IDENTIFYING A PREDICTABLE PROPERTY CRIME TREND MODEL IN THE NORTH EAST OF ENGLAND

MARK WILLIAM PITT

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None of the material contained in the thesis has previously been submitted for a degree in the University of Durham or any other university. None of the material contained in the thesis is based on joint research.

ABSTRACT

This research examines the association of property crime sub-groups at police force district or basic command unit level, using official monthly police statistics and official claimant count (unemployment) data. The research focused on the region of the North East of England, encompassing the police force areas of Cleveland, Northumbria and Durham. The research used a post National Crime Recording Standards, (NCRS) sampling period, (April 2002 to March 2008) inclusive. The results based upon monthly time series data suggest that crime data is indeed integrated to the order one or I(1) and that there exists a co-integrating relationship between a number of property crime sub-groups, claimant counts and related crime sub-groups. The results suggest that the geographical area type has an influence on crime modelling. The research also gives an indication that further research may be warranted in the areas of crime substitution and crime recording practices at a sub-police force level. This research was supported by Cleveland Police and the National Police College Bramshill Fellowship Programme.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF APPENDIX

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GLOSSARY

ADF – Augmented Dickey Fuller Test.

AIC - Alkaike Information Criterium

BCS – British Crime Survey

BCU – Basic Command Unit, this is a sub-police force area or district.

ECM – Error Correction Model

HO – Home Office

LFS – Labour Force Survey

NCRS – National Crime Recording Standards

ONS – Office of National Statistics

RBI – Reducing Burglary Initiative

SDP – Strategic Development Projects

UK – United Kingdom

US – United States

"We may regard the present state of the universe as the effect of its past and the cause of its future. An intellect which at any given moment knew all of the forces that animate nature and the mutual positions of the beings that compose it, if this intellect were vast enough to submit the data to analysis, could condense into a single formula the movement of the greatest bodies of the universe and that of the lightest atom; for such an intellect nothing could be uncertain and the future just like the past would be present before its eyes."

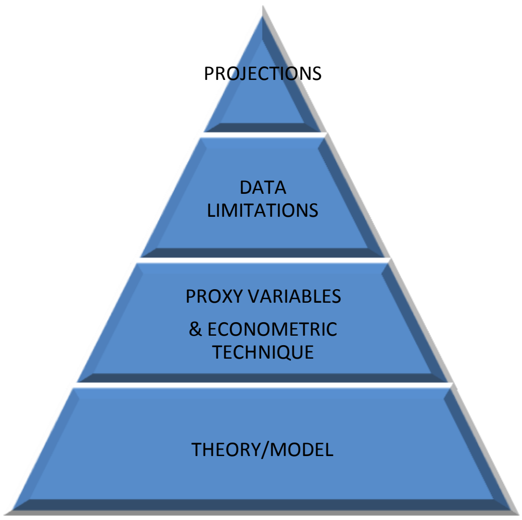
Marquis Pierre Simon de Laplace (1820)

1.1 Introduction

The police service suffers from poor forecasting of crime and as a result there have been recommendations to continue to develop locally owned and tailored forecasting skills amongst practitioners (Hamilton-Smith 2004). This is supported in the research conducted by Deadman (2003) who concludes that more development is required at police force level. This was reinforced by Dhiri et al. (1999) who, during the first ever projections of property crime in England and Wales, encouraged further research in this area with specific reference to regional predictability.

The ability to predict future empirical crime rates has been based on the ability to select a supporting crime theory, which in turn can be used as the basis of an empirical model. The model, coupled together with econometric modelling techniques, can be tested using explanatory direct variables or proxy variables. The quality and source of data variables is an essential ingredient to the modelling process and the results. This process is depicted in Figure 1 below.

Figure 1 – Crime modelling pyramid



There has been recent criticism of macro based studies based on the inability to accurately predict future trends (Dhiri et al. 1999 and Pudney et al. 2000). This theory is also supported by Chiricos (1987). Focusing our attention at the police force level area (micro based studies) would give us the benefit of a supply of historical data, limited geographical changes and provides a cross sectional dimension to the empirical work.

Given the recent downturn in the national economy there has been a huge increase in the number of reports that suggest that this will have a huge impact upon crime rates, (Ilston 2008). But is this really the case? It is the intention of this research to identify a predictable property crime trend model at the police force level to allow for short term forecasting and to help improve the understanding of influencing factors on property crime at a local level.

1.2 Structure of Report

The thesis will open up with a review of the relevant literature regarding crime theory and crime modelling, (see Chapter 2). The basis for the research and the research hypotheses will also be stated. The methodology will be discussed in Chapter 3 with specific focus upon model specification, geographical area selection, data parameters and collection and statistical analysis and software. Chapter 4 breaks down the analysis results in detail for unit root tests, co-integration tests and error correction models. Chapter 5 looks at model forecasting for a number of the error correction models. Chapter 6 discusses the findings of the research. Finally Chapter 7 draws conclusions to the research and outlines potential future research areas.

Chapter 2 Background

2.1 Crime Theory and Modelling

The concepts of the utilitarian social philosophers Cesare Beccaria and Jeremy Bentham in the eighteenth century form the basis of much of the recent empirical modelling of crime. This being based upon the concept of deterrence theory, (Sampson and Cohen 1998 and Levitt 1997). Deterrence theory suggests that an offender takes into account the probability of being caught, the severity of the punishment and the time interval between the two.

Becker (1968) used economic analysis to further develop the deterrence theory and suggested that an offender makes a rational choice to commit a crime. This rational choice theory is based on economic choice between legitimate and illegitimate employment, switching between the two based on expected effort and reward, measured by expected financial return. This way of thinking goes against many of the more traditional crime theories which have underpinned our knowledge of the causation of crime.

Sutherland (1947) suggested for example that criminal behaviour is learned behaviour like any other behavioural response. He goes on to say that boys are more likely to become delinquent than girls, as they are less controlled by the socialisation process and they are taught to be tough, aggressive and active risk seekers, (pre-requisites for involvement in the criminal world). Parsons (1937) places the family at the centre of the learning process.

Strain theory predicts that poor labour market conditions may cause stress or strain and result in people moving to crime due to not achieving a socioeconomic goal (Merton, 1957 and Cloward and Ohlin, 1960).

Social control theory sees unemployment as a major source of social bonding. Predicting that those at the lower end of the labour market may be less attached to society and thus less deterred from breaking the law, (Hirshi; 1969 or Box 1971).

Farrington et al. (1990) however are critical of the rational choice theory as developed by Becker and state that a large proportion of criminals are too young to compete in the formal labour market hence there is no 'choice' to be made, rational or otherwise. This conflict of opinion highlights the potential different motivational influences that are experienced at different times in a life cycle. Careful consideration should therefore be given to the factor of age during the research.

The routine activities theory (RAT) was proposed by Felson and Cohen (1979) and is a sub-field of the rational choice theory proposed by Becker. RAT develops the deterrence theory and looks at the criminal act itself, what is needed for it to occur and is very much based upon a rational choice model. The theory states that for a crime to be committed there must be a convergence in space and time of three minimal elements, namely: a motivated offender, suitable target and lack of capable guardian. These convergences are affected by the routine activities of targets and offenders. RAT therefore, by focusing on the criminal act itself instead of the criminal, attempts to explain how the dynamics of daily activities of social interaction such as employment and recreation affect crime rates. While people conduct their routine activities, motivated offenders select their targets based upon the elements of opportunity theory. Felson and Clarke (1998) suggested the concept of opportunity theory. It has four components, (attractiveness) value, inertia, (accessibility) visibility and access. RAT has a big empirical advantage over other crime theories in that it has an explicitly spatial dimension to it and this is very useful when it comes to the modelling of crime.

Recent Home Office crime models have been based on the routine activities theory (Fields 1990). Research such as this has shown that routine activity theory is more consistent in explaining levels of property crime than other crime categories such as violent crime. Consequently RAT has had a number of links to intervention programmes which are designed around the three key components of the theory, as previously discussed.

There have been numerous studies such as Tseloni (2002) who tested RAT by regressing data from England and Wales, the United States and the Netherlands. The research concluded that despite the differences in data there were many cross-national patterns which support RAT. Wiles and Costello (2000) also note the importance of the routine activities of those involved in crime.

There have however been a number of criticisms of the RAT, in that other traditional criminology theories are not integrated into it, such as biological indicators and social disorganisation theory. Routine activity theory is controversial with sociologists as they believe in the social causes of crime.

It is the intention of this study to build upon previous research which has been based on the RAT by developing the understanding of the effects on crime of the dynamics of daily activities. The research will be based upon an empirical model which will examine the effects on crime sub-group categories of changes in unemployment. Unemployment being an influencing factor on the theory of RAT, due to its impact in routine activities of people as unemployment changes.

Why should we model crime?

Crime patterns such as repeat victimisation, burglary localisation and hotspot areas tend to suggest that there is a basis behind the crime trends. This gives rise to the belief that a better understanding of the interactions between different contributing dimensions can lead onto the development of a crime model.

A crime model is one of the tools that can be used to identify future trends in crime. A stronger local understanding of crime modelling will help to provide local decision makers with the valuable short to medium term information they require on influential causes of crime. Therefore allowing them to defend against such influences by movement of the relevant resources (staffing and direct preventative interventions) to the areas of need. This is not only useful for resource allocation but can help evaluate interventions. In the simplest terms, models measure past relationships between variables and then try to forecast how changes in some variables will affect the future course of others.

A model is therefore implicit for forecasting requirements. Using statistical analysis it is possible to attach a measure of confidence to the model's forecasts so that an informed decision can be made on its use.

What has been done?

Compared to the vast literature on the theoretical concepts of criminality, the use of mathematical modelling in crime research is still in the infancy stages of its development.

There have been significant advances over the last few decades and this has been largely due to the availability and demand of crime data in a more available and comparable format. In particular during the 1970s crime levels became a major source of concern to the general public and as a result it became a major political issue. This led to further academic research and critique into crime trends and their causes. This also fuelled the need for more accurate and detailed crime data and led onto improved crime recording detail such as locational and circumstance details. The crime categories themselves have been further developed and broken down into more accurate sub-crime categories. More checking mechanisms have been introduced such as the National Crime Recording Standard, (NCRS) which has helped to improve the comparable nature of crime data in different geographical areas. Crime data collection, storage and analysis has improved due to the advances in information technology during the same period. All this development has given us a better understanding of how official statistics are produced.

A great deal of property crime modelling research, which has been predominately based in the United States, has concentrated on national data (Machin and Meghir, 2000; Raphel and Winter-Ebnor, 1999; Austin, 1993; Cohen, 1980; Danziger, 1975; Henry and Short 1954). There has also been an increased use of short term spatial analysis at a local level by individual crime agencies in England and Wales for tasking and co-ordination of local resources due to the introduction of the National Intelligence Model. The United States has had access to a wider selection of data which has helped to fuel research there.

Much of the recent work in relation to property crime modelling during the last decade placed a greater interest on aggregated research at national and regional levels using both non-criminal justice variables and criminal justice variables as their basis (Witt, 1998; Witt, Clarke and Fielding, 1999; Levitt and Lochner, 2001; Hansen and Machin, 2001; Fougere, 2006; Cohen et al, 2007). However there is still a distinct lack of resent research at below the regional geographical area and in particular to sub-police force level.

The British government has been particularly forward thinking in relation to predicator variables and it has funded some of the recent research (Field, 1990; Field, 1998; Dhiri et al., 1999). This research has concentrated on econometric modelling based on time series models that are used to correlate crime trends with the movement of predicator variables such as unemployment and Gross domestic product. This research has concentrated however on national aggregated data.

Willis (1983) was one of the first to carryout crime modelling at police force level in England and Wales. This study exploited the ability to compare crime trends over time for a given area. Using data from 1979 he found that a one per cent rise in unemployment was associated with a small increase in theft and violence against the person, but was unrelated to sexual crimes. However Willis only used a single cross-section during his research which was badly affected by persistent crime variables such as the theft and violence crime categories.

The modelling of crime trends has generally been focused around two modelling techniques, namely time series modelling and regression models. Time series models, such as Pyle and Deadman (1994) are based on the presumption that little is known with regards to the causality that affects the variable we are trying to forecast. Instead it examines the past behaviour of the time series in order to infer something about the future. Time series rely on a large number of data points to make forecasting meaningful and have been used in the past for short term forecasting. The use of a simple deterministic model such as linear extrapolation can be used or a more complex stochastic model for adaptive forecasting.

The time series models developed by Field (1990; 1998), which correlate macro-economic expansion and consumer expenditures with a growth in property crime in the U.K., anticipated an increase in crime rates in 1999 through to 2003.

The problems with developing accurate crime forecasts are also reflected in greatly divergent predictions, despite the use of the same data and analytical models. For example, while the same data and statistical modelling procedures were used by Dhiri et al. (1999) and Deadman (2000), the former predicted a rise in the U.K. crime rate while the latter predicted a decline. This difference stemmed not from the data used for the predictions, but from the use of different analytical techniques.

A large proportion of recent crime trend modelling has been based upon multiple regression models. Multiple regression models, by their very nature, provide the ability to account for not only individual relationships but also allow for describing the dynamic structure of simultaneous relationships. A basic multiple regression equation can be seen below: -

$$y = X_1 + X_2 + X_3 \ldots\ldots + E$$

Were Y is the dependent variable, the X's are the independent explanatory variables and E is the error term. An example of applied multiple regression models within the field of crime trend modelling can be seen below (Pyle and Deadman 1994):-

$$\Delta\Delta CRIME_t = \beta_1 \Delta Eco_t + \beta_2 \Delta Con_t + \beta_3 \Delta Pol_t + E_{t-1}$$

E-Economic dimension (Suitable Target)

Con – Conviction rate (Motivation)

Pol – No. Of police officers (Guardianship)

As can be seen in the above example regression model, crime for a given time can be predicted by three variables based upon an economic dimension, conviction rate and number of police officers. These very basically represent the three elements of routine activities Theory, suitable target, motivation and guardianship respectively. It is accepted that there is also links between some elements and there needs to be consideration of the more complex nature of variables and their potential impact on a crime model. A multiple regression model coupled with a large number of data points can be used for forecasting of data, largely short term forecasting.

Regression modelling is based upon a set of statistical assumptions and this effects the inferences which are derived from it. The assumptions include normality, independence, homoscedasticity, linearity, structural stability and exogenetity. A number of related statistical tests have developed around testing these important areas. Previous studies did not fully test these areas, for example, Wolpin (1978) only used the Durbin-Watson statistic as a test for independence which can be inconclusive and did not determine the existence and nature of the non-stationarity of the crime data. The study used a time series for England and Wales in the period 1894 to 1967 to estimate the effect on the length of sentences for differing crime categories.

One of the areas that appeared to be ignored in a number of earlier studies is the non-stationarity of variables. This problem area first combated by Engle-Granger (1987) states that for standard results of multiple regression analysis to be valid, the variables used must be stationary. Stationarity is important because when regressions are estimated using non-stationary variables either as the dependent or independent variable, the resultant regression coefficients may be biased. A time series is said to be non-stationary if (1) the mean and/or variance does not remain constant over time and (2) covariance between observations depends on the time at which they occur (Witte and Witt, 2000).

There has been a recent example of the importance of stationarity, observed in discussions around the findings of Deadman and Pyle (1997) who re-examine their previous study (Pyle and Deadman 1994). This study examined the association between property crime and economic activity using annual and quaterly time-series data for England and Wales. In particular they found that the property crime data was not stationary. When a time series is non-stationary, it can often be made into a stationary series by taking first differences of the series or I(1). This is simply calculating the change in the value of a variable from one period to the next. If first differences do not convert the series to stationary form, then one can create first differences of first differences. This is called second-order differencing or I(2). Deadman and Pyle highlight the importance of differencing data and established the property crime variables of theft and burglary to be I(2) whilst other economic variables are I(1).

Hale (1998) showed that Deadman and Pyle did not have to intergrate the crime variables to order 2, I(2). They concluded that the crime variables were in fact intergrated to the order 1 or I(1). This finding is supported by both Hale and Sannagh (1991) and Osborn (1995). This oversight cast doubt over their findings, (possible spurious regressions) and resultant conclusions that were drawn by Pyle and Deadman.

Therefore one of the first stages of modelling data is to establish the stationarity of the data and identify the correct order of intergration. Stationarity can be established by transforming variable data into logs and then subjecting it to a Augmented Dickey-Fuller Test (ADF) (Field 1999).

A substantial number of research results have described their result using the measure of elasticity. Elasticity measures the effect on the dependant variable of a 1 per cent change in an independent variable.

Therefore the elasticity of Y with respect to X, for example, is the percentage change in Y divided by the percentage change in X. Single elasticity figures are generally calculated from the mean point of the independent variable. They can be positive or negative, for example, if two variables have an elasticity of 2.0, then a 1 per cent increase in X will lead to a 2 per cent increase in Y. If two variables have an elasticity of -1, then a 1 per cent increase in X leads to a 1 per cent decrease in Y. Large elasticises imply that the dependent variable is very responsive to changes in the independent variable. Modelling results, divided into both crime and non-criminal justice dimensions are described in the next chapter.

In time series models a substantial period of time may pass between the dimension variable and the crime taking place. If there is a sufficiently long period of time between the two then a lagged explanatory variable should be used explicitly in the model (Beki 1999).

Deadman (2000) uses econometric and time series models to identify the role of error correction. Deadman states that there appears to be an important difference in forecast levels depending upon whether error-correction models or time series models are used.

