5.062)
Change in Clear Up Rate	.164 (.113)	.123 (.111)	.157 (.112)
Change in Log(Unemployment Rate)	.104 (.093)	.110 (.092)	.107 (.093)
Change in Average Age	.077* (.041)	.079* (.041)	.076** (.042)
Proportion of Young Males	-.365 (1.86)	-.014 (1.87)	-.435 (1.88)
Proportion with no Qualifications	-.160 (.763)	-.498 (.777)	-.260 (.773)
Proportion Female	-.243 (.1.67)	.376 (1.65)	-.212 (1.65)
Proportion Public Sector Jobs	.058 (.780)	.344 (.857)	.037 (.797)
R-Squared	.240	.248	.239

Benchmarking Against Earlier Time Periods

[Change in financial year 1998/99 to 1999/2000 benchmarked against change in financial year 1996/97 to 1997/98 and change in financial year 1995/6 to1996/7 in (1), (2), (3) and (5);
Change in financial year 1998/99 to 1999/2000 benchmarked against change in financial year 1997/98 to 1998/99 (scaled by Home Office factors for reporting changes), change in financial year 1996/97 to 1997/98 and change in financial year 1995/6 to1996/7 in (4)]

	(1)	(2)	(3)	(4)	(5)
	Basic Specification	(1) + Clear Up and Demographics	(2) + Unemployment	(3) + Add Definition Change Year	(3) + Area Trends
Change in Log (Total Crime Rate)					
Proportion Paid Beneath Minimum Wage in Year Before Introduction in Period Surrounding Introduction	-.963*** (.317)	-.770*** (.255)	-.764*** (.257)	-.917*** (.270)	-.479 (.298)
Change in Clear Up Rate		-.181*** (.053)	-.193*** (.056)	-.121* (.072)	-.166** (.082)
Change in Log(Unemployment Rate)			.103 (.053)	.131* (.049)	.135* (.073)
Change in Average Age		.026 (.017)	.032* (.017)	.005 (.025)	.035 (.028)
Proportion of Young Males		-.085 (1.17)	-.366 (1.24)	-.485 (.978)	-.735 (1.23)
Proportion with no Qualifications		-.061 (.416)	-.137 (.398)	-.228 (.378)	-.169 (.428)
Proportion Female		.362 (.730)	.053 (.744)	.068 (.617)	.260 (1.16)
Proportion Public Sector Jobs		.283 (.556)	.182 (.552)	.153 (.492)	.116 (.639)
R-Squared	.372	.421	.437	.284	.615
Change in Log (Property Crime Rate)					
Proportion Paid Beneath Minimum Wage in Year Before Introduction in Period Surrounding Introduction	-.962*** (.359)	-.806*** (.250)	-.804*** (.249)	-1.209*** (.388)	-.667*** (.214)
Change in Clear Up Rate		-.201*** (.039)	-.204*** (.040)	-.088 (.082)	-.158*** (.042)
Change in Log(Unemployment Rate)			.038 (.035)	.068* (.036)	.049 (.034)
Change in Average Age		.032** (.014)	.034** (.014)	.021 (.014)	.024 (.017)
Proportion of Young Males		.713 (.710)	.611 (.754)	-.020 (.822)	.379 (.827)
Proportion with no Qualifications		.228 (.352)	.200 (.343)	.025 (.341)	.198 (.352)
Proportion Female		.412 (.617)	.300 (.630)	-.146 (.704)	-.099 (.802)
Proportion Public Sector Jobs		-.282 (.360)	-.319 (.362)	-.051 (.410)	-.282 (.393)
R-Squared	.488	.591	.595	.540	.763