<u>What has not been done?</u>

There has been little research based at or below regional level and virtually zero at force and ward levels. The regional study carried out by Witt, Clarke and Fielding (1999) although conducted at regional level, only focused on 10 regions of England and Wales and did not include the north east of England. The study looked at long term unemployment effects on the four broad crime categories of burglary, other theft, handling stolen goods and theft. They concluded that there was no significant short term relationship between unemployment and the crime categories. They do however suggest that individuals are more likely to commit crime the longer they are unemployed. This research thesis intends to build upon the basis of the research of Witt, Clarke and Fielding by focusing its attention on property crime sub-crime categories and the north east region of England at sub-police force geographical area. One of the huge benefits of modelling crime at force levels is that we can follow the same units of observation over time.

There has also been little research post the introduction of the new National Crime Recording Standard (NCRS), probably as it was only introduced in April 2002.

Crime trend research has also concentrated on the relationships of predicator variables on crime rates of various crime categories. There has been little research which takes account of relationships between one crime category and another, e.g. the effects of local police crime recording policy on similar or close offences resulting in possible crime substitutions and manipulations.

Virtually all of the research has concentrated upon the Home Office aggregated crime categories and not the crime sub-groups that are recorded at a police force area level. This aggregated crime category data has also generally been researched on an annual basis. Crime data is theoretically available at a sub police force level and at a higher time frequency, e.g. monthly data.

There has also been little research which has explored the time lagging effect associated with certain indicator variables and crime trends. Hansen and Machin (2003) provide evidence that future modelling techniques should also look at the timing of the comparative variables.

As previously discussed there has historically been some fundamental research errors made with regards to statistical analysis and associated assumptions, e.g. stationarity of the data.

2.2 Crime Research Literature

The crime research literature can be broken down into two broad areas, the first being non-criminal justice dimensions and the second being criminal justice dimensions. Figure 2 depicts a visual summary of the research conducted in both areas. Past research regarding the main dimensions will be discussed here.

2.2.1 Non-Criminal Justice Dimensions

Seasonal Dimensions

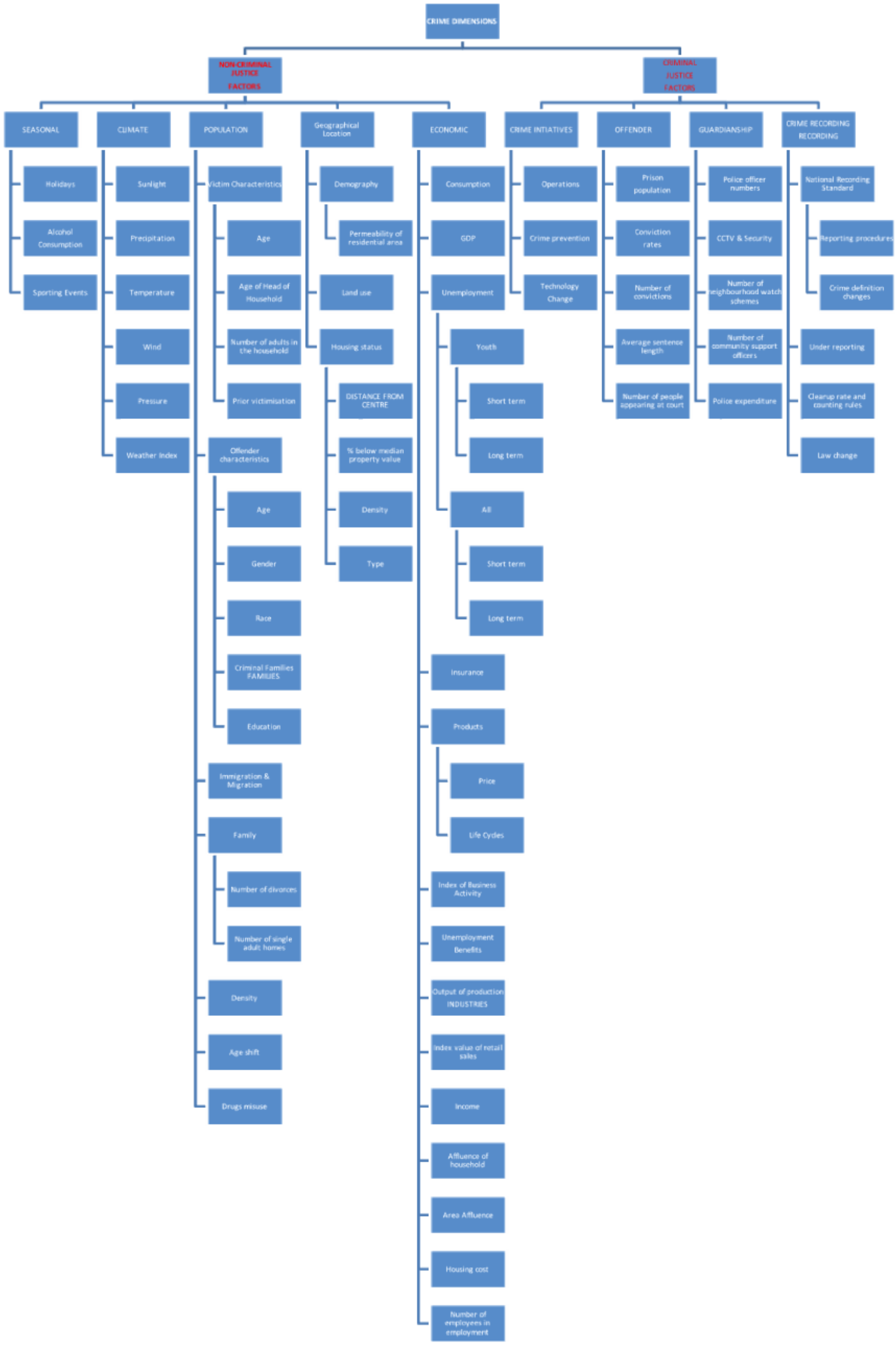
Seasonality was studied by Farrel and Pease (1994) in relation to rates of motor vehicle crime. They concluded that there was no long term or short term trends. Osbourn et al. (1995) however found a positive relationship between seasonality and property crime. Cohen and Felson (1979) link seasonality to routine activity theory.

The latest study by Hird and Ruparel (2007) has recently placed an empirical value to seasonality in their research using national monthly data between the years 2000 and 2005. Reporting on preliminary findings of the seasonality in recorded crime they have produced a M7 statistic for each area of crime. If the M7 statistic has a value greater than 1 it suggests no seasonality is present, whilst a value close to zero shows a strong seasonal pattern. Criminal damage to a vehicle was found to have a M7 statistic of 0.481, domestic burglary had 0.575 and theft from shops 0.62.

It has been common for seasonal variations in crime data to be removed. Field (1992) during temperature research removes the seasonal patterns caused by holiday periods or sporting events, e.g. Christmas. The removal of seasonality in crime research is also supported by Farrel and Pease (1994).

Raistrick et al. (1999) noted that perpetrators of acquisitive crimes such as burglary and theft have alcohol in their blood at the time of the offence. This finding is supported by Lombroso (1911) who suggests that men sometimes seek drink to give them the courage to commit the crime. It has also been established that heavier users are more likely to have criminal records.

Figure 2 – Non-Criminal Justice and Criminal Justice Dimensions



Climate Dimensions

Research into periods of daily light show no correlation to cases of robbery (Heller and Markland 1970 and Cohen 1990). This is supported by Field (1992) who finds no effect by sunlight and rain. Perry and Simpson (1978) and Cohen (1990) however do find a positive correlation between rain and robbery.

Feldman and Jarmin (1979) conclude that temperature is a more important factor on crime than precipitation and pressure. Although Cohen (1990) shows that there is no correlation between days of so called heat and occurrences of robbery, the research goes onto show a positive association between so called cold days and robbery rates. This view is also supported by Defronzo (1984). Cohen (1990) also shows a positive relationship between overall temperature and burglary offences. Field (1992) finds a positive relationship between most property crime (theft, burglary, criminal damage), but not robbery and temperature. Cohen (1990) also suggests that the use of weather variables as determinants for crime may allow for hourly or even daily prediction of crime. The effectiveness of this particular modelling dimension appears to be uncertain for the modelling of property crime.

Population Dimensions

Crime research in relation to offender age has shown that there is a sharp peak in crime offending around the ages of 14 to 18 (Soothill et al. 2002). This pattern is observed in both males and females. In the early eighties Hirschi and Gottdfredson (1983) researched the crime-age relationship, suggesting that age was an independent variable. They stated:-

Individuals vary in their propensity to antisocial and criminal behaviour, but the rate of offending and anti-social behaviour varies by age in the same way for everyone.

However Rowe and Tittle (1988) argued that the crime-age relationship could be explained by other variables, such as social integration, fear of sanctions, moral commitment and utility of crime. This view was supported more recently by Ezell and Cohen (2005) showing that there are several groups within having individual crime-age relationships. It has been established that the crime-age group relationship was also dependant on the categories of crime used (Steffensmeir et al. 1989). This has been supported more recently by Laub and Sampson (2001) and Hanson(2003). Hanson found that different crime areas, (property, handling and violent crimes), had different crime-age profiles. It has also been suggested by Greenberg (1977) that crime-age profiles change over time dependant on other variables. More recently however the age of offenders has been shown to be stable and have a predictability of behaviour (Laub and Sampson 2003). This is evidenced by the significant relationship between male age and convictions for burglary, showing a significant reduction post twenty years of age (Hanson 2003).

Crime-age profiles have also been found to be different in relation to gender (Graham and Bowley 1995). There has been much discussion around the issue of a gender gap in crime research but it has widely been accepted that women commit a smaller share of all crimes (Steffensmeier 1996).

There have been a number of positive relationships between crime and education established (Rutter 1979 and Thornberry et al. 1985). More recently it was found by Hanson (2003) that with property and handling offences that there were two distinct crime-age profiles dependent upon whether a person left school at 16 years of age or stayed on into further education. Hanson found that for those leaving school at 16 years of age the crime-age profile for the above offences peaked at aged 16. However for those that stayed on in education the corresponding peak was between 19 and 21 years and tailed off to virtually zero by 25 years of age. The overall findings found a distinct gap between the two crime-age profiles. Hanson went onto to completely explain the gap between the two profiles by using other variables to account for the differences, thus supporting the theory of Rowe and Tittle (1977). Hanson used variables associated to Neighbourhood/area, school, individual, family and labour market. Field (1990) also found a positive relationship between property crime and young men.

Trickett et al. (1992) found rates of property crime rising in the worst compared to best areas, the components being prevalence and vulnerability, (many people becoming victims or because few people are repeatedly victimised). Multiple victimisations have been recognised by Sparks et al. (1977), Forrester et al. (1988) and Barr and Pease (1990). Trickett (1992) found that consistently fewer people are victimized than would be anticipated if crimes were completely random in their nature. This theory is supported by Polvi et al. (1990) who concluded that a number of further crimes are likely soon to be attempted following the first victimization.

Drug relationship with crime is commonly placed into one of two ways of thinking, the first being ‘a criminal lifestyle facilitates the exposure to drugs’ and the second being ‘drugs dependency leads onto involvement in crime’

(Bennett and Holloway 2005). Bennett et al. (2000) suggest that heavy users of heroin and crack cocaine may be committing a considerable amount of acquisitive crime. These findings are supported by Jarvis and Parker (1989) who show that involvement in drugs use causes crime and state that addiction leads onto to acquisitive crime.

Seddon (2002) argues that there are only about three per cent of drug users who form the link between drug use and crime. Allen (2005) found that the initial use of drugs tends to lead onto petty shoplifting based crimes and more prolonged use can result in more serious street crime. The last couple of years have seen the introduction of drugs testing on arrest of an accused for listed acquisitive crimes. Research findings based on arrest figures have shown that 69 per cent of them tested positive for at least one drug. During drugs testing most reported that drug expenditure was funded by crime (Bennett 2000).

Wells and Rankin (1991) used fifty previous studies, which had been conducted between 1926 and 1988 in relation to delinquency and broken homes and reanalysed the data. They found that the prevalence of delinquency in broken homes was 10-15 per cent greater than in intact homes. This finding was also supported by Farrington (1995) who found that marriage within a family discouraged offending. Farrington also found that the relationship between delinquency and broken homes was weaker for more serious offences, such as burglary. McCord (1982) actually places an empirical value on the prevalence of offending depending on the family circumstances:-

Broken home without a loving mother	-	62 per cent
Intact home, with parental conflict	-	52 per cent

Intact home, no parental conflict	-	26 per cent
Broken home with loving mother	-	22 per cent

Wadsworth (1979) also found that there was a stronger likelihood that a child would become delinquent if the broken home was as a result of divorce as opposed to a death in the family.

Geographical Dimensions

Wikstrom (1991) shows that residential dwelling burglaries appear to occur disproportionately in areas of high socio-economic status, especially in areas closer to high offending rate areas. This theory is supported by Nicholas et al. (2005). Other research summarised by Mawby (2001) suggests however that the higher rates of residential burglary are found in areas, or close to areas, with socially disadvantaged housing areas.

A study by Wiles and Costello (2000) in Sheffield found that ninety per cent of victimisations occurred within the residence area of the offender. Their research showed that offenders travelled an average of 1.93 miles away from their homes to commit crime, (1.88 miles for domestic burglary- according to police data and 1.6miles according to self report interviews). The findings suggest that offenders travel short distances to commit property crime, particularly burglary. This view is supported by Neale and Evans (2003).

Research of the DNA database by Wiles and Costello also found that fifty per cent of offender movement was within force and basic command unit area, (BCU), and that a further thirty six per cent of offender movement was also within force but a different BCU. Only seven percent movement of offenders to adjoining and non-adjoining forces respectively was found. In contrast Wiles and Costello also found that rural areas that neighbour urban areas are of higher risk of offender movement to them. In Hambleton, North Yorkshire they found that thirty seven per cent of burglary offenders were from outside the county area. They did still however conclude that the average travel was still a low 1.68 miles. They concluded that offending appeared to be dependent upon opportunities presenting themselves during normal routines.

Area of residence and offender rates might be statistically related due to distribution by the dynamics of the housing market to certain areas (Bottoms 2007). Wilkstrom and Loeber (2000) found that juveniles living in a disadvantaged area with public housing, (areas of severe and concentrated economic disadvantage), significantly increased the risk of offending. It was also found that if the offender’s first serious offence was conducted below the age of 12 that there was no apparent effect from the neighbourhood.

Roger Houchin (2005) found in Scotland that there was a positive relationship between the homes, (located in wards) of convicted offenders and the official Index of Multiple Deprivation. Craglia and Costello (2005) repeated this research in South Yorkshire, looking at the smaller area unit of Census output area. They found that poverty or unpopular housing stock were predominant factors associated to offender rates.

Hoyle and Zedner (2007) write that risk of victimisation generally is closely related to geographical area and risk of personal victimisation correlated with age, sex and patterns of routine activity. They also state that the risk of being a victim to burglary is much higher if victims live in areas of higher rented accommodation. Households with lower levels of income, with single-adult or unemployed heads of households, are also at greater risk of being victims. Similar findings were found by Neale and Evans (2003) who conducted repeat victimisation research for domestic burglaries in the Cleveland force area. Amongst other findings they characterised those who are at a high risk of victimisation as: - single, female, 25-44 years of age, in older rented housing, on a council estate and in a deprived area.

Economic Dimensions

Studies that have incorporated developments in the econometric analysis of time series data have reaffirmed a much earlier conclusion that property crime is strongly related to economic activity, at least in the short term.

Thomas (1927) used an ‘index of business activity’ as an indicator of the state of the economy. Using data in England and Wales between 1857 and 1913, he showed a definite rise in burglary and robbery in periods of a business depression and a decrease in periods of business prosperity. Thomas also stated that the link between crime and unemployment was not an especially strong one. This is supported by Long and Witte (1981) and Freeman (1983), who conclude that the link between crime and unemployment is moderate. Box (1987) shows that the relationship between unemployment and crime is inconsistent and weak. Box (1987) does however argue that young males, especially those who have been unemployed for a long period of time, are most likely to turn to crime. Willis (1983) conducted one of the first police force area studies, showing that for a one per cent rise in unemployment there resulted in a small rise in theft and violence, (based on data for England & Wales (1979). Sampson and Wooldredge (1987) conclude in their study that the ‘Risk of being a victim’ of burglary, household theft and personal theft are possibly related to level of unemployment in the victims community.

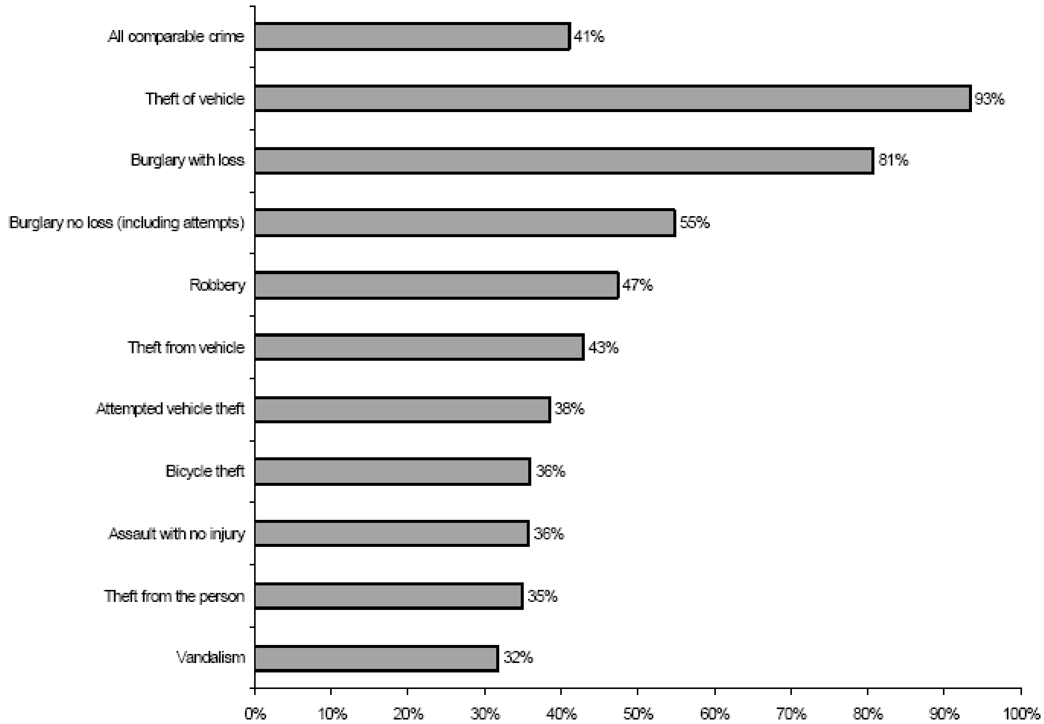
Timbrell (1988) found that there is no suggestion that unemployment is an independent factor in determining crime. However he found that if considered by age groups there is some evidence that unemployment may increase the number of criminals. Raphel & Winter-Eboner (1999), using data between 1970 and 1993 in the United States also found no large or systematic relationship between unemployment and crime rates. However they did find a highly significant positive unemployment effect on property crime.

Chiricos (1987) suggests that there is a time delay for the financial stresses of unemployment to take effect. There is a suggestion that unemployment lags behind the cycle of the economic activity by 6, 12 or even 24 months. Tarling (1982) conducted a review of 30 separate studies and concluded that there is more ‘no evidence’ than of evidence of a link between unemployment and crime.

Field (1990) studied recorded crime in post war England and Wales and established that some of the fluctuations in recorded property crime could be linked to the national economy. The study looked at two economic variables Consumption and Employment. Field suggested that there was no causal relationship between unemployment and property crime and suggested that the official unemployment figure suffered from a ‘dark figure’ like that found in official crime statistics.

The concept of a ‘dark figure’ was recently described in the 2006/07 British Crime Survey which estimates that the official crime statistics only record 41 per cent of actual crime, (this being based upon comparable crime subsets), (see Figure 3 below). This suggests and supports the widely accepted theory of the existence of a ‘dark figure’, a level of unreported crime within official crime statistics. Sparks (1977) estimated the overall crime ‘dark figure’ to be a staggering 11 times the official police figures.

Figure 3 – Reporting rates based on 2006/07 BCS interview, (using comparable subset), (Nicholas et al. 2007)



Field also suggested that particular categories of unemployment may present as a more useful indicator, such as unemployment of young men or long term unemployed. Field states that the correlation between property crime and consumption are stronger than the correlation for unemployment.

Field did find a link between personal spending, as measured by annual household consumption and changes in property crime. Field (1990) suggested that consumption not only had a motivating factor but also affected the number of capable guardians, (people were more likely to go out when consumption increased). Field also used a ‘stock of crime opportunities’ variable which represented by proxy the number of acquisitive goods. This was made up from an aggregate of the last 4 years worth of household consumption. This however was found to be limited due to its 99.8% correlation to the current year under study.

Pyle and Deadman (1994) further developed the work of Field in another macro study using data from England and Wales between 1946 and 1991. They also found that consumption along with Gross Domestic Product, (GDP) was negatively associated with changes in crime. They however suggest that GDP is the more important. They found a positive relationship between crime and unemployment. However in a similar study in Scotland they failed to find the same relationship, (Pyle and Deadman 1994b). Hale (1998) is also supportive of the correlation between consumption and property crime. Hale (1998) despite being unable to find a long term relationship, is supportive of the short term relationships between unemployment and property crime.

The positive link between crime and unemployment is supported by a number of studies conducted in the US, (Raphael and Winter-Ebmer, 2001 and Gould et.al, 2002). Gould et.al (2002) however find that wages of low skilled workers is a more important correlate of crime.

According to Farrington (1995) delinquents are likely to come from lower class families. Those that are convicted by the age of 18 were likely to come from low income families. Machin and Meghir (2000) researched the effects of low wages on crime. They found a negative correlation between theft and handling, burglary, vehicle crime and total property crime and low wages. This relationship was further reinforced by the research of Hansen and Machin (2001) which looked at crime effects pre and post introduction of the National minimum wage. They showed that the effects on crime were lower in areas that had more low paid workers.

Witt et al. (1999), using aggregate data from 42 police forces in a economic model of crime based on the theory of Becker (1968) concludes that high crime is associated with (1) increases in male unemployment, (2) high growth in the amount of property potentially subject to theft, (using the number of cars available per capita as proxy variable) and (3) high wage inequality associated with the distribution of weekly earnings of full time manual men.

In a US study Danziger and Wheeler (1975) report a positive association between income inequality and crime rates for robbery and burglary. Patterson (1991) found no real evidence to suggest income inequality in a given area is correlated to household burglary. Fowles and Merva (1996) also found no link between wage inequality and property crimes. Witt et al. (1998) found that wage inequality increase offences of robbery, other theft, and theft from a vehicle and burglary. This finding is also supported by Boroorah and Collins (1995) who report a positive association between income inequality and burglary.

Risk factor research was conducted by Tseloni et.al. (2002) and concluded that Household affluence has a positive effect on property crime victimisation in contrast to the negative effect exerted by area affluence.

2.2.2 Criminal Justice Dimensions

During research into the forecasting of burglary offences, Deadman (2000) showed empirical grounds for supporting causal links to not only economic factors, but demographic and criminal justice dimensions.

Crime Initiatives

Deadman and Pyle (1997) showed that predictions based on their forecasting of recorded crime using a time-series econometric model tended to over-estimate. They conclude that this could be a prima facie evidence of the effects of crime prevention measures undertaken by the police, e.g. extension of neighbourhood watch schemes and widespread use of surveillance equipment.

Hirschfield (2004) summarises the impact upon the offence of burglary by certain strategic development projects within the reducing burglary initiative, (RBI), conducted by the government. One of the big issues faced during this research was caused by the fact that the study areas tended to be deprived areas that were heavy in local intervention and funding for the like. This made it difficult to establish the source of successful reductions.

The research looked at trying to solve this problem by making the assumption that if the initiative had had no effect then the crime rate would follow the general pattern elsewhere. Presumably this process could be reversed if an unexpected outcome in crime rate was identified during analysis compared to the wider area, thus suggesting that a local initiative was responsible for the change.

Following analysis of the 21 RBI areas and taking into account the police force area trends, it was shown that the strategic development project's, (SDP), effect on burglary was significant; 15 SDP's (71 per cent), had significant reductions in burglary once the police force area trend had been removed.

Geographical displacement was found in only 5 out of 21 SDP's, with 7 SDP's showing signs of diffusion into surrounding areas. Generally it was found that diffusion effects were greater than the displacement effect.

It was found that location-specific situational crime prevention (e.g. target hardening), stake holding interventions with stand-alone publicity campaigns were the key to having the greatest impact upon burglary. Diversionary schemes were shown to have mixed results, particularly those that did not provide any parallel challenging of behaviour. A study by Farrington and Burrows (1993) suggests that explanations for a decrease in recorded shoplifters based on, for example, success of crime prevention efforts in schools and youth clubs can be rejected.

Even after age adjustment Steffersmier (1999) still showed a decline in burglary rates in the United States. Steffersmier concluded that a number of other reasons were behind the decline. The first being a substitution effect, in that as burglary was no longer attractive due to other reasons there was a move to other crime areas, in particular theft from and off motor vehicles. The second reason was supply and demand of consumer goods and the current increase in the abundance of consumer items (Cohen 1980). Steffermier finally suggests that security and enforcement against career criminals has also an effect.

Some argue that it was the crime reducing tactics of the late 1990s, such as targeting of criminals, hotspots, problem orientated policing and intelligence led policing that caused the crime rates to drop (Bowling and

Foster 2002). This view is supported by a number of researchers (Stockdale and Gresham 1995 and 1998, Best et al. 2001, Maguire 2000, Sherman and Berk 1984 and Heaton 2000).

During the RBI the role of publicity in crime prevention was studied (Johnson and Bowness 2003). It was found that the timing, intensity of publicity and implementation of interventions had a significant effect on crime prevention. Correlation analysis found that two types of intervention were significantly associated with burglary reduction. The first being interventions involving stakeholders and individual publicity campaigns. The second being location specific situational crime prevention initiatives, such as target hardening and risk surveys. It was also found that promoting schemes prior to their implementation may further enhance crime prevention efforts. This was evidenced in the reducing burglary initiative where it was shown that in the quarter leading up to the initiative there was a significant drop in crime rate. It is suggested that this was caused by pre-initiative publicity.

Offender

Hansen and Machin (2001) showed that conviction rates and sentence lengths are negatively associated with crime. Levitt (1998) supports part of this view and finds that higher levels of punishment are associated with lower crime rates for both property and violent crimes.

Fields (1990) found that prison population, clear up rate and the number of offenders guilty or cautioned had a patchy relationship to crime. His research showing that the number of offenders found guilty or cautioned had a positive relationship to the growth of crime the following year, therefore showing no deterrent effect.

Guardianship

Research by Clarke and Hough (1984), Kelling et al. (1974) and Sherman and Berk (1984) suggest that the police may not be central to crime prevention and control as initially thought. Kelling (1974) found that crime rates were unaffected in a US study when police presence was doubled. Random patrol was also found to be ineffective in cutting crime rates. Rapid response to crime calls by police also has little effect (Pate et al. 1976). Similar effects were seen in the UK (Morgan and Newburn 1997).

Evidence however from Mehay (1977), Hakim (1979) and Fabrikant (1979) show that police deployment has a significant effect on the allocation of regionally based property crime but not on violent crime. This view is evidenced in Becker (1968) who found that growth in police strength is negatively correlated with property crime. This was further suggested by Witt et al (1999) who found that a growth in police strength is negatively correlated with property crime. Levitt (1997) studied the effects of increases in police numbers at the time of elections and found that an increase in police reduces violent crime but had a smaller impact on property crime. Field (1990) did show police strength to be negatively related to theft of and from the vehicle and other theft. Whereas Thaler (1997) found that arrest rates deter crime and that police presence per acre had a significant effect on crime rates.

However the general view of effects of police officer numbers on crime rates changed in the mid 1990s when crime rates both in the US and the UK began to fall. These declines followed sizable increases in police resources. This fuelled further support for a link between police strength and crime rates.

A study by Greenbery & Kessler (1983) in the US found a marginal deterrence effect associated between property crime rates and police employment both within city and other suburban areas. However they did find a higher rate of crime reporting and recording of crime when police force strength increased. It has been found that an increase in police preventative patrol has led to an increase in reported crime (Thaler 1997).

Mehay (1977) argued that increasing expenditure on police activities within a society was likely to shift crime to its boundary areas.

It was found during the RBI that the change in staff during the implementation of the scheme had no significant effect on the success of it. But evidence did suggest that ring-fenced time and effective community engagement appeared to have a positive effect on the outcome of the scheme and the resulting crime rates.

Clear up rates have long been and still are seen as an indicator of police effectiveness in the detection of crime. As discussed earlier clear up rates are notoriously malleable (Young 1991) and they can result in problematic comparisons over a long period of time and for different police force areas. The effectiveness of police numbers still remains inconclusive and lack of research within this field has been blamed on the complex links to crime and the difficulty in disentangling their effects on crime rates.

There has been very little research within the UK regarding the private security sector and as a result it is a crime dimension area that is difficult to quantify. One of the primary reasons for this is the definition of private security and what should be and should not be included (Newburn 1995). From census data Jones and Newborn (1998) found that the proportion of private security versus the police between 1951 and 1991 has remained relatively constant.

2.3 Crime Measurement

How do we measure accurately the occurrences of crimes within society? Broadly speaking there have been two main crime measuring categories. These are official statistics and victimisation surveys.

Official Statistics

The first official crime statistics were made in France in 1827 (Beeive 1993). It was not until 1876 that similar statistics were recorded in England and Wales at a national level. Criminal statistics are now published nationally, six monthly and annually by the Home Office, (HO). Regional summaries are also published. Criminal statistics are based on 100 crime categories of notifiable offences which are recorded by individual police forces. Statistical returns are currently sent to the HO via the IQUANTA computer system. The categories are placed into one of nine broad crime headings.

The numbers of crimes recorded by the police are influenced both by changes in the reporting of crime by the public and changes in the rules and practice of the police for recording crimes.

Crime reporting underpins crime modelling, as the resultant crime data is the quantitative crime information required for modelling. A number of criminology theories have been built upon on the use of such data. But how accurate is the information and can it be relied upon in crime modelling?

Prior to 1968 there was little consistency between police forces in the way they counted crime offences. Clearer Counting Rules were established following recommendations of the PERKS committee in 1967. The rules were revised again in 1980 and more recently in 1998. In April 1998, the Home Office Counting Rules for Recorded Crime were expanded to include certain additional summary offences and the methods of counting crimes became very much victim focused. The 1998 revision had a significant impact on the overall total number of recorded offences between the years 1997/98 and 1998/99, showing an overall 14 per cent drop, (HO 2001). The most recent revision to the counting rules was made in September 2007.

It has been suggested that recording rates have also suffered by manipulation during the initial control room procedure and the resulting crime management phase of the reporting process. This has resulted in deliberate and unintended manipulation of crime reporting, therefore resulting in crime statistics that are less reliable. Bottomley & Coleman (1981) mention the art of 'Cuffing' crimes and suggest that the reason behind this is to avoid work or improve the overall clear-up rates.

In April 2002, the National Crime Recording Standard, (NCRS), was introduced to ensure greater consistency between forces in recording crime and to take a more victim-oriented approach to crime recording (Simmons et al. 2003).

Simmons (2001) stated that this change would lead to an artificial increase in the crime rates of several percentage points, making trends measurement covering the introduction of NCRS more difficult.

There are a number of other factors which can affect official crime statistics. Criminal statistics are expressed in numbers of recorded offences per 100,000 populous. This process can introduce a further aggravating factor which makes assumptions, based on census data, around population sizes at the time of the data.

Legislation has added offences and abolished offences. The basis of the crime definitions themselves also change based on legislative and judicial decisions. For example, due to the changes introduced by the Criminal Law Act of 1977 it affected the direct comparison of offences before that date to those after. In 1968 the theft act radically redefined a number of key offences including burglary and stealing. This made it difficult to compare data prior to that date.

Classification of a crime can change at a later date as a result of later investigation or proceedings. This can result in recorded crimes being written off as “no crimes”. These are generally deducted from the total figures that are submitted to the HO. Pollack (1961) reports that offences committed by women were less likely to be reported and detected and suggests that there are omissions but also systematic bias. Similar effects are observed within the area of ‘White Collar Crime’, (Merton’s theory of anomie).

These changes to counting rules and the constant problem of the ‘dark figure’ make comparison difficult. It is not easy to understand and interpret this data without some knowledge of the system which produces them based on the rules, procedures and definitions already discussed (Coleman & Meynikia 1996). Burrows et al. (2000) also found that the processes by which crimes are recorded in different parts of England and Wales vary substantially. These findings were based very much on pre-NCRS crime records.

Victimization Surveys

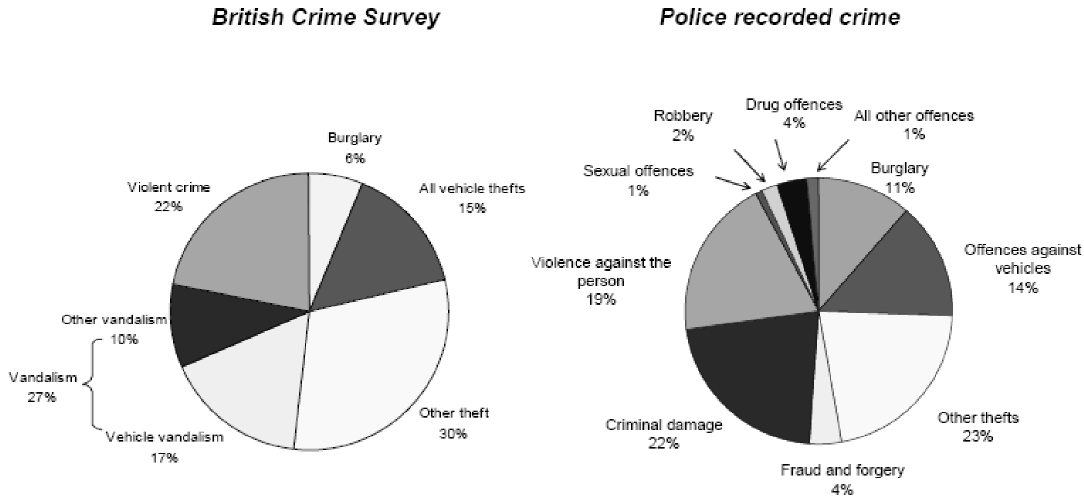
The basis of official statistics are summed up by Sellin's dictum, 'the value of criminal statistics as a basis for the measurement of criminality in geographical areas decreases as the procedures take us further away from the offence itself', (Sellin, 1951).

In 1970 the belief was that the general rise in crime in England & Wales was due to reporting and recording practices of official crime statistics. The quest for a more detailed and better quality data lead to the birth of crime surveys in England & Wales. Initial surveys had been conducted in the USA in the 1960's and experimental surveys took place in London in the early 1970's (Sparks, Genn & Dodd 1977). This later resulted in the British Crime Survey, (BCS) being borne in 1982 (Hough & Mayhew 1983). Further BCS were conducted in 1984, 1988, 1992, 1994, 1996, 1998, 2000, 2001 and annually thereafter.