Change in Log (Vehicle Crime Rate)					
Proportion Paid Beneath Minimum Wage in Year Before Introduction in Period Surrounding Introduction	-.850 (.331)	-.657** (.300)	-.656** (.302)	-.853*** (.287)	-.596* (.355)
Change in Clear Up Rate		-.278*** (.059)	-.280*** (.059)	-.241*** (.060)	-.246** (.061)
Change in Log(Unemployment Rate)			.013 (.054)	.046 (.050)	.135* (.073)
Change in Average Age		.026 (.018)	.026 (.019)	.013 (.018)	.026 (.061)
Proportion of Young Males		.284 (.951)	.248 (.991)	.402 (.917)	.008 (.025)
Proportion with no Qualifications		-.039 (.503)	-.049 (.498)	-.018 (.447)	-.238 (1.17)
Proportion Female		1.04 (.940)	1.00 (.959)	.808 (.773)	.258 (.577)
Proportion Public Sector Jobs		-.333 (.523)	-.346 (.528)	-.374 (.497)	.495 (1.29)
R-Squared	.461	.558	.558	.782	.686
Change in Log (Violent Crime Rate)					
Proportion Paid Beneath Minimum Wage in Year Before Introduction in Period Surrounding Introduction	-.962* (.581)	-1.104* (.645)	-1.098* (.645)	-1.155* (.599)	-1.121 (.720)
Change in Clear Up Rate		.179 (.111)	.168 (.112)	.289** (.113)	.237* (.140)
Change in Log(Unemployment Rate)			.106 (.092)	.120 (.085)	.069 (.097)
Change in Average Age		.072* (.040)	.077* (.041)	.025 (.047)	.067 (.052)
Proportion of Young Males		-.098 (1.78)	-.387 (1.87)	-2.05 (2.04)	-.577 (1.94)
Proportion with no Qualifications		-.123 (.768)	-.201 (.769)	-.992 (.860)	-.305 (.932)
Proportion Female		.170 (1.61)	-.148 (1.66)	-2.03 (1.75)	-.456 (2.19)
Proportion Public Sector Jobs		.157 (.786)	.053 (.792)	-.046 (.838)	-.028 (.796)
R-Squared	.186	.235	.245	.319	.480

Notes: Coefficients (heteroskedastic consistent standard errors) reported. Sample sizes are 123 for columns (1), (2), (3) and (5) and 164 for column (4). All regressions weighted by population. The demographic controls entered were – change in average age, change in the population share of young (<25) men, change in population share with no educational qualifications, change in proportion female, change in share of public sector job. All equations include dummy variables for time period and the proportion low paid variable.

Property Crime Rates on Female Employment

	(1)	(2)	(3)	(4)	(5)
Female Employment	.287** (.136)	.242** (.135)	.242* (.135)	.256* (.134)	.255* (.134)
No. of Police Officers				-.056*** (.018)	-.055*** (.019)
Proportion Found Guilty			-.057 (.063)		-.039 (.072)
Proportion under twenty-five		-.231** (.094)	-.225** (.095)	-.233** (.094	-.229** (.095)
Controls for Demographics	No	Yes	Yes	Yes	Yes
Time Controls	Yes	Yes	Yes	Yes	Yes
Area Fixed Effects	Yes	Yes	Yes	Yes	Yes
R Squared	.958	.958	.959	.959	.959
Observations	943	943	943	943	943

Robust standard errors in parenthesis, *** significant at 1%, ** 5%, * 10%

Male Property Crime Rates on Female Employment

	(1)	(2)	(3)
Female Employment	.331** (.108)	.361** (.107)	.369* (.107)
No. of Police Officers			-.029** (.014)
Proportion under twenty-five		.174*** (.051)	.116 (.073)
Controls for Demographics	No	Yes	Yes
Time Controls	Yes	Yes	Yes
Area Fixed Effects	Yes	Yes	Yes
R Squared	.987	.987	.987
Observations	943	943	943

Robust standard errors in parenthesis, *** significant at 1%, ** 5%, * 10%

Male Mean Wages on Female Employment

	(1)	(2)
Female Employment	-.405*** (.079)	-.368*** (.072)
Proportion of males under twenty-five		.156*** (.046)
Controls for Demographics	No	Yes
Time Controls	Yes	Yes
Area Fixed Effects	Yes	Yes
R Squared	.996	.996
Observations	943	943

Robust standard errors in parenthesis, *** significant at 1%, ** 5%, * 10%

Property Crime and Female Employment in Low Wage Occupations – 25th. Percentile

	(1)	(2)	(3)	(4)	(5)
Female Employment in Low Skill Occupations	.333** (.137)	.353** (.137)	.366*** (.138)	.317** (.135)	.328*** (.136)
No. of Police Officers				-.051*** (.018)	-.050*** (.018)
Proportion Found Guilty			-.066 (.063)		-.048 (.063)
Proportion under twenty-five		-.260*** (.093)	-.253*** (.093)	-.261*** (.092)	-.257*** (.093)
Controls for Demographics	No	Yes	Yes	Yes	Yes
Time Controls	Yes	Yes	Yes	Yes	Yes
Area Fixed Effects	Yes	Yes	Yes	Yes	Yes
R Squared	.958	.959	.959	.959	.959
Observations	943	943	943	943	943

Robust standard errors in parenthesis, *** significant at 1%, ** 5%, * 10%

Property Crime and Female Employment in Low Wage Occupations – 50th. Percentile

	(1)	(2)	(3)	(4)	(5)
Female Employment in Low Skill Occupations	.382*** (.067)	.415*** (.066)	.419*** (.066)	.402*** (.065)	.406*** (.065)
No. of Police Officers				-.046*** (.018)	-.044** (.018)
Proportion Found Guilty			-.074 (.061)		-.058 (.061)
Proportion under twenty-five		-.335*** (.090)	-.328*** (.091)	-.334*** (.090)	-.329*** (.091)
Controls for Demographics	No	Yes	Yes	Yes	Yes
Time Controls	Yes	Yes	Yes	Yes	Yes
Area Fixed Effects	Yes	Yes	Yes	Yes	Yes
R Squared	.960	.961	.961	.962	.962
Observations	943	943	943	943	943

Robust standard errors in parenthesis, *** significant at 1%, ** 5%, * 10%

<u>Probit Model for Property Offences for Males aged 16-25</u>

	(1) **Basic specification**	(2) **Add Neighbour-hood Variables**	(3) **Add school Variables**	(4) **Add family Variables**	(5) **Add individual Variables**	(6) **Add Labour Market Variables**	(7) **Add All Variables**
Age_ns	-0.383	-0.332	-0.300	0.896	-0.245	-0.576	1.580*
	(0.528) [-0.084]	(0.556) [-0.701]	(0.543) [-0.062]	(0.705) [0.201]	(0.558) [-0.051]	(0.569) [-0.110]	(0.852) [0.238]
Age^2_ns	0.008	0.006	0.005	-0.025	0.004	0.012	-0.044**
	(0.013) [0.002]	(0.014) [0.001]	(0.013) [0.001]	(0.018) [-0.006]	(0.014) [0.001]	(0.014) [0.002]	(0.021) [-0.007]
Age_s	1.156***	1.222***	1.220***	1.503***	1.502***	0.593	1.331**
	(0.417) [0.255]	(0.430) [0.260]	(0.444) [0.253]	(0.463) [0.338]	(0.433) [0.310]	(0.466) [0.113]	(0.662) [0.201]
Age^2_s	-0.030***	-0.032***	-0.032***	-0.038***	-0.039***	-0.018	-0.037**
	(0.011) [-0.006]	(0.011) [-0.001]	(0.011) [-0.007]	(0.012) [-0.008]	(0.011) [-0.008]	(0.012) [-0.003]	(0.017) [0.048]
Unemployed						0.418	-0.385
						(0.259) [0.093]	(0.336) [-0.049]
Employed FT						0.096	-0.442
						(0.273) [0.019]	(0.364) [-0.059]
£1-10 (wk inc)						-0.104	-0.371
						(0.235) [-0.019]	1.241** [-0.047]
£11-20						-1.568**	-1.565**
						(0.674) [-0.128]	(0.741) [-0.094]
£21-30						0.030	0.179
						(0.266) [0.006]	(0.376) [0.030]
£31-40						0.092	0.236
						(0.229) [0.018]	(0.290) [0.040]
£41-50						0.404*	0.409
						(0.240) [0.094]	(0.314) [0.078]
£51-70						0.753***	0.706**
						(0.239) [0.203]	(0.346) [0.159]
£71-90						0.111	-0.386
						(0.281) [0.022]	(0.423) [-0.045]
£91-110						0.630***	0.365
						(0.232) [0.160]	(0.304) [0.068]
£111-130						-0.208	-0.295
						(0.391) [-0.035]	(0.474) [-0.037]
£131-150						0.523*	0.211
						(0.306) [0.129]	(0.405) [0.036]
£151-200						1.275***	(0.333)
						(0.291) [0.396]	(0.359) [0.337]
Black					-0.490**		-0.410
					(0.242) [-0.079]		(0.374) [-0.048]
Religious					-0.152		0.030
					(0.135) [-0.033]		(0.181) [0.004]
Children					0.355		0.326
					(0.233) [0.086]		(0.333) [0.059]