Essentially the survey asks members of the public to describe crimes committed against them in the last 12 months (survey period). Complex sampling techniques are employed to provide a representative cross section of the given area. The BCS supports the existence of the "dark figure" in official crime statistics. In the 1992 BCS the results showed that individual victims did not report crime, showing that 55 per cent as they thought it too trivial, 25 per cent thought police could not do anything and 12 per cent dealt with it privately (Mayhew et al., 1993).

Despite the under reporting identified in the BCS, (see Figure 3), between the years 1981 and 2000, BCS data suggests that the rise in crime rose by 22 per cent and not 52 per cent as per official statistics. This supports the argument of the complex nature of official statistics. Figure 4 (below) shows the composition difference between police recorded crime (official statistics) and BCS crime of various crime categories (BCS 2007). Property crime accounts for the majority of both BCS and police recorded crime, 78 and 73 per cent respectively.

Figure 4 – BCS crime and police recorded crime by type of crime, 2006/07, (Nicholas et al. 2007)

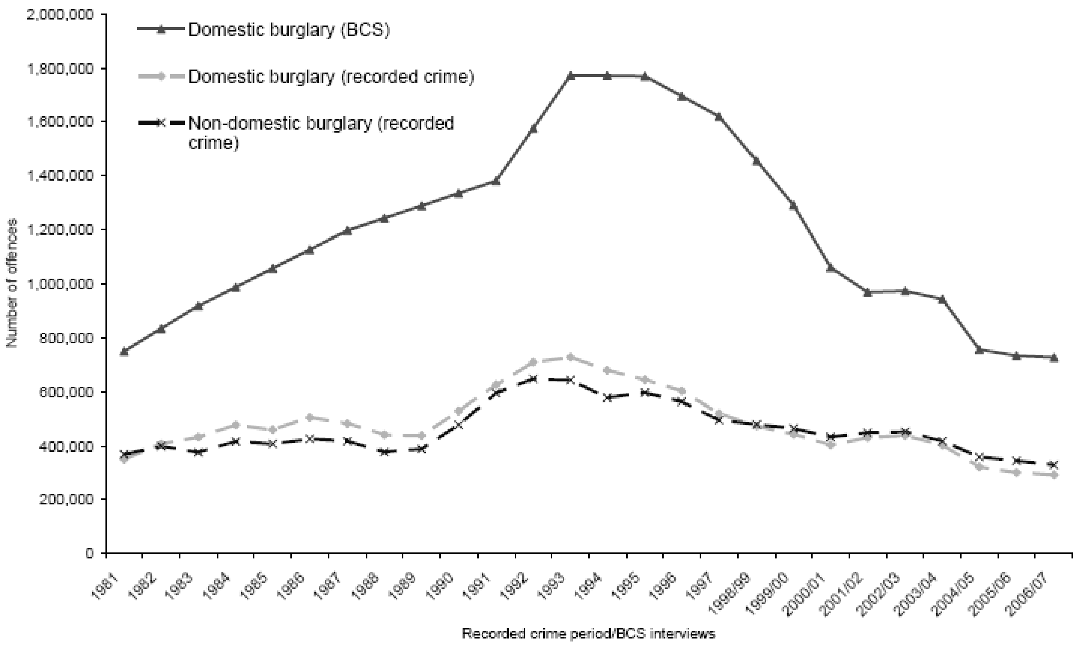


The BCS suffers from a 'dark figure' of its own. BCS obviously does not cover victimless crimes or commercial or corporate victims. Neither does BCS cover offences against under 16 year olds, although these areas are to be improved in the near future. In the 1980's there was criticism that BCS tended to distort victims accounts of crime (Matthews & Young 1986). Genn (1988) describes counting problems which found that it was easier to account for burglary, car theft or stranger incidents as opposed to other violent crimes. An artificial limit of 6 incidents is placed upon each member of the public and can lead to negative effects on repeat victim data (Sparks 1977).

BCS crime categories are not the exact match to police crime categories used in official statistics. Only about 3 quarters of the categories can be used as a direct comparable subset (Kersh et al. 2001). The comparable subset being: - Theft of/from vehicles, Vandalism of private property, Burglary Dwelling, Assault/Wounding, Robbery, Theft from person and Bicycle theft.

Despite differences in BCS crime figures and official statistics the basic shape of the trends displayed by both BCS and crime statistics are roughly similar (Maguire 2000). Farrington & Langen (1998) support this and found that between the two sets of data during 1981 and 1996 close correlation was found in four categories; vehicle theft, burglary, robbery and assaults. Figure 5, below, shows trends in BCS and recorded burglary crime between 1981 and 2006. The BCS 06/07 highlights the convergence of several crime categories.

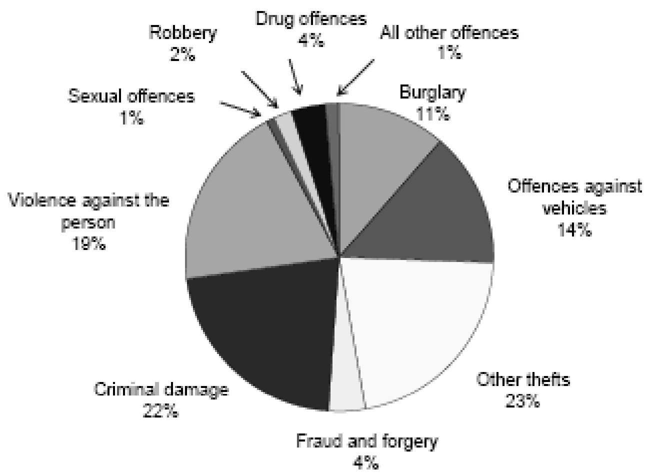
Figure 5 - Trends in BCS and police recorded burglary, 1981 to 2006/07 (Nicholas et al. 2007)



2.4 What is property crime?

Official crime statistics, as governed by the Home Office counting rules can be broken down into one of 9 crime categories, see categories in Figure 6. Offences against vehicles is shown in a separate segment but is part of the 'Other thefts' crime category.

Figure 6 – Percentage breakdown of recorded crime by Home Office crime categories, 2006/07 for England and Wales, (Nicholas et al. 2007)



Property crime is an expression used to describe a combination of the above crime categories and is made up of the burglary, offences against vehicles, other thefts, fraud and forgery and criminal damage crime categories. As can be seen from Figure 6, property crime currently accounts for a total of 73 per cent of all recorded crime in England and Wales.

The North East of England region during the same year suffered a total of 185670 property crimes. This figure accounts for 74 per cent of all the crime recorded in the region during the financial year of 2006/07, reflecting that found at national level. At a force level there is a slight change in crime breakdown with property crime accounting for 74, 76 and 73 percent respectively for Cleveland, Durham and Northumbria.

This slight fluctuation at a force level appears to be caused by the criminal damage element of property crime, which shows an overall four per cent difference in proportion of property crime across the three force areas.

There is a range of crime sub-groups that exist within each of the nine crime categories described above. These sub-groups are based on specific offences. The 12 crime sub-groups with the highest number of offences, (based on 2006/7 England and Wales data) are detailed in Table 1.

Table 1 - The 12 crime sub groups with highest offence count, based on 2006/7 crime statistics for England and Wales (Nicholas et al. 2007)

Category	Sub-Group	Number of Crimes England and Wales 2006/7
Other Theft	49 Other theft or unauthorised taking	536762
Offences against vehicles	45 Theft from m/v	502663
Criminal Damage	58C Criminal damage to vehicle	483266
Violence against the person	8A Less serious wounding	481844
Burglary	30 Burglary in a building other than a dwelling	329480
Other Theft	46 Shoplifting	294304
Burglary	28 Burglary in a dwelling	290479
Criminal Damage	58A Criminal damage to building	288296
Violence against the person	8C Harassment	228842
Violence against the person	105A Assault without injury	202717
Offences against vehicles	48 Theft or unauthorised taking of m/v	182491
Criminal Damage	58B Criminal damage to building other than dwelling	160229

<u>What to use in research</u>

It is noticeable that a third of the top 12 crime sub-groups, as per Table 1, are part of the burglary and offences against vehicle crime categories. As discussed earlier these crime categories are significant in relation to accuracy of crime recording in official statistics. The 2006/7 BCS shows that theft of vehicle and burglary with loss are the most likely offences for the public to report to police, stating 93 and 81 per cent respectively. It has also been shown that this level of reporting to police has remained stable over recent years.

In addition to minimising the effects of under reporting, as 4 of their crime sub-groups appear in the top 12 for number of offences, they also provide an adequate volume of data for the research. Three of the four crime sub-groups have corresponding aggravated crime sub-groups, (see below).

29 Aggravated burglary in a dwelling
31 Aggravated burglary in a dwelling other than a dwelling
37.2 Aggravated vehicle taking

There are also six further crime sub-groups within the criminal damage category which are closely related to the burglary and vehicle offence categories. They are criminal damage to a dwelling, criminal damage to a building other than a dwelling, criminal damage to a vehicle and their respective racially/religiously aggravated crime sub-groups, (the first three being in the top 12 sub-groups, as shown in Table 1).

Finally there is the vehicle interference and tampering crime sub-group which also has strong links to the crime category of offences against vehicles.

2.5 Research Hypothesis

The basis of this research will estimate a model in which crime counts are explained only by claimant counts (unemployment) and other related crime counts. The variable 'crime counts' being based upon monthly official police recorded crime statistics and broken down into crime sub-group categories. The 'claimant counts' variable is based upon the monthly measure of the number of people claiming job seekers allowance, as compiled by Office of National Statistics from data from the administrative records of Jobcentre Plus local offices. For further explanation see chapter 3 and Appendix 1. More specifically my research hypotheses will be: -

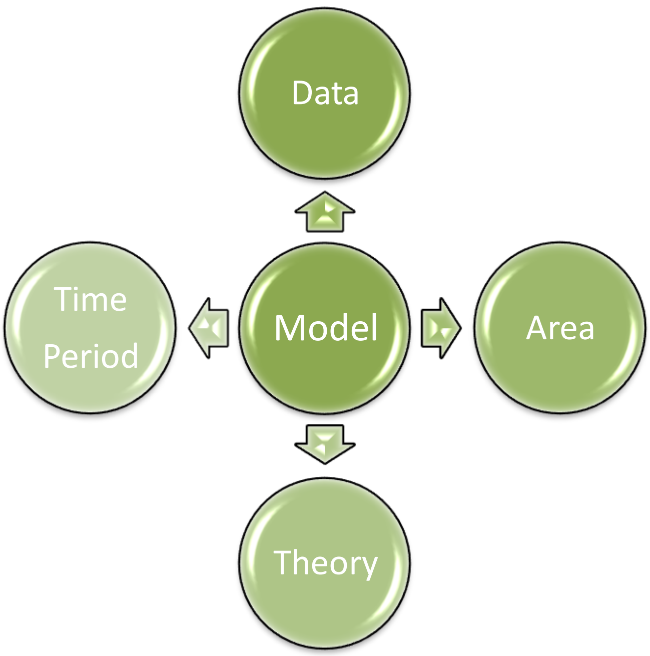
(1) The level of property crime is affected by claimant counts.

(2) The level of property crime sub-groups are affected by other related property crime sub-groups.

3.1 Model Specification

To test my research hypotheses careful consideration needs to be given to the dimensions as dipicted in Figure 2 and in particular to the following areas:- time period of research, crime theory, geographical area and data selction (explantory and dependant), as depicted in Figure 7.

Figure 7 – Model building diagram



3.1.1 Theory

This research will be based on a model that has its grounding in the criminological theory of routine activity theory. This has been chosen as a result of previous robust research, as discussed earlier. The model regression equation will take a similar form as per Pyle and Deadman (1994), which is based upon this theory.

$\Delta\Delta CRIME_t = \beta_1 \Delta E_t + \beta_2 \Delta C_t + \beta_3 \Delta P_t + E_{t-1}$
E- (Suitable Target) C – (Motivation) P – (Guardianship) E – Potential error term

Where $\Delta\Delta CRIME_t$ is the dependant variable and E, C and P are explanatory variables.

3.1.2 Time Period

It has been highlighted that very little research has been conducted post the introduction of NCRS in April 2002. Given the positive impact upon the recording of official crime counts as a result of the introduction of the NCRS, the decision was made to conduct the research post NCRS. This however poses a problem for analysis as the introduction of NCRS only occurred six years ago (at the point of data collection) and therefore annual data would clearly not provide sufficient sampling points for analysis. Given this and the fact that the majority of research in this field has been conducted based upon annual data the decision was made to use monthly data. The move to monthly data in order to research post NCRS data is supported by statistical sampling size rules, see below.

3.1.3 Data Sample Size

Green (1991) states if you are interested in the overall fit of the regression model and the contribution of the individual predicator variables then you use the higher of the two rules: -

Testing the overall model : - 50 + 8k

Testing individual explanatory variables: - 104 + k

Where k is the number of explanatory variables used. The above is a general rule of thumb and it is dependent on the size of the effect that we are trying to measure. Miles and Shevlin (2001) produced some extremely useful graphs which help with this issue. If you are using one explanatory variable and measuring a medium effect then they recommend you use a sample size of approximately 70, moving to 100 if you use 6 predicators at the same effect level.

Therefore to control for area specifics we need approximately we need 58/105 samples, (if using one explanatory variable at medium effect) according to the two respective rules of Green (1991) and approximately 70 according to Miles and Shevlin (2001). Therefore the six years of monthly data in the post NCRS period, (April 2002 to March 2008) would cover the Miles and Shevlin (2001) rule and would be in the middle of the two respective Green (1991) rules.

3.1.4 Dependant variable selection

It is noticeable that a third of the top 12 crime sub-groups, as per Table 1, are part of the burglary and offences against vehicle crime categories. As discussed earlier these crime categories are significant in relation to accuracy of crime recording in official statistics. The 2006/7 BCS shows that theft of vehicle and burglary with loss are the most likely offences for the public to report to police, stating 93 and 81 per cent respectively. It has also been shown that this level of reporting to police has remained stable over recent years.

In addition to minimising the effects of under reporting, as four of their crime sub-groups appear in the top 12 for number of offences they also provide an adequate volume of data for the research. Three of the 4 crime sub-groups have corresponding aggravated crime sub-groups, (see below).

29 Aggravated burglary in a dwelling
31 Aggravated burglary in a dwelling other than a dwelling
37.2 Aggravated vehicle taking

There are also six further crime sub-groups within the criminal damage category which are closely related to the burglary and vehicle offence categories. They are criminal damage to a dwelling, criminal damage to a building other than a dwelling, criminal damage to a vehicle and their respective racially/religiously aggravated crime sub-groups, (the first three being in the top 12 sub-groups, as per Table 1).

Finally there is the vehicle interference and tampering crime sub-group which also has strong links to the crime category of offences against vehicles.

Table 2 therefore summarises the crime sub-groups as discussed above. All crime sub-groups listed fall into the property crime description and the dominate ones have also been shown to be relatively accurate in terms of crime recording. Other crime sub-groups have been included in the list due to their strong relationship with others and the possibility for crime recording substitution taking place during recording. There has been very little research on the effect of crime substitution in the recording phase, particularly since the advent of NCRS in 2002. Overall the list of crime sub-groups accounts for approximately 59 per cent of all property crime, (as per data E&W 2006/7) and therefore provides adequate data for research.

Table 2 – Selected crime sub-groups for research

Category	Sub-Group	Number of Crimes 2006/7	Percentage of total property crime
Burglary	28 Burglary in a dwelling	290479	7.35%
Burglary	29 Aggravated burglary in a dwelling	1806	0.05%
Burglary	30 Burglary in a building other than a dwelling	329480	8.33%
Burglary	31 Aggravated burglary in a dwelling other than a dwelling	279	>0.01%
Offences against vehicles	37.2 Aggravated vehicle taking	10919	0.28%
Offences against vehicles	45 Theft from m/v	502663	12.72%
Offences against vehicles	48 Theft or unauthorised taking of m/v	182491	4.62%
Offences against vehicles	126 Interfering with a m/v (inc tampering)	68983	1.75%
Criminal Damage	58A Criminal damage to building	288296	7.29%
Criminal Damage	58B Criminal damage to building other than dwelling	160229	4.05%
Criminal Damage	58C Criminal damage to vehicle	483266	12.23%
Criminal Damage	58E Racially/religiously aggravated criminal damage to a dwelling	1543	0.04%
Criminal Damage	58F Racially/religiously aggravated criminal damage to a building other than dwelling	1073	0.02%
Criminal Damage	58G Racially/religiously aggravated criminal damage to a vehicle	1711	0.05%

3.1.5 Explanatory variables selection

The choosing of explanatory variables is probably the most important part of the research process. I have therefore decided to base my rationale on selecting variables that not only comply with Dhiri et al. (1999) but have also been shown to have a significant correlation to property crime in previous research.

According to Dhiri et al. (1999) the variables should:-

- Have some statistical basis in criminological theory
- Be Integrated to the order of one, I(1)
- Be co-integrated with the crime and stock variables

Not all possible explanatory variables that may influence the dependant variable can be included if the analysis is to be successful. For some it is difficult to measure, e.g. criminal justice interventions and initiatives and recorded data frequency. Others may make little difference as previously discussed.

Based on previous research, (as discussed in Chapter Two) the following explanatory variables were initially selected based on their previously identified correlations with crime variables. Additionally their co-integration properties and finally their strong grounding in well established and accepted crime theory. Therefore meeting with a number of the requirements as set out by Dhiri et al. (1999). Consideration was also given to variables that were available from a single source point to help reduce the potential errors involved in multiple sources.

Table 3 summarises the overall lists of the explanatory variables thought to be significant in the research.

Table 3 – Preferred Explanatory Variables

Population
GVA
GDHI
Police strength
Sentence Length
Crime Clearup rates
Claimant Counts

Initial explanatory variables

Population

Young people and males are more likely to take part in crime. This is based on the theory of Easterlin (1968) who states that if a larger number of young men are present in a society then it is more difficult for them to find a position in society and as a result they are more susceptible to crime. We would therefore expect a positive relationship between the number of young men and crime. (see appendix 1 for details of this data source).

GDHI (or Consumption)

Gross Disposable Household Income, (GDHI) has recently replaced the Consumption variable that has featured in much of previous economic crime research. This variable is indicative of a number of effects; an increase in GDHI leads to an increase in available goods with more goods then leading onto more opportunities for crime, (opportunity effect). Therefore with an increase in consumption we would expect to see a positive relationship with theft related crime.

An increase in GDHI is also linked with an increase in outdoor activity, effecting routine activity. In the case of burglary there is a reduction in a proper guardian.

Finally GDHI can have a short term motivation effect on the need to commit crime, as an increased expectation of future legal income can decrease the need for illegal gain through crime. We would then expect to see GDHI be negatively related to crime. Beki (1999) has shown that the motivation effect dominates in the short run. (see appendix 1 for details of this data source).

GVA (or GDP)

Gross Value Added, (GVA), represents the incomes generated by economic activity within the UK economy. GVA data presented in the Regional Accounts uses the income approach or GVA(I) and comprises:

- compensation of employees (wages and salaries, national insurance contributions, pension contributions, redundancy payments etc);
- gross operating surplus (self-employment income, gross trading profits of partnerships and corporations, gross trading surplus of public corporations, rental income etc).

(See appendix 1 for details of this data source).

Police Strength

Police service strength has been measured using a number of different data collection methods. The police strength figures produced in March 2003 first introduced the ‘all staff’ measure of police strength. This ‘all staff’ figure is the total full time equivalent (FTE) strength employed by the police force, including staff seconded in to the force and staff on any type of long or short term leave of absence. Previously figures did not include absent staff, such as those taking career breaks or on parental leave. Therefore the figures published in publications prior to March 2003 are not directly comparable with later publications, although a comparable series is also available. As of March 2007 staff employed by the National Crime Squad (NCS) and the National Criminal Intelligence Service (NCIS) have been excluded due to the launch of the Serious Organised Crime Agency (SOCA).

An increase in police strength has been shown to lead to an increase in recorded crime, this indicating a registration effect. It has also been shown that an increase may also lead to less crime, showing a negative relationship, (deterrence effect). (See appendix 1 for details of this data source).

<u>Clear up rates</u>

This has been shown to have a negative relationship with recorded crime, (deterrence effect). There is also a slight positive effect, (registration effect), when there is more crime reported as a result of increases in detections. The data for the research will be sourced from a single point. Full details of data to be used during research can be found in Appendix 1.

<u>Unemployment</u>

The ONS publish two different types of measurement of people who want to work but do not. This can be broadly categorised into unemployment and claimant count figures. Unemployment, as measured by the Labour Force Survey, (LFS), has high sampling variability for areas below regional level. Thus changes in estimates of unemployment are difficult to interpret for local areas. Unemployment rates are calculated using the economically active population as the denominator. The claimant count records the number of people claiming unemployment related benefits. These are currently the Jobseeker's Allowance (JSA) and National Insurance credits, claimed at Jobcentre Plus local offices. Claimant count data is therefore directly affected by the changes in the benefits system. The last major change was the introduction of the Job Seekers Allowance in 1996. The claimant count data is not seasonally adjusted and is accurate down to very small geographic areas and is unaffected by sampling variability since it is a 100 per cent count. It does suffer from a slight rounding error however. This means it can be used as an indicator of those without work down to small areas, see appendix 1 for data sources. This is in line with the suggestions of Field (1999) who suggests the use of another measure of unemployment due to the 'dark figure' associated with unemployment figures.

An increase in claimant counts tends to lead to a decrease and reduction in value of goods stolen, (opportunity effect). We would therefore expect a negative relationship between claimant counts and theft crimes.

An increase in claimant counts would also lead to more income problems and therefore effect motivation. We would expect a positive relationship between unemployment and theft.

As can be seen in appendix 1 the availability of explanatory data variables is hugely influenced by the choice of time frequency required, i.e. whether annual or monthly data counts are required for analysis. As we have already discussed we need to use monthly data due to the decision to base this research upon a post NCRS period of time and taking into account sampling rules. This seriously affects the choice of explanatory variable for the research due to the lack of availability of monthly data for a given period of time. Therefore based upon this, the choice of explanatory variables will be limited to claimant counts and detections, (where available for the specified period). As this data is available in monthly counts and for the given geographical area it will allow us to concentrate upon the post-NCRS period of time. Claimant counts can have an impact on all three areas of the routine activity theory, impacting upon the availability of a victim, guardian and a motivation offender, see Figure 8 below. As we will discuss later in detail, the model will concentrate upon two variables so that we can be certain that there is not multiple co-integrating vectors contained within it.

Figure 8 – Routine Activity Theory diagram

3.2 Geographical Units of Comparison

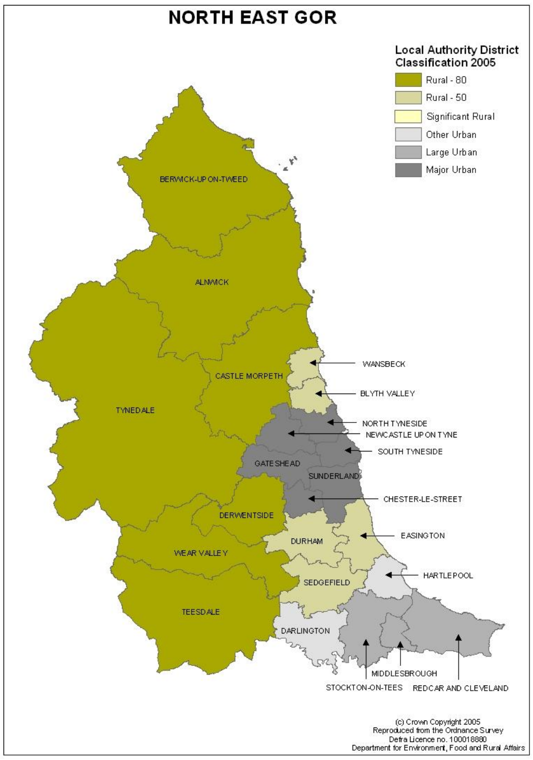
3.2.1 Area Description

The north east of England covers approximately 8592 square kilometres, approximately 6.5 per cent of the land mass of England. The area has a total population of over 2.5 million. Some areas are amongst some of the most heavily populated areas in the country i.e. Middlesbrough has a population density of 25.4 persons per hectare which is much higher than the national average is 3.5 people per hectare.

Employment in the area has traditionally been centred around large-scale heavy industry, which has declined over the last twenty years. Unemployment in the area is slightly above the national average.

The region has distinctive urban and rural aspects to it as described in Figure 9 below.

Figure 9 – North East Region of England, area type (DEFRA 2005)



We can see from Figure 9 that the north east of England can be broken down into various categories of urban and rural classification. The six categories are: -

<u>Rural80</u>	-	Local authorities that have at least 80 per cent of their population resident in rural settlements.
<u>Rural50</u>	-	Local authorities with at least 50 percent but less than 80 percent of their population in rural settlements
<u>Significant Rural</u>	-	Local authorities with more than 26 percent but less than 50 percent of their population in rural settlements.
<u>Major Urban</u>	-	Local Authorities with *either* a minimum of 100,000 people *or* a minimum of 50 percent of their total population resident within a major urban area.
<u>Large Urban</u>	-	Local Authorities with *either* a minimum of 50,000 people *or* a minimum of 50 percent of their total population resident within a large urban area (i.e., an urban urea with between 250,000 and 750,000 population).
<u>Other Urban</u>	-	Local Authorities that have less than 26 percent of their population living in rural settlements (including larger market towns) and do not have a substantial quantity or proportion of their population living within major or large urban areas.

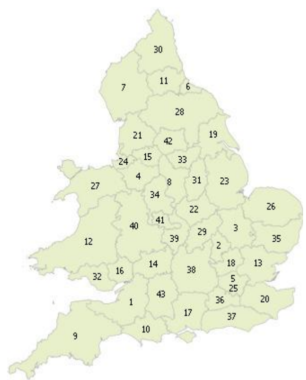
The region also currently has some of the most socially deprived wards in the country. These areas sit alongside areas of affluence and industry and as a result present challenging policing issues.

The region has significant high density areas with regards to special populations groups such as armed forces and students.

3.2.2 Police Force Coverage

The north east of England is covered by three separate police forces, Cleveland, Durham and Northumbria, See Figure 10 below, showing the forces numbered 6, 11 and 30 respectively.

Figure 10 – Police Force areas in England and Wales (ONS)



Area command/districts

Each police force area can be sub-divided into basic area commands (BCU) or districts. There a total of 23 BCU/districts within the 3 police force areas and north east England region, see Table 4 below.

Wards

Each of the 23 BCU/districts can further be separated into administrative wards. There are a total of 482 administrative wards in the north east region (as of 2004 boundary changes), see Table 4 below showing breakdown by force and area command/district.

Table 4 – Number of administrative wards per police force and BCU/district area for the north east of England region, (source National Statistics, wards as of December 2004)

	00CK	North Tyneside	20
	00CL	South Tyneside	18
	00CM	Sunderland	25
	35UB	Alnwick	16
	35UC	Berwick-upon-Tweed	17
	35UD	Blyth Valley	20
	35UE	Castle Morpeth	20
	35UF	Tynedale	31
	35UG	Wansbeck	16
		Total Northumbria	**231**
Durham	20UB	Chester-le-Street	16
	20UD	Derwentside	22
	20UE	Durham	20
	20UF	Easington	20
	20UG	Sedgefield	19
	20UH	Teesdale	19
	20UJ	Wear Valley	19
	00EH	Darlington	24
		Total Durham	**159**
Cleveland	00EB	Hartlepool	17
	00EC	Middlesbrough	23
	00EE	Redcar & Cleveland	22
	00EF	Stockton-on-Tees	30
		Total Cleveland	**92**
	Total no. Of wards - North		**482**

Ward changes in region

Unfortunately, ward geography is not consistent over time. There is a continually changing administrative geography largely due to local government reorganization and redrawing of electoral wards by the Boundary Commission. This is predominately due to incorporation of large-scale population changes such as new areas of housing within wards.

At region and district level there has been little change in administrative boundaries since the early 1970's. However there have been significant physical boundary changes made at administrative ward level.

There are only 65 wards in the region that have remained un-physically changed since the 1991 census year. During the year 2004 significant ward boundary changes in the region took place. A total of 213 wards had physical boundary changes made during this period. A further 77 wards had physical boundary changes made post 2004. This has a significant impact upon the ability to make comparisons at a ward level within the region. All data will therefore be provided for at the administrative area level, (see Figure 11 below).

Figure 11 – North East of England Administrative Areas (ONS)

It is worth noting at this stage that although it is possible to obtain the required data to ward level this would result in a huge increase in the number of corresponding statistical tests that would result. Ward level crime and claimant count data would, whilst combined with the monthly frequency and the disaggregation of the data, result in very low variance in the data. This would make it difficult to use for statistical analysis. As explained above additional consideration and steps would have to be included during the cleaning and transformation of the data sets to take account of any ward changes.

Although Durham has eight local authority administrative areas the crime data was provided in respective north and south basic command unit areas. As a result of this the area of Durham will be split into two separate BCU areas as opposed to eight administrative areas, (see Figure 12 below).

Figure 12 – Durham Police Basic Command Units (Durham Police 2007)

Therefore for the purpose of this research the area of interest will be the north east of England split down into 17 separate areas as detailed in Table 5 below. For the purpose of the research Durham North will be classified as an other urban area, (due it containing Durham city and Chester-le-street areas) and Durham South will be classified as a significant rural area, (due to containing predominately rural areas but also containing Darlington).

Table 5 – North east England research areas

Force		District
Northumbria	1	Gateshead
	2	Newcastle Upon Tyne
	3	North Tyneside
	4	South Tyneside
	5	Sunderland
	6	Alnwick
	7	Berwick-upon-Tweed
	8	Blyth Valley
	9	Castle Morpeth
	10	Tynedale
	11	Wansbeck
Durham	12	Durham North
	13	Durham South
Cleveland	14	Hartlepool
	15	Middlesbrough
	16	Redcar & Cleveland
	17	Stockton-on-Tees

3.3 Data Parameters

The decision was made to use official crime data counts whilst giving careful consideration to the crime sub-categories to be used, (see previous sections). The decision was also made to obtain raw crime data counts directly from police force areas. This made logistical sense as data could be requested in the format required and it would keep any formatting errors to a minimum. Much of the HO data has been through transformation and is produced based upon crime rates per 1000 head of population. This type of crime rate reporting allows for a further error to creep into the figures. This error being based upon estimation of population counts in a given area.

The decision was made to conduct the research to sub-police force level areas, (districts or BCU’s), given that there little research at this level and also because there is research that supports the thought that the majority of crime is committed within the same sub-police force area and that burglaries in particular are committed a relatively short distance away (Wiles and Costello 2000).

The choice of claimant counts was made on the basis of data availability to the geographical level required and to the time frequency required. The data is also less likely to introduce significant recording errors into the equation. This explanatory variable may also have an impact upon the motivation of the offender, availability of a suitable victim (property) and the availability of a suitable guardian (people at home). Significant research indicates that there is a positive link between property crime and the number of young males (Hansen 2003). Therefore the claimant count data will be split into age related categories.

The choice of crime type (property crime) although the topic of interest was specifically chosen as a result of their respective reduced official crime statistics errors in terms of crime recording, (BCS 2007).

3.4 Crime Data Collection

Official monthly crime count data was obtained directly from three police force areas; Cleveland Police, Northumbria Police and Durham Police for the period April 2002 to March 2008 for 23 sub- police districts. This included the number of offences reported to police in each police BCU/district for 14 crime sub-group categories. The crime data was provided to me in three very different raw formats.

Cleveland Police data was in a very raw format indeed and came as an Excel spreadsheet containing a single row entry for every crime recorded during the required period in the Cleveland Police area. As a result of my employment as a police officer with Cleveland Police I was granted direct access to the Cleveland Police crime database for this research and the data was downloaded directly from the database personally. This resulted in a considerably large data file that was kept initially on a number of separate files as a result of the size of it. The downloaded data also contained additional crime information including personal information in relation to the crime victims. As a result the data was stored in an encrypted file and later the personal information was removed for the purpose of analysis. The individual Excel spreadsheets were developed and a mechanism was created that counted the specific monthly figures for each of the crime sub-groups required. The mechanism also took account of crime records that were later linked to ‘no crime’ submissions. Detection data for the Cleveland Police area was also cleaned and formatted in the same way and from the same raw data file. It is also worth noting at this stage that the Redcar and Cleveland district area of Cleveland has been coded as the “L District” as Redcar and Cleveland was historically called the Langbaurgh administrative area. Therefore reference to Redcar and Cleveland and Langbaurgh or L district are all one of the same and were not corrected during the cleaning stage and may appear in the text in the different forms.

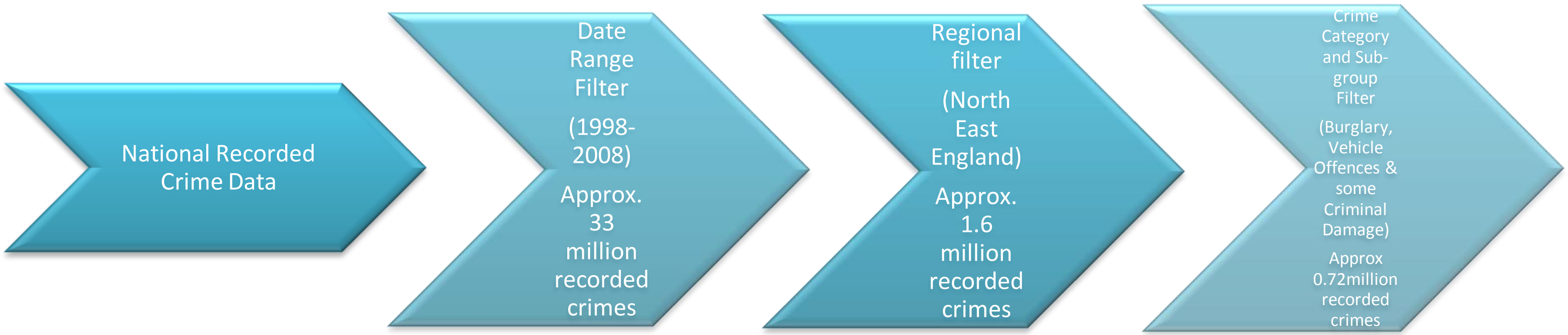
Northumbria Police data came in a slightly different physical format known as a CRIMSEC 3 return which they submit to the HO on a monthly basis. Again this was in monthly Excel spreadsheets and comprised of crime sub-group annually cumulative figures which took account of no crime submissions. As a result a considerable amount of time was spent back aggregating the separate monthly crime data spreadsheets and then back calculating the annual cumulative figures into useable monthly data. I wish to point out that during the cleaning and coding of the Northumbria crime data set the Warren geographical area was coded as Wansbeck in error. The mistake was only noticed towards the end of the analysis stage and therefore a decision was made to retain the Wansbeck label for the Warren area. Therefore any reference in tabulated results which refers to Wansbeck is actually referring to the Warren geographical area.