Live with parents					-0.487***		-0.591***
					(0.129)		(0.170)
					[-0.092]		[-0.082]
Father SES V				0.088			-0.078
				(0.231)			(0.304)
				[0.021]			[-0.011]
Family in trouble				0.577***			0.816***
with police				(0.217)			(0.267)
				[0.163]			[0.189]
Excluded			-0.009				-0.162
			(0.170)				(0.256)
			[-0.002]				[-0.022]
Truanted			0.682***				0.766***
			(0.116)				(0.158)
			[0.156]				[0.135]
Affluent /		0.409*					0.278
prosperous		(0.233)					(0.322)
		[0.101]					[0.048]
Aff. Prof. met		0.623**					0.303
		(0.287)					(0.390)
		[0.174]					[0.055]
Middle class /		0.060					0.019
comfort		(0.270)					(0.365)
		[0.013]					[0.003]
Skilled working		0.645**					0.543
class		(0.266)					(0.346)
		[0.180]					[0.110]
New home material		-0.550					-1.456**
comfort		(0.377)					(0.639)
		[-0.087]					[-0.093]
White collar		-0.256					0.070
working affluent		(0.307)					(0.409)
eth.		[-0.048]					[0.011]
Older people		0.262					0.002
		(0.467)					(0.599)
		[0.064]					[0.000]
Council, better off		0.123					0.003
		(0.249)					(0.351)
		[0.027]					[0.000]
Council high		0.367					-0.297
unemployment		(0.374)					(0.454)
		[0.094]					[-0.037]
Council poorest		0.251					0.172
		(0.437)					(0.559)
		[0.061]					[0.029]
Multi-ethnic low		-0.025					-0.505
income		(0.235)					(0.342)
		[-0.001]					[-0.062]
Social housing		0.271*					0.040
		(0.153)					(0.233)
		[0.063]					[0.006]
Obs	**867**	**845**	**858**	**681**	**840**	**866**	**640**
Test: age_ns=age_s, age2_ns=age2_s	5.63	4.94	5.15	3.32	7.11	2.68	0.06
P-value	0.06	0.08	0.08	0.19	0.03	0.26	0.97
Test: neighbourhood variables		29.43					23.53
P-value		0.00					0.02
Test: school variables			34.75				23.69
P-value			0.00				0.01
Test: family variables				7.59			9.52
P-value				0.02			0.01
Test: individual variables					21.24		14.35
P-value					0.00		0.01
Test: labour market						43.71	32.92

variables							
P-value						0.00	0.00
Test: all variables							27.18
P-value							0.00

Standard errors in parentheses
Marginal in [ ]
* significant at 10%; ** significant at 5%; *** significant at 1%
Controls included for still being in full time education, leaving school at 16 and missing information on education.

Probit Model for Handling Offences for Males aged 16-25

	(1) Basic specific-ation	(2) Add Neighbour-hood Variables	(3) Add school Variables	(4) Add family Variables	(5) Add individual Variables	(6) Add Labour Market Variables	(7) Add All Variables
Age_ns	-0.567	-0.677	-0.532	0.674	-0.436	-0.901	0.456
	(0.552) [-0.093]	(0.584) [-0.104]	(0.565) [-0.083]	(0.753) [0.110]	(0.591) [-0.062]	(0.607) [-0.122]	(0.924) [0.039]
Age^2_ns	0.012	0.015	0.011	-0.020	0.008	0.020	-0.017
	(0.014) [0.002]	(0.014) [0.002]	(0.014) [0.002]	(0.019) [-0.003]	(0.015) [0.001]	(0.015) [0.003]	(0.023) [-0.001]
Age_s	1.697***	1.554***	1.750***	1.978***	2.235***	0.957*	1.515*
	(0.497) [0.279]	(0.504) [0.239]	(0.521) [0.273]	(0.557) [0.322]	(0.537) [0.316]	(0.547) [0.130]	(0.789) [0.131]
Age^2_s	-0.042***	-0.039***	-0.044***	-0.049***	-0.056***	-0.026*	-0.042**
	(0.012) [-0.007]	(0.013) [-0.006]	(0.013) [-0.007]	(0.014) [-0.008]	(0.013) [-0.008]	(0.014) [-0.004]	(0.020) [-0.004]
Unemployed						0.403	-0.485
						(0.287) [0.066]	(0.389) [-0.033]
Employed FT						0.206	-0.230
						(0.297) [0.030]	(0.399) [-0.018]
£1-10(wk inc)						-0.116	-0.520
						(0.301) [-0.015]	1.327*** [-0.033]
£11-20						-1.016	-0.923
						(0.714) [-0.072]	(0.782) [-0.041]
£21-30						0.397	0.565
						(0.302) [0.069]	(0.421) [0.075]
£31-40						0.169	0.523
						(0.278) [0.025]	(0.355) [0.063]
£41-50						0.827***	1.109***
						(0.266) [0.178]	(0.348) [0.201]
£51-70						0.809***	0.824**
						(0.276) [0.175]	(0.403) [0.130]
£71-90						0.383	-0.193
						(0.316) [0.066]	(0.498) [-0.014]
£91-110						0.938***	0.827**
						(0.261) [0.210]	(0.333) [0.127]
£111-130						0.032	0.158
						(0.417) [0.004]	(0.519) [0.016]
£131-150						0.799**	0.410
						(0.326) [0.173]	(0.427) [0.048]
£151-200						1.287***	(0.463)
						(0.319) [0.338]	(0.387) [0.272]
Black					-0.429		-0.149
					(0.270)		(0.403)

					[-0.047]		[-0.011]
Religious					-0.256*		-0.172
					(0.148)		(0.198)
					[-0.040]		[-0.016]
Children					0.422*		0.392
					(0.248)		(0.369)
					[0.076]		[0.045]
Live with parents					-0.569***		-0.691***
					(0.154)		(0.207)
					[-0.072]		[-0.054]
Father SES V				-0.102			-0.785*
				(0.271)			(0.431)
				[-0.016]			[-0.038]
Family in trouble with police				0.762***			1.118***
				(0.224)			(0.285)
				[0.182]			[0.204]
Excluded			0.016				-0.452
			(0.187)				(0.317)
			[0.003]				[-0.029]
Truanted			0.514***				0.539***
			(0.128)				(0.181)
			[0.088]				[0.204]
Affluent / prosperous		0.575**					0.828**
		(0.280)					(0.356)
		[0.114]					[0.117]
Aff. Prof. met		1.078***					1.271***
		(0.325)					(0.416)
		[0.284]					[0.256]
Middle class / comfort		0.425					0.843**
		(0.310)					(0.392)
		[0.082]					[0.128]
Skilled working class		0.524					0.790**
		(0.322)					(0.400)
		[0.108]					[0.118]
New home material comfort		-.361					Dropped
		(.438)					
		[-0.044]					
White collar working affluent eth.		-0.083					0.586
		(0.372)					(0.482)
		[-0.012]					[0.078]
Older people		0.616					0.766
		(0.492)					(0.622)
		[0.137]					[0.120]
Council, better off		0.341					0.845**
		(0.297)					(0.370)
		[0.062]					[0.126]
Council high unemployment		0.820**					0.653
		(0.407)					(0.485)
		[0.200]					[0.094]
Council poorest		0.160					0.455
		(0.526)					(0.646)
		[0.027]					[0.057]
Multi-ethnic low income		0.128					0.254
		(0.286)					(0.379)
		[0.021]					[0.025]
Housing tenure		0.306*					0.076
		(0.168)					(0.256)
		[0.054]					[0.007]
Observations	**864**	**842**	**855**	**678**	**837**	**863**	**637**
Test: age_ns=age_s, age2_ns=age2_s	10.55	8.80	10.06	5.49	13.59	5.43	0.68
P-value	0.01	0.01	0.01	0.06	0.00	0.07	0.71
Test: neighbourhood variables		29.74					12.20
P-value		0.00					0.35
Test: school			16.53				11.46

variables							
P-value			0.00				0.00
Test: family variables				11.56			14.98
P-value				0.00			0.00
Test: individual variables					21.15		15.68
P-value					0.00		0.00
Test: labour market variables						41.59	35.5
P-value						0.00	0.00
Test: all variables							27.18
P-value							0.00

Standard errors in parentheses
Marginals in [ ]
* significant at 10%; ** significant at 5%; *** significant at 1%
Controls included for still being in full time education, leaving school at 16 and missing information on education.