Durham Police provided the crime data on a single spreadsheet for the required crime sub-group categories and in an already monthly formatted state. I am aware and grateful that Durham Police analysts spent some time creating this spreadsheet for me. As a result there was less issues in cleaning the raw data provided by Durham Police. There were however a couple of crime sub-group categories with missing data. Due to boundary area changes in the Durham area whilst taking account of Claimant count data the data had to be aggregated to the level of BCU.

The overall cleaning and formatting of monthly data for three separate police force areas for the north east region for a period of six years, accounted for a considerable amount of time in this research. Finally all three cleaned and formatted police force area spreadsheets were combined to produce a single regional data spreadsheet.

To give an overall feeling of the research Figure 13 shows that over the specified research period there were approximately 33 million recorded crimes in all crime categories in England and Wales. When the North East of England filter is applied to it the figure drops to 1.6 million crimes for the same period. Finally when we select for specific property crime sub-groups, as discussed earlier, this figure further drops to 0.7 million crimes. Therefore the final Excel spreadsheet had a combined accumulated crime count of approximately 0.7 million crimes from the three police force areas.

Figure 13 – Crime filtering process conducte



Claimant Count data

The claimant count data was obtained from a single source, namely NOMIS, see appendix 1. The data was provided in a gender split format and split into 13 age range sub-categories for each gender. Conducting the research on all age group areas, 26 in total, when combined with the number of geographical areas and crime sub-groups, would have resulted in an unrealistic number of potential models for this research. It would have resulted in nearly a 14 fold number of regressions, (approximately 6000) and subsequent tests. Given the recent research regarding male involvement in crime and the age profiles for offending, (see previous sections), a decision was made to aggregate the claimant count data into two broad age categories for males only. This resulted in two new claimant count variables; namely males claimant counts under 30 years of age and male claimant counts over 30 years of age.

3.5 Statistical analysis and Software

Software

The cleaned data was initially stored in a Microsoft Excel (2007) spreadsheet. It was clear in the initial stages of the analysis process that Microsoft Excel, although could provide the statistical processes, could not easily deal with the number of tests to be conducted for this research. There was some time spent locating and securing additional add-ins for Microsoft Excel in terms of more specialised statistical procedures such as the augmented Dickey-Fuller test. Following further advice on the matter, the data, in its basic cleaned format was transferred from Microsoft Excel to the statistical software package PcGive, (version 12.1). All Statistical procedures for this research were conducted within this package as it met all the requirements for statistical analysis and provided a more suitable package for multiple model analysis.

Statistical Analysis

Conventional regression analysis presupposes the variables to be stationary. However there has been a general agreement that crime variables in England and Wales have been non-stationary since the Second World War. The use of non-stationary variables led Field (1990) to relate growth rates in recorded crime to annual rates in explanatory variables.

Pyle and Deadman (1994) showed that by estimating models in differences to overcome problems with non-stationary variables this can cause the loss of information contained in it for long-run relationships.

Hale (1998), using the Perron test (Perron 1990) has already disputed other findings and has found that both burglary and theft offences are at most I(1) and hence only need differencing once for stationarity. This was in contrary to Pyle and Deadman (1994) who considered theft as I(2). However as identified by Hale (1998), Hale and Sabbagh (1991) and Osborn (1995) crime variables are in fact I(1) and therefore only need differencing once for stationarity.

The effects on data that has been differenced purge it of any long-run information. So we lose a certain long term aspect to our data. Error correction models (ECM) can be used to combat this problem and they will include aspects of both long and short-runs. This is only possible when there exists a linear combination of non-stationary variables which are stationary (Hale 1998). If the data conforms to this rule they are said to be co-integrated. Alternatively a short-run OLS regression will be used.

Therefore as a result of the previous research and following the cleaning of the data, the individual dependant variables and explanatory variables had stationarity and co-integration tests conducted upon them. This took place prior to the decision as to what type of regression analysis to conduct on the data.

3.6 Method Summary

In summary I have attempted to encapsulate as many of the key dimensions into my model, as described in Figure 2. Specifically I have used the following: -

1. Dependant and Explanatory data is examined on a monthly frequency (allowing us to consider seasonality).
2. Claimant count data incorporates population dynamics and allows for gender and age selection.
3. Data broken down into sub-police force level geographical areas.
4. Claimant count data also includes elements of guardianship.
5. Period of time selection, uses a post NCRS period, (improved crime recording standards).
6. Use of property crime data to combat under reporting of crimes.

3.7 Forecasting

Following the analysis of the cleaned data and dependent upon the results and conclusions drawn from the analysis, a further chapter will contain details of methods used for forecasting.

4.1 Data Description

The period of time under analysis is April 2002 to March 2008 inclusive, (post NCRS introduction), giving a total time series monthly count of 72. The crime data, specifically selected for its relationship around the broad area of property crime, has been broken down into crime sub-group categories as previously outlined and detailed below: -

28 – Burglary in Dwelling

29- Aggravated burglary in a dwelling

30 - Burglary in a Building other than a Dwelling

31 - Aggravated Burglary in a Building other than a Dwelling

37/2 - Aggravated vehicle taking

45 - Theft from a Vehicle

48- Theft or unauthorised taking of a motor vehicle

57a- Criminal Damage to a Dwelling

57b - Criminal Damage to a Building other than a Dwelling

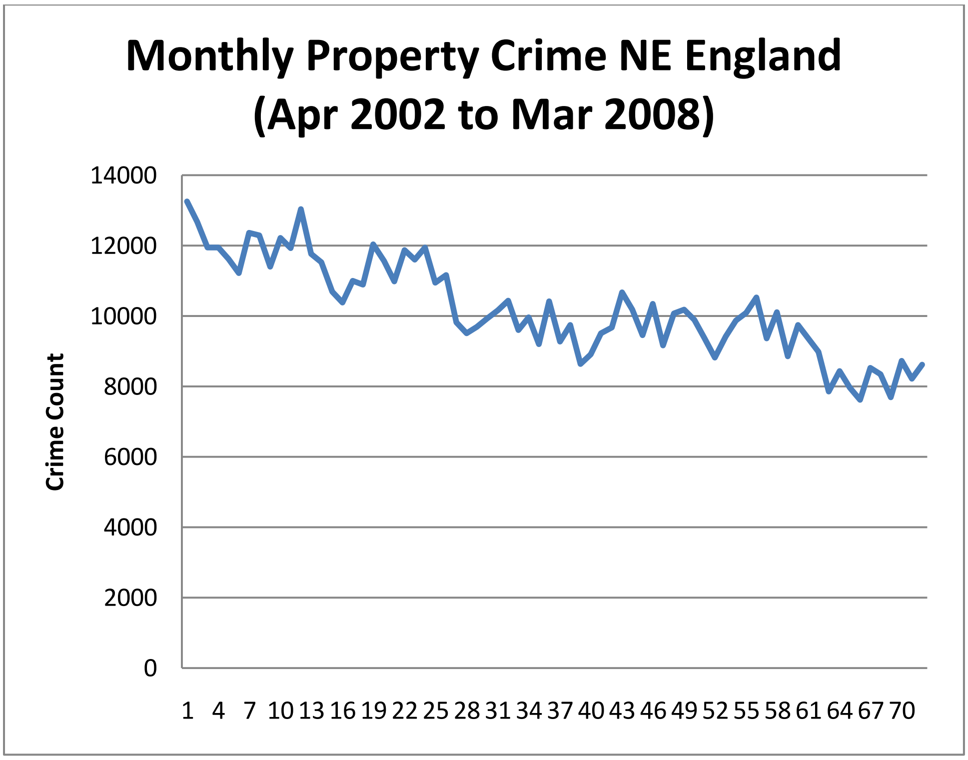
57c - Criminal Damage to a Vehicle

126 - Vehicle Interference and Tampering

Therefore the total number of crimes for the north east of England for the above crime types and for the given period was 735684. Figure 14 below shows the monthly time series plot of these crimes for the north east of England. This made up of 386217 (52 per cent) of the crimes from the Northumbria police area, 218778 (30 per cent) of the crimes from the

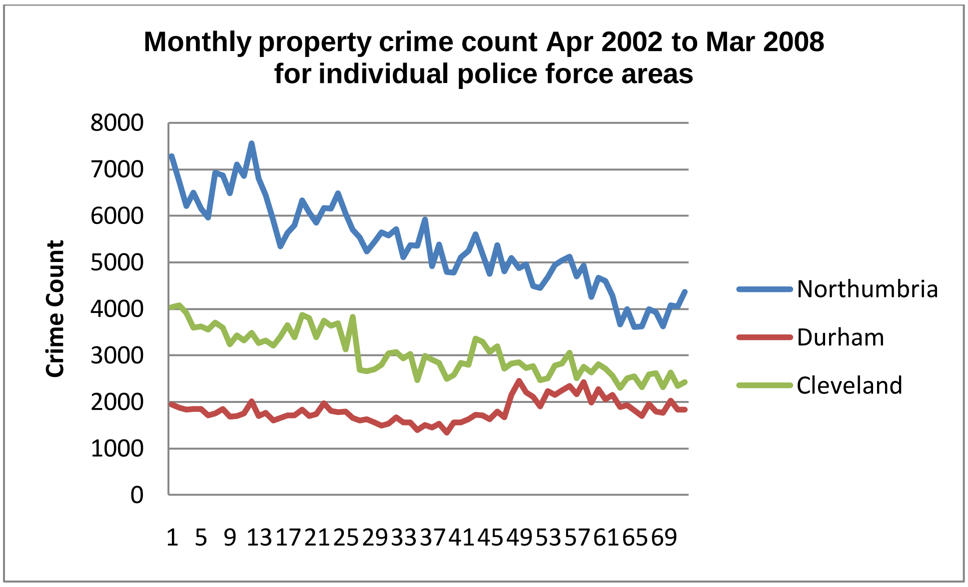
Cleveland Police area and 130689 (18 per cent) of the crimes from the Durham Police area.

Figure 14 – Monthly property crime count Apr 2002 to Mar 2008 for north east of England



The monthly reported property crimes between April 2002 and March 2008 fell from a peak of approximately 13000 in 2002 to approximately 7800 in 2007. This represents an overall drop in property crime over the research period of 40 per cent. This appears to be in line with the overall drop in recorded official statistics for the same period of time in England and Wales, (see appendix 2). Figure 14 also indicates that there is a possible seasonality to it as it peaks approximately every 12 months during the six year period. Figure 14 can be further broken down by police force area as detailed in Figure 15 below.

Figure 15 – Monthly property crime count Apr 2002 to Mar 2008 for individual police force areas



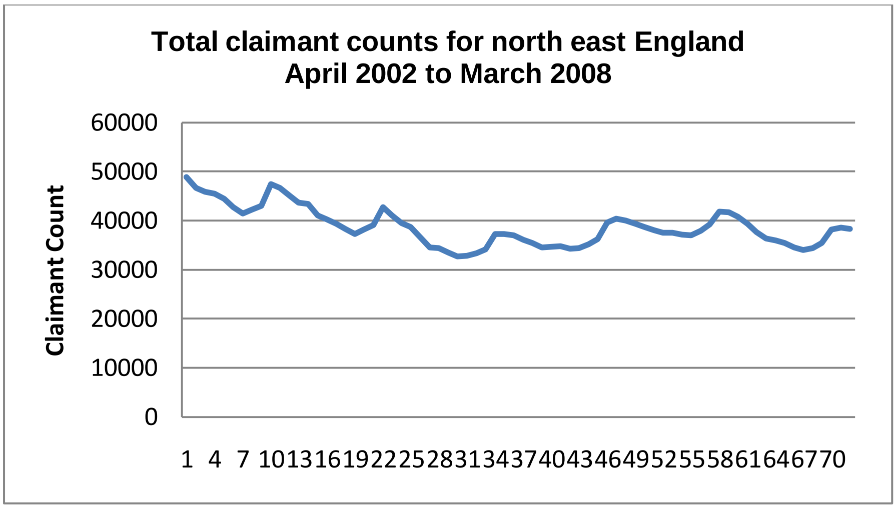
Northumbria crime (as per research specifications), fell from a high of 7557 in 2003 to approximately 3650 in 2007. It has shown a consistent fall during this period. This represents an overall fall of 51 per cent within these categories over this time period.

Durham has also shown a decline in this type of crime falling from approximately 2000 in 2002 to 1300 in 2005. However there was an increase back up to approximately 2500 in 2006 before it fell back to approximately 2000 in 2008.

Cleveland also displays a fall in this area of crime from a high of approximately 4000 in 2002 to a low of 2310 in 2006 an overall fall of 42 per cent within these categories over this time period.

The total number of claimant counts for the north east of England for the given period was 2787205. Figure 16 below shows the monthly time series plot of these claimant counts for the north east of England. This is made up of 1556595 (56 per cent) of the claimant counts from the Northumbria police area, 759220 (27 per cent) of the claimant counts from the Cleveland Police area and 471390 (17 per cent) of the claimant counts from the Durham Police area. It is interesting to note that the claimant count percentage ratios are very similar to that of the property crime percentage ratios for the respective police force areas.

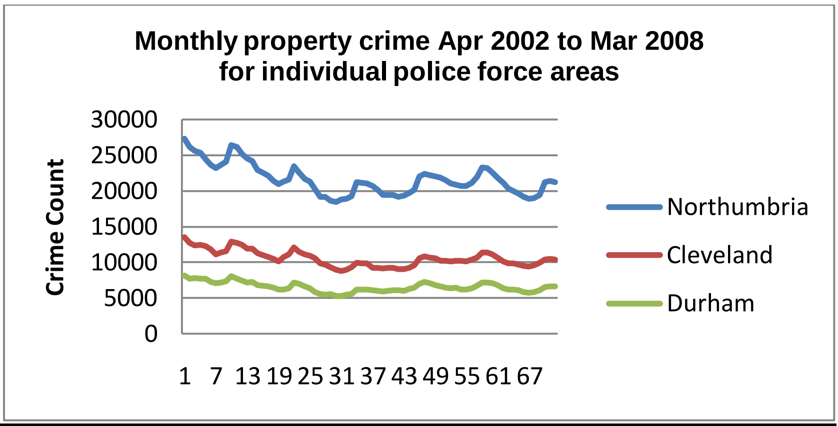
Figure 16 - Total claimant counts for north east England April 2002 to March 2008



The monthly reported Claimant counts between April 2002 and March 2008 fell from a peak of approximately 50000 a month in 2002 to approximately 32500 in 2005. There was an undulating increase in claimant counts back up to approximately 39000 in 2008. This represents an overall drop in claimant counts over the research period of 22 per cent.

Figure 16 can be further broken down by police force area as detailed in Figure 17 below.

Figure 17 – Monthly property crime Apr 2002 to Mar 2008 for individual police force areas



It is noticeable at this stage that the police force area claimant count data appears to follow the same trend. The trend also appears to have a turning point at around 2005 and also displays a seasonal fluctuation within the trend. This would be expected as the claimant count data obtained was not seasonally adjusted.

Both the crime data and claimant count data follows_the national trends, see appendix 3 for comparison national crime and claimant count graphs. It is interesting to note at this stage from visual examination of the claimant count and crime levels at a regional level that there appears very little seasonal lag between them.

4.2 Unit root tests

Before testing for co-integration and subsequently estimating a vector error correction model (VECM), we test for the order of integration of all categories of dependant and explanatory variables.

The data is monthly, covers a six year period, includes three force areas in the north east of England and is further broken down to 17 district/BCU areas. Together with detection time series for Cleveland and two claimant count time series for all districts/BCU areas there will be a total of 328 times series presented for unit root testing and each will comprise of 72 items of monthly data.

We know that this is a very important stage in the analysis as it has caused problems in the past where testing has not been completed (Wolpin 1978 and Field 1990). This has led onto spurious regression results and invalidated research results. Researchers have also disputed the level of integration required to make crime data stationary. Pyle and Deadman (1994, 1997) report their crime series as I(2) and Osborn (1995), Hale (1998), Field (1998), Pudney et al. (2000) and Saridakis (2008) report their crime series as I(1).

A spurious Regression

The following example regression is based on the basic regression form:-

$$\gamma_t = \beta x_t + \varepsilon_t$$

Where $\gamma_t$is the dependant variable, x_t is the explanatory variable, β and $\varepsilon_t$are the regression coefficient and error term respectively. For the purpose of this example I have chosen Sunderland (28+29) variable and Sunderland (30+31) variable as the dependant and explanatory variable respectively. As we will later confirm both variables are non-stationary and are therefore trending over time. The data have not been transformed and the regression was conducted using ordinary least squares (OLS). In the presence of a trend we would expect to see a high coefficient of determination (R^2) which will give the illusion of a strong relationship. However we would also expect to see a poor DW result.

As we can see with the below regression example between the variables Sunderland28+29 and Sunderland30+31, Table 6 shows the R^2 figure is relatively high (0.52) but the DW figure is very poor (0.618). It is a key indicator of a potential spurious regression if the DW figure is close to or less than the R^2 value. Using only the R^2 figure as a guide we could make the wrong assumption that there is a strong relationship in existence between the two variables.

Table 6 Regression Example – Sunderland28+29 and Sunderland30+31

```
                    Coefficient  Std.Error  t-value  t-prob Part.R^2
Constant                -34.5741      22.05    -1.57  0.1215   0.0339
Sunderland 30+31         1.25636     0.1434     8.76  0.0000   0.5231

sigma                 42.0885  RSS              124000.768
R^2                  0.523082  F(1,70) =     76.78 [0.000]**
log-likelihood       -370.413  DW                    0.618
no. of observations        72  no. of parameters         2
When the log-likelihood constant is NOT included:
AIC                   7.50693  SC                  7.57017
HQ                    7.53211  FPE                 1820.65
When the log-likelihood constant is included:
AIC                   10.3448  SC                  10.4081
HQ                    10.3700  FPE                 31095.7
mean(Y)               153.722  var(Y)              3611.17

AR 1-2 test:      F(2,68)    =   27.952 [0.0000]**
ARCH 1-1 test:    F(1,68)    =   23.143 [0.0000]**
Normality test:   Chi^2(2)   =   5.9661 [0.0506]
Hetero test:      F(2,67)    =   1.7507 [0.1815]
Hetero-X test:    F(2,67)    =   1.7507 [0.1815]
RESET test:       F(1,69)    =   1.6965 [0.1971]

Sunderland 28+29 =  - 34.57 + 1.256*Sunderland 30+31
(SE)               (22.1)   (0.143)
```

There are two approaches to testing a variable to see if it is stationary; an informal (visual examination via graphs) and a formal method (statistical tests). Prior to conducting these two procedures I made a further examination of the raw data to ensure validation for unit root testing.

4.2.1 Examination of raw data

During the initial examination and validation of the 328 individual time series the following issues were identified:-

- Three time series had missing data (Crime categories 58a, 58b and 58c for Durham South)
- Five time series with negative figures (Crime categories Tyneside South 126, Tyndale 45, Berwick 28+29, 48+37/2 and 58b)
- 21 time series contained months with a zero recording (Crime categories Wansbeck 126, Tyneside South 126, Tyndale 28+29, Tyndale 126, Alnwick 28+29, 48+37/2 and 126, Berwick 28+29, 48+37/2, 58b and 126, Blyth 126, Castle 126. Crime detection categories H district det 30+3, 126 and 45, S district det 45 and 126, L district det 126 and M district det 126.
- There were very low crime counts in relation to the respective aggravated offences, (crime sub-group categories 29, 31 and 37/2) and the racially and religiously aggravated offences, (crime sub-group categories 58E, 58F and 58G).

All four areas identified above could potentially have a detrimental effect on the formal unit root testing procedures. The missing Durham crime data figures are genuine missing data and have not been able to be replaced prior to the analysis stage of the study. Therefore a decision was made to withdraw the three time series from the analysis.

The five Northumbria crime data figures displaying negative figures were found to be mistakes caused during the construction of the time series from the tabulated Crimsec 3 home office returns created by Northumbria police, all five time series have had the errors corrected prior to the analysis.

The 21 time series that have data entries that equate to a zero value will create an error during the log-transformation process, (as explained later). This is caused by the inability to log non-positive integers during the log-transformation process. All 21 time series identified have been transformed as per pre-logarithmic transformation by adding a constant value of 1 to all 72 time series entries. This transformation, which affected 10 per cent of the time series being studied is discussed in further detail later.

There were significantly low individual crime counts for the directly related aggravated offences of crime sub-group categories of 29, 31 and 37/2. A decision was therefore made to add these crime sub-groups categories to their respective related sub-group categories, namely crime sub-group categories 28, 30 and 48 respectively. As a result crime sub-group 28 was added to sub-group 29, (making a new total dwelling burglary sub-group category), crime sub-group 30 was added to sub-group 31, (making a new total burglary other than a dwelling sub-group category) and crime sub-group 48 was added to sub-group 37/2 , (making a new total theft of motor vehicle sub-group category).

Careful consideration was given to the very low crime counts recorded by the racially and religiously aggravated criminal damage sub-group categories 58E, 58F and 58G. It was decided that due to the very low crime counts experienced and that by their very definition they represent a different type of motivation, it was decided to omit them from this research study.

Therefore the total number of crime data sub-group categories was reduced from 14 to 8. The eight crime count sub-categories are summarised below:-

28 + 29
30 + 31
48 + 37/2
45
126
58A
58B
58C

As a result of the identified issues the number of resultant time series for analysis fell from 328 to 199 time series.

Visual examination of data (via graphs)

The first stage of examining the data for unit roots is to make a visual audit of the time series data graphs. All 199 time series data sets are graphed using line graphs and have been organised into crime sub-group, detection and claimant count categories for ease of comparison, (see appendix 3).

Careful consideration and identification was given to outliers, missing data or elements of non-stationarity, trend and seasonality. Identification of potential breaks in data continuity were also considered. All areas could potentially reduce the effectiveness of the analysis and therefore require identification for potential corrective work, suitable statistical procedures or for explaining results. The identification of outliers was carried out during the visual examination of the raw data stage. This, as previously mentioned, identified a number of outliers which were found to have been caused by either missing data or caused during the data cleaning stage, (predominately caused during the disaggregation of the Northumbria police force data).

Most of the crime sub-group categories graphs display a downward trend and are stochastic in their nature. This suggests that the majority of the time series are non-stationary as the series display a definite negative trend over time, thus indicating that they have a unit root. It is worth highlighting at this stage that, although in the minority, there are 16 time series that also trend over time but display a strong positive trend over time, (see Table 7). Most interestingly they are all from the criminal damage sub-group category.

Table 7 – Crime sub-group category displaying positive trend

Crime sub-groups series	Detection series
L District 58a	H District det 58a
S District 58a	M District det 58a
H District 58a	H District det 58c
L District 58c	M District det 58c
S District 58c	L District det 58c
M District 58c	S District det 58c
Durham North 58c	L District det 58a
	S District det 58a
	H District det 58b

From visual examination of the time series graphs we conclude that a couple of the crime sub-groups could potentially be stationary, (see Table 8 below). It is also worthy of note that many of these crime sub-groups have a low count in data and this has an impact on the variance of the time series.

Table 8 – Crime sub-group categories displaying possible stationary series

	28+29	45	48+37/2	58a	58b	58c	126
Tyndale		x		x		x	
Newcastle							
Alnwick	x	x					x
Berwick			x	x			x
Warren							x
Blyth							x
Castle			x	x	x	x	

There appear to be noticeable visual breaks in continuity of the time series data, for Tyndale 28+29, Gatehead 28-29, M District 45 and Newcastle 45. This may affect the reliability of the formal unit root testing procedure.

A further noticeable trend within the claimant count series is that there appears to be a seasonal trend within the structure and also a noticeable turning point is also evident around the month 29 point (approximately

September 2004). The cause of this potential turning point has yet to be identified.

Claimant count figures have been presented in a seasonally unadjusted form and this is preferred in many circumstances as filters often distort the true relationship of the data. In particular, seasonally adjusted data can lead to a bias in the rejection of the null hypothesis during unit root testing (Harris 1995).

In summary the visual examination of the time series graphs have identified a number of important issues; missing data, possible breaks in continuity, possible stationary and non-stationary data and positive and negative trending. Most of the 199 time series, if not all, are displaying a stochastic trend and therefore confirmation could and should be made with formal unit root testing.

4.2.2 Logarithm Transformation of data

Prior to the formal unit root testing process consideration was given to using the natural logarithm of the remaining 199 data time series. Logarithmic transformations are sometimes used when constructing statistical models to describe the relationship between two measurements so that a comparison is not skewed, (Saridakis 2008).

Taking the natural logarithm of a series squashes the right tail of the distribution and reduces positive skew. Care needs to be taken when taking the log of a time series as you cannot log a negative or zero value. As discussed earlier during by visual examination and validation of the raw data 21 time series were identified that contained zero values and five had negative values. The negative values, having being found to be mistakes, were corrected. To avoid a log error during the first stages of statistical analysis, (log transformation of the time series), I have added a constant to the 21 time series which have zero values. Where the time series contains zero's I have taken the $\log(X_t + 1)$.

4.2.3 Unit root statistical tests

One statistical test for unit roots is the augmented Dickey--Fuller (ADF) test where I(1) against I(0) is provided by the t-statistic on $\hat{\beta}$ in:

$$\Delta x_t=\alpha+\mu t+\beta x_{t-1}+\sum_{i=1}^{n}\gamma_i \Delta x_{t-i}+u_t.$$

The constant or trend can optionally be excluded. The specification of the lag length n assumes that u_t is white noise. The null hypothesis is H_0: $\beta=0$; rejection of this hypothesis implies that x_t is I(0). A failure to reject implies that Δx_t is stationary, so x_t is I(1).

ADF testing was conducted with use of PcGive Software, version 12.1. The default of PcGive is to report a summary unit root test output for the sequence of ADF(n)...ADF(0) tests. The summary Table consists of:

D-lag	j (the number of lagged differences),
t-adf	the t-value on the lagged level: t_β ,
beta Y_1	the coefficient on the lagged level: β,
t-DY_lag	t-value of the longest lag: $t_{\gamma j}$,
t-prob	significance of the longest lag: $1-P(\,|\tau| \leq |t_{\gamma j}|\,)$,

AIC	Akaike criterion
F-prob	significance level of the F-test on the lags dropped up to that point,

for j=n,...,0. Critical values are listed and significance of the ADF test is marked by asterisks: * indicates significance at 5%, ** at 1%.

The null hypothesis is that the time-series are non-stationary *(i.e. series have a unit root or are integrated of order one, I(1)).* The critical values used for accepting or rejecting the null hypothesis of non-stationarity depend on whether an intercept or intercept and time trend terms are included in the test regressions.

4.2.4 Unit root results

The ADF unit root test was applied to all 199 time series, (202 original time series with 3 missing data time series omitted, as previously discussed). Unit root analysis was conducted using PCGive software, version 12.1 and as a result the PCGive output file 'Results unit root tests final.out' was created. The resultant file is too large to document here, however Appendix 4 is a basic summary of the unit root results.

It is important to note that undetected structural breaks in the series may lead to under-rejecting of the null and the correct ADF test specification is required as reported by Dhiri et. al. (2008).

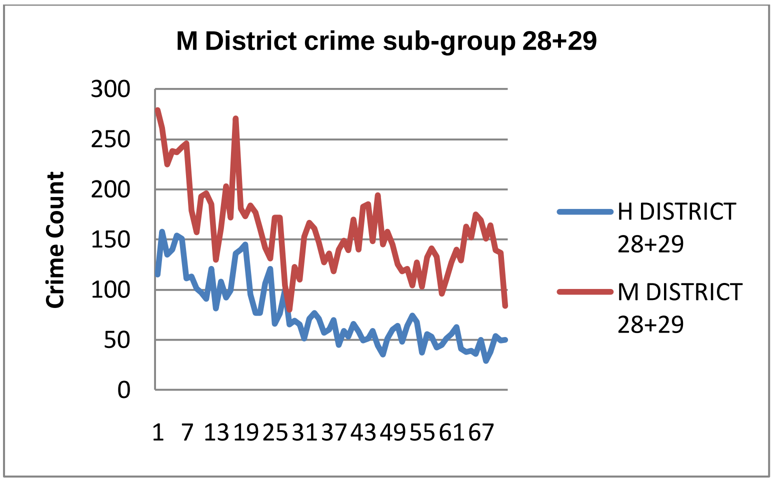
This unit root testing was repeated for all 199 time series variables and produced a total of 796 unit root tests as saved in PCGive 10.1 file Results Unit Root Final.out and as summarised in appendix 4.

The unit root tests suggested that there were two time series, (Alnwick 126 and Berwick 126), that appeared stationary on all counts of testing, (as highlighted in appendix 4 in yellow). It is believed that this is due to the very low variance in the data, the overall level of reporting for this crime sub-group category and the low geographical area. On closer inspection of the other areas for the crime sub-group of 126 there is some indication that like the above two time series are possibly stationary. Therefore greater care is required in interpreting any results involving this crime sub-group category as it may have greater potential to result in a spurious regression result. This would appear to be evidence of the outer limit for disaggregation for this offence based upon the crime count for this geographical area size.

I can conclude that most of the crime sub-categories, detection figures and claimant counts tested for unit roots by both visual graph observation and root testing, (via the Augmented Dickey-Fuller test), suggest that they are all integrated to the order one, or I(1). Although this is for a post NCRS period of time and is looking at sub-groups of crime, it supports the findings that crime is indeed I(1) as reported in Hale (1998).

In summary the ADF unit root tests suggest that the use of a static regression by Ordinary Least Squares (OLS) may be expected to produce spurious results as a result of the majority of the time series being I(1). To avoid the problem of non-stationary time-series, the first difference of the variables can be used. However, using relationships where the variables are expressed in differences provides short-run information and leads to the loss of useful long-run information. To discuss my reasoning in more detail I fully explain one of the time series M District 28+29, as shown in Figure 18.

Figure 18 – M District crime sub-group 28+29



We can see from the graph of the 'M District 28+29' time series that the data displays a random walk (negative trend) and therefore indicates that it is not a stationary series of data, (stochastic trend non-stationarity).

To confirm the stationarity of the data 3 regression tests are to be conducted, as per the Augmented Dickey-Fuller test.

The 3 tests are described as cases with: -

1 no intercept, no trend

2 intercept, no trend

3 intercept and trend

For the purpose of the ADF procedure our null hypothesis will be 'Log(M District 28+29) has a unit root'. The 3 tests were conducted, see results, See Table 9.

Table 9 – ADF test results for M District

crime sub-group category 28+29 (no constant or trend)

LM DISTRICT 28+29: ADF tests (T=69; 5%=-1.95 1%=-2.60)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	**F-prob**
2	-0.9239	0.99575	0.1917	-1.107	0.2725	-3.261	
1	-0.8567	0.99606	0.1920	-2.570	0.0124	-3.272	0.2725
0	-0.7449	0.99644	0.1997	-3.207			0.0245

The ADF statistic for all 3 lag settings is greater than -2.6 and -1.95 "tau t-adf" values at 1 and 5 per cent significant levels respectively. We cannot conclude to reject the null hypothesis "tseries has a unit root" Therefore it has a unit root problem and is a non-stationary series.

Table 10 – ADF test results for M District

crime sub-group category 28+29 (constant, no trend)

LM DISTRICT 28+29: ADF tests (T=62, Constant; 5%=-2.91 1%=-3.54)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	**F-prob**
2	-2.739	0.61967	0.1863	0.1155	0.9084	-3.299	0.9452
1	-2.925*	0.62558	0.1847	-1.034	0.3055	-3.331	0.9714
0	-3.865**	0.56325	0.1848			-3.345	0.9525

As can been seen in Table 10 the ADF statistic for the 0 lag setting is less than -3.54 "tau t-adf" value at 1 per cent significant level. We can conclude to reject the null hypothesis "tseries has a unit root". Therefore it does not have a unit root problem and is a stationary series.

Table 11 – ADF test results for M District

crime sub-group category 28+29 (constant and trend)

LM DISTRICT 28+29: ADF tests (T=62, Constant+Trend; 5%=-3.48 1%=-4.11)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	**F-prob**
2	-3.218	0.51281	0.1836	0.4321	0.6673	-3.313	0.9279
1	-3.356	0.53955	0.1823	-0.7129	0.4788	-3.342	0.9525
0	-4.311**	0.49049	0.1815			-3.366	0.9569

As can be seen in Table 11 the ADF statistic for the 0 lag setting is less than -4.11 "tau t-adf" value at 1 per cent significant level. We can conclude to reject the null hypothesis "tseries has a unit root". Therefore it does not have a unit root problem and is a stationary series.

Due the confusion in the ADF results the next stage is to take the 1st difference of the crime series I(1), (See Table 12).

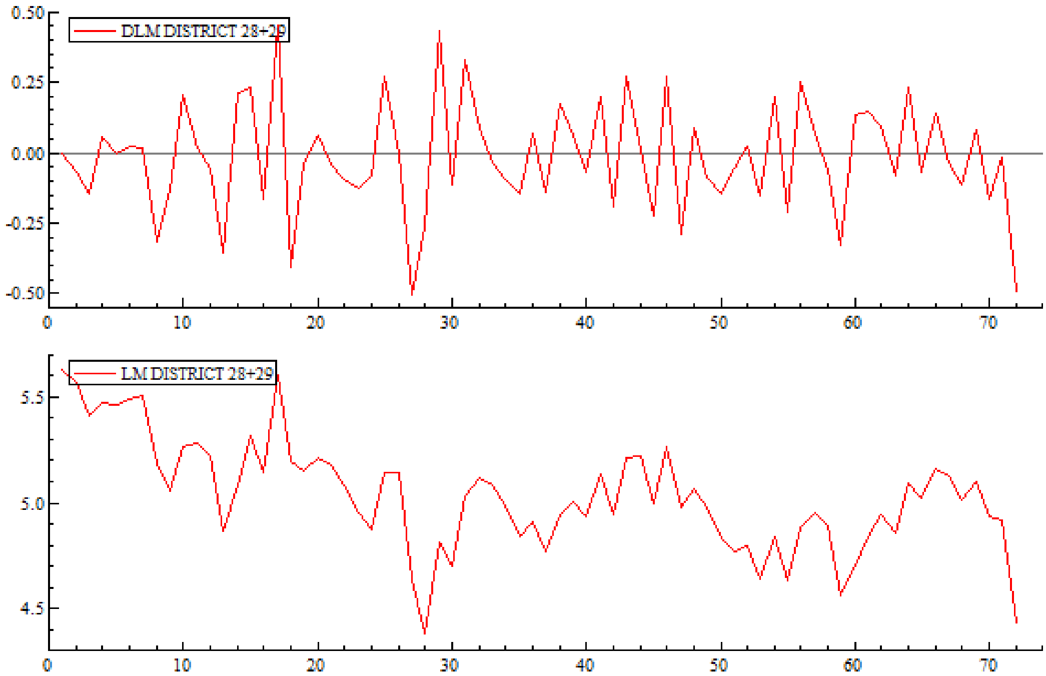
Table 12 – ADF test results for the 1st difference of the M District crime sub-group category 28+29 (constant and trend)

DLM DISTRICT 28+29: ADF tests (T=61, Constant+Trend; 5%=-3.48 1%=-4.11)							
D-lag	t-adf	beta Y_1	sigma	t-DY_lag	t-prob	AIC	**F-prob**
2	-5.229**	-0.64994	0.2001	0.6971	0.4886	-3.139	0.7827
1	-6.647**	-0.49655	0.1992	0.8766	0.3844	-3.163	0.8134
0	-10.25**	-0.33579	0.1988			-3.183	0.8162

From Table 12 we can conclude that the Middlesbrough crime data for this period for the crime sub-group 28 – Burglary in a dwelling is an integrated of order one, I(1) crime series, (series non stationary but series I(1) is stationary). This is shown to be significant to the one per cent significance level. Therefore we can conclude that the ADF testing suggests that the M district 28+29 crime sub-group category variable to be I(1).