Probit Model for Violent Offences for Males aged 16-25

	(1) Basic specific-ation	(2) Add Neighbour-hood Variables	(3) Add school Variables	(4) Add family Variables	(5) Add individual Variables	(6) Add Labour Market Variables	(7) Add All Variables
Age_ns	-0.146	-0.015	0.016	-0.400	-0.216	-0.362	-0.347
	(0.545) [-0.027]	(0.565) [-0.003]	(0.566) [0.003]	(0.658) [-0.071]	(0.574) [-0.038]	(0.579) [-0.062]	(0.827) [-0.004]
Age^2_ns	0.002	-0.001	-0.003	0.007	0.003	0.006	0.004
	(0.013) [0.000]	(0.014) [0.000]	(0.014) [-0.000]	(0.016) [0.001]	(0.014) [0.001]	(0.014) [0.001]	(0.020) [0.000]
Age_s	0.159	0.240	0.363	0.263	0.315	-0.263	0.878
	(0.539) [0.029]	(0.542) [0.043]	(0.584) [0.061]	(0.585) [0.047]	(0.562) [0.055]	(0.570) [0.044]	(0.763) [0.102]
Age^2_s	-0.009	-0.010	-0.014	-0.011	-0.012	0.000	-0.029
	(0.014) [-0.052]	(0.014) [-0.019]	(0.015) [-0.002]	(0.015) [-0.002]	(0.014) [-0.002]	(0.015) [0.000]	(0.019) [-0.003]
Unemployed						0.378	-0.037
						(0.274) [0.074]	(0.343) [-0.004]
Employed FT						0.241	-0.176
						(0.283) [0.044]	(0.365) [-0.020]
£1-10 (wk inc)						-0.587**	-0.607*
						(0.260) [-0.075]	1.098*** [-0.051]
£11-20						-0.134	0.069
						(0.282) [-0.021]	(0.377) [0.008]
£21-30						0.079	0.185
						(0.286) [0.014]	(0.374) [0.025]
£21-30						0.003	-0.443
						(0.246) [0.000]	(0.314) [-0.040]
£31-40						0.218	-0.054
						(0.270) [0.041]	(0.364) [-0.006]
£41-50						0.214	-0.402
						(0.285) [0.040]	(0.453) [-0.035]
£51-70						0.083	-0.426
						(0.310) [0.014]	(0.429) [-0.037]
£71-90						0.337	0.164
						(0.272) [0.068]	(0.359) [0.021]
£91-110						0.081	-0.934

						(0.335) [0.014]	(0.702) [-0.057]
£111-130						-0.052	-0.619
						(0.359) [-0.009]	(0.499) [-0.047]
£131-150						1.030***	(0.346)
						(0.312) [0.280]	(0.376) [0.243]
Black					-0.312		-0.272
					(0.262) [-0.046]		(0.385) [-0.026]
Religious					0.000		0.286
					(0.147) [0.000]		(0.213) [0.030]
Children					-0.037		-0.301
					(0.281) [-0.006]		(0.404) [-0.029]
Live with parents					-0.140		-0.510***
					(0.130) [-0.024]		(0.185) [-0.055]
Father SES V				0.453*			0.612**
				(0.237) [0.101]			(0.308) [0.106]
Family in trouble with police				0.659***			0.838***
				(0.232) [0.161]			(0.270) [0.163]
Excluded			0.179				0.000
			(0.171) [0.033]				(0.262) [0.000]
Truanted			0.584***				0.755***
			(0.130) [0.109]				(0.180) [0.106]
Affluent / prosperous		-0.078					-0.235
		(0.255) [-0.014]					(0.367) [-0.024]
Aff. Prof. Met		0.016					-0.535
		(0.345) [0.003]					(0.546) [-0.043]
Middle class / comfort		0.016					-0.260
		(0.271) [0.003]					(0.390) [-0.026]
Skilled working class		0.237					0.339
		(0.275) [0.049]					(0.377) [0.049]
New home material comfort		-0.045					-0.201
		(0.311) [-0.008]					(0.429) [-0.020]
White collar working affluent eth.		-0.233					-0.371
		(0.349) [-0.037]					(0.590) [-0.033]
Older people		0.326					0.247
		(0.507) [0.071]					(0.709) [0,035]
Council, better off		-0.156					-0.350
		(0.261) [-0.026]					(0.384) [-0.033]
Council high unemp / poorest		-0.317					-0.486
		(0.370) [-0.047]					(0.470) [-0.040]
Multi-ethnic low income		-0.026					0.026
		(0.234) [-0.005]					(0.350) [-0.003]
Housing tenure		0.392**					0.461**
		(0.154) [0.082]					(0.221) [0.069]
Observations	**814**	**793**	**806**	**638**	**790**	**813**	**602**
Test: age_ns=age_s, age2_ns=age2_s	3.12	3.11	3.31	1.02	3.22	4.24	2.31

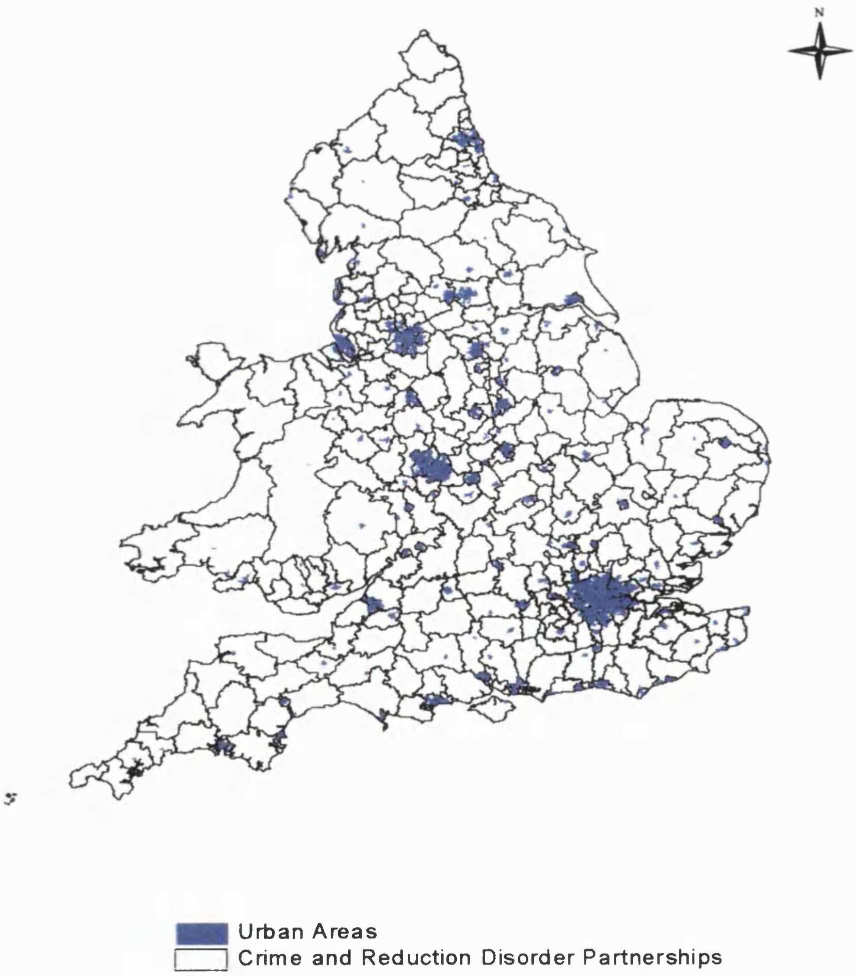
P-value	0.21	0.21	0.19	0.60	0.20	0.12	0.32
Test: neighbourhood variables		10.35					12.06
P-value		0.50					0.36
Test: school variables			23.44				17.95
P-value			0.00				0.00
Test: family variables				12.97			15.68
P-value				0.00			0.00
Test: individual variables					2.44		9.85
P-value					0.66		0.04
Test: labour market variables						26.66	28.02
P-value						0.01	0,01
Test: all variables							67.94
P-value							0.00

Standard errors in parentheses, Marginals in [ ]
* significant at 10%; ** significant at 5%; *** significant at 1%
Controls included for still being in full time education, leaving school at 16 and missing information on education.

Appendix D: Map Appendix

Chapter 3: ***Spatial Patterns of Crime: Can Labour Market Variables Account for Them?***

Crime and Disorder Reduction Partnerships – Urban Areas



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