This conclusion is visually depicted in Figure 26 below, which shows the times series M District 28+29 in a raw format, (the bottom graph), displaying a negative stochastic time trend. Figure 19 also shows the first difference of the same time series, (the top graph). We can see visually that it now displays a stationary time series.

Figure 19 – M28+29 crime sub-group time series and 1st differenced M28+29 time series



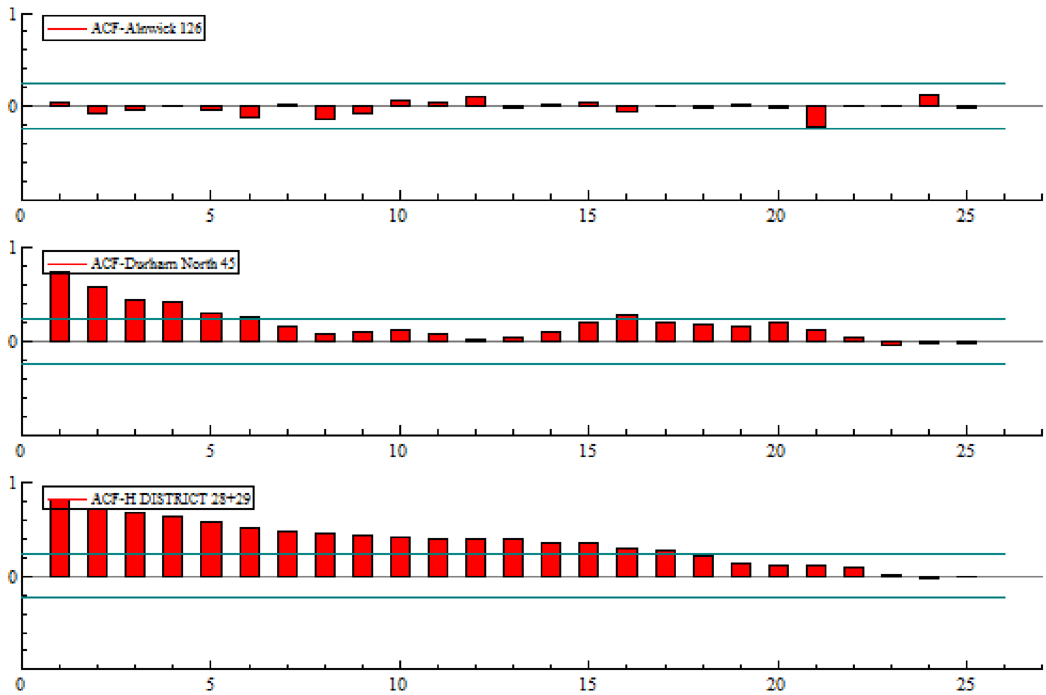
In conclusion there were however two time series identified as being potentially I(0) from the ADF testing procedure. These are highlighted in yellow in the results summary Table, appendix 4. This is believed to be due to the low variance in the time series data. As a result of this finding the two series will be omitted from further analysis work. Therefore, leaving 197 time series suitable for co-integration testing.

4.2.5 Confirmation of ADF test results

ADF testing can be difficult to interpret at times but it is critical that this is correct as otherwise this could lead to spurious results in the co-integration testing. Therefore having completed the ADF unit root testing on all time series I have employed the use of the autocorrelation function as a way of adding support to the ADF unit root test findings. To do this we need to look at an autocorrelation plot, (a correlogram), for each of the time series. The autocorrelation function for a stationary series drops off as k, the number of lags, becomes large, but this usually is not the case for a non-stationary series.

Rather than produce correlograms for all 199 time series, as tested for in the ADF tests, I have decided to select three crime series from the three different force areas to test this procedure and to see if it supports the formal ADF testing procedure as previously described. I have produced the three correlograms of time series data that are undifferenced for the crime sub-group categories of Alnwick 126, Durham North 45 and H District 28+29, (see Figure 20 below).

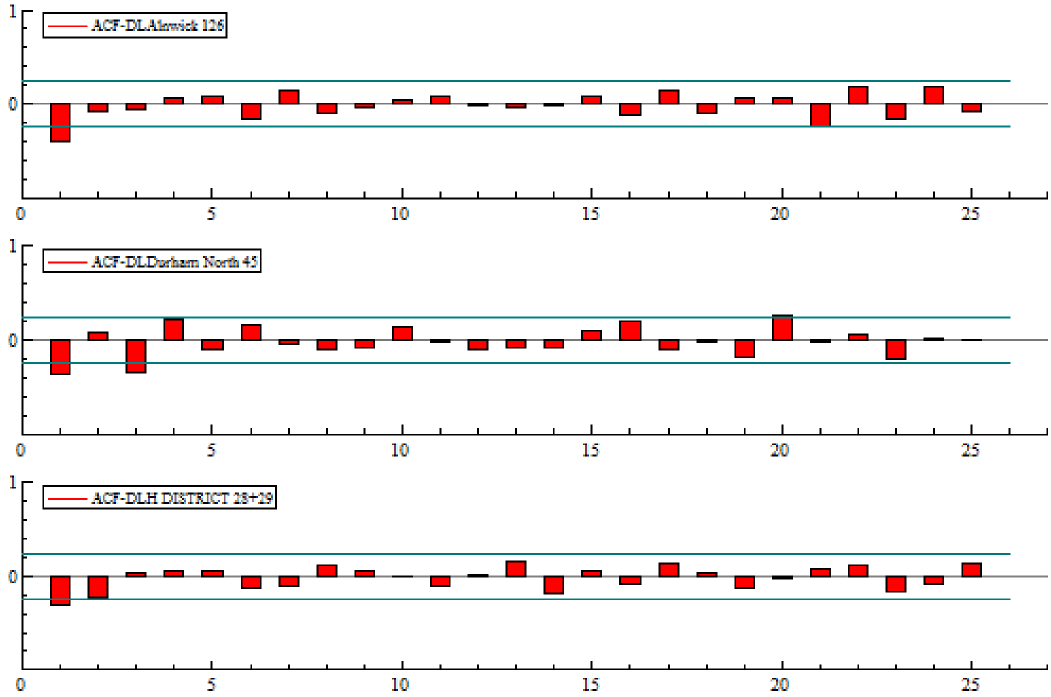
Figure 20 – Correlograms for three undifferenced logged time series



The autocorrelation function for the time series of Durham North 45 and H District 28+29 does decline as the number of lags becomes large, but only very slowly. Both series show a trend so the mean is not constant over time. As a result we would suspect that both series have been produced by a nonstationary process. On the other hand, the correlogram for the time series Alnwick 126 displays very different properties. This series shows a mean which is about constant. This series declines very rapidly and this is consistent with a stationary series. The ADF testing results also suggests that this series is stationary.

I have now differenced the three time series once, recalculated the sample autocorrelation function and produced the graphs in Figure 21.

Figure 21 – Correlograms for three differenced logged time series



The differenced series all decline rapidly which is consistent with a stationary series. The above three time series correlograms would support the findings of our formal ADF testing. Therefore we conclude that differencing once should be sufficient to ensure stationarity in the time series.

4.3 Co-integration tests

Having completed our unit root tests and identified that most of the variables are of the same order of integration I(1), we examine the co-integration properties of the I(1) variables. The concept of co-integration looks at the possibility that linear combinations of variables also remove unit roots and therefore become stationary resulting in the existence of a co-integrating vector.

Co-integration vectors are of considerable interest when they exist, since they determine I(0) relations that hold between variables which are individually non-stationary. If two or more series are linked to form an equilibrium relationship spanning the long-run, even when the series themselves may contain stochastic trends, (non-stationary), they will nevertheless move closely together over time and the difference between them will be stable (stationary). Such relations are often called 'long-run equilibria'.

If co-integration exists between variables then an Error correction model, (ECM), can be used in the modelling of the data. ECM's can incorporate long and short term aspects of the data. If variables are found not to be co-integrated then only short term modelling can be carried out. However if this element of the analysis is ignored then the model will be miss-specified (Hale 1998).

We need therefore to identify any co-integrating relationships between the data so that a decision as to use the standard short run equation model or an ECM can be made. As a result we need to know exactly what the hypothesis of this research is:-

(1) The level of property crime is affected by claimant counts.

(2) The level of property crime sub-groups are affected by other related property crime sub-groups.

Therefore to conduct the research into the above two hypotheses each of the 197 time series (minus detection and claimant count time series) will need to be regressed against the two claimant count explanatory variables and the related crime sub-group category variables. Additionally regression will take place against detection data where available, (Cleveland Only). The related crime sub-group categories were chosen as follows:-

	30+31	48+37/2	58a	58b	58c	126
45		*				
45					*	
45						*
28+29	*					
28+29			*			
30+31				*		
48+37/2					*	
48+37/2						*

Therefore co-integrating regressions will be performed between Theft from a motor vehicle (45) and the related offences of Theft of motor vehicle (48) and it's respective aggravated offence (37/2), Criminal damage to a motor vehicle (58c) and Tampering with a motor vehicle (126). Co-integrating regressions will be performed between burglary in a dwelling (28), plus its respective aggravated offence (29) and burglary in a building other than a dwelling (30), plus its respective aggravated offence (31) and also against the related offence of criminal damage to a dwelling (58a). Burglary in a building other than a dwelling (30) plus its respective aggravated offence (31) will also be regressed against the related offence of criminal damage to a building other than a dwelling (58b). Finally the combined offences of theft of motor vehicle (48) and its aggravated offence (37/2) will be regressed against the related offences of criminal damage to a motor vehicle (58c) and tampering with a motor vehicle (126).

Each crime series variable will therefore be regressed against each of the explanatory variables (claimant counts, detections and related crime sub-groups), see appendix 5 which provides a tabulated summary of all co-integrating regressions required for this research. Appendix 5 describes a total of 401 co-integrating regressions in a tabulated matrix.

There are a number of alternative statistical methods for testing for co-integration. Due to the number of regression tests required a faster, slightly less refined test, the Engle and Granger two step test, will be employed rather than that of the more complex Johansen method.

4.3.1 Engle and Granger two step procedure

Engle and Granger's two step procedure is a quicker but less refined method of testing for co-integration. The first step is to run a co-integrating regression using ordinary least squares, (OLS). The second stage is to test if the residuals of the estimated equation come out to be stationary. The residuals can be tested for stationarity using the ADF process used in our first stage of statistical analysis. If the residuals are stationary this would indicate that there is a stationary co-integrating relationship in existence. Therefore we will be testing the null: no co-integration, so residual is a random walk.

The theory behind it is explained as follows: - if x and y are two time series which both display random walks (i.e. not stationary) and z is stationary in the equation z = x –*h*y, where *h* is the co-integrating parameter or vector? We can then estimate h by running an OLS regression of x and y. Unlike the case of 2 random walks that are not co-integrated, the OLS should provide a consistent estimator of *h*.

Therefore we can summarise the 2 stages of the Engle and Granger two step procedure as follows:-

1. Estimate the static long-run relation using OLS on the identified regression series, (see appendix 5) and save the estimated residuals, (performed using PcGive, version 12.1).
2. Perform Engle-Granger residual-based test, (i.e. ADF test on estimated residuals) for whether the long-run relation is a co-integrating relation, (performed using PcGive, version 12.1).

Number of co-integrating regression tests to be conducted (individual)

Out of 202 original time series and following unit root testing, the number of time series for analysis was reduced to 197. This was as a result of 3 time series with incomplete data sets and 2 time series showing I(0) characteristics (stationary). Therefore there will be a total of 401 individual co-integration regression tests, as detailed in appendix 5.

4.3.2 Stage 1 – E & G Procedure

As with the initial unit root testing, individual graphs can provide a rough guide to whether a time series is stationary or not. Therefore individual OLS residual plots can be examined following the ADF testing on the residuals, as a checking mechanism in the analysis.

Co-integration may or may not exist between variables that do or do not 'look co-integrated' and the only real way to find out is through a careful statistical analysis, rather than rely on visual inspection.

4.3.3 Stage 2 –E& G Procedure

Unit root testing of the OLS residuals was conducted using ADF in a similar process as described in the unit root testing earlier. PcGive software, (version 12.1) was used to conduct 401 OLS co-integrating regressions. Hansen (1992) has shown, based on the Monte Carlo experimentation that irrespective if the residuals contain deterministic trend or not, including a trend results in loss of power and could lead to under rejecting of the null of no co-integration. We can also assume that we should not use a constant since the residuals will have a mean of zero. As a result I did not include a trend or constant in the respective co-integrating regressions. Critical values used for the ADF test are discussed in detail below. The number of lags were chosen by the Akaike Information Criterion, (AIC).

4.3.3.1 Critical Values

Relevant critical values are found in Engle and Granger (1987). Use of the standard Dickey-Fuller critical values may lead to over rejecting of the null. The critical values are also affected by the number of regression variables, sample size and whether a constant and/or trend are included. The critical value can be calculated using the regression equation below and by the table of coefficients from MacKinnon (1991) below, where N is the number of regressed variables and % is the ADF significance levels.

$$C(p) = a + bT-1 + cT-2$$

N	Model	%	a	b	c
1	no trend	1	-2.5658	-1.960	-10.04
	No constant	5	-1.9393	-0.398	0
		10	-1.6156	-0.181	0

(MacKinnon 1991)

Therefore for the purpose of calculating our critical values for the ADF tests on using our co-integrating regression residuals, we can calculate the following critical values:- N=1

No constant, no trend	1%	-2.5658-1.960/59-10.04/59(sq)=		-2.601
	5%	-1.9393-0.398/59-0	=	-1.946
	10%	-1.6156-0.181/59-0	=	-1.618

If the *t*-statistic of the ADF test is lower than the critical value is, we would reject the null hypothesis of non-stationary time series and conclude that the error term was stationary. We can then conclude that there is a level of significance that points to the variables being co-integrated.

If the residual is regarded as stationary it can be used as an error correction expression in a single equation error correction model.

4.3.3.2 Residual Graphs

Plotting the residuals individually can also provide a crude way of visually observing whether they are displaying a random walk or are stationary. Appendix 6 shows a selection of the 401 time series graphs from the co-integration regression residuals. We can conclude from visual inspection that the following residuals are suspected of being random walks; Residuals 18, 19 and 20 as they show a tendency to drift from the mean. Comparison of these results will be made later with the formal ADF results.

4.3.3.3 DW test

Alternatively one can simply look at the Durbin Watson statistic of the co-integrating regression. If the residual is a random walk then the expected DW statistic should be close to zero.

We need to calculate the critical values for the test results for 72 observations at the 1, 5 and 10 per cent significant values, the critical values have been calculated, (Engle and Granger 1987). Thus if the calculated DW value is above that of the critical value, (dependant on which significant level is used), we can reject the null of a unit root in the residuals and conclude that the series is co-integrated.

4.3.4 Interpreting ADF results

We pick the largest AIC value and read off the corresponding t-ADF value and then compare it against the critical value as calculated above, (see example of below in Table 13). The highest AIC value is highlighted red and the corresponding t-ADF value also highlighted in red indicates the residual to be stationary at the five per cent significance level. This highlights the above procedure. This procedure is carried out for all residual ADF tests and the significance of the finding is detailed in Table 14.

Table 13 – Example Interpretation of ADF results – Residuals53

D Lag	t-ADF	AIC
10	-1.196	-3.034
9	-1.071	-3.059
8	-1.227	-3.089
7	-1.500	-3.111
6	-1.790	-3.133
5	-2.272*	-3.146
4	-1.782	-3.116
3	-2.138*	-3.126
2	-2.424*	-3.153
1	-2.476*	-3.186
0	-3.585**	-3.134

Before interpreting the co-integration results, it is necessary to emphasise that the Engle-Granger method does not prove whether the relationships are really long run ones. This is an assumption and cannot be statistically verified. We need to have a strong belief in a long run equilibrium relationship between the variables that is supported by relevant economic theory where the theory suggests a suitable assumption about a long run relationship (Charemza and Deadman, 1992). A test for co-integration therefore can be considered a test of the theory.

Table 14 summarises the ADF unit root tests conducted on all co-integration suspected relationships, as per appendix 5. Blank cells that are coloured yellow depict residuals that are non-stationary and therefore suggest that no co-integrating relationship exists between the respective variables. One and five represent one and five per cent confidence limits for a stationary residual and therefore suggests a co-integrating relationship exists.

Table 14 – Co-integration regression residual analysis

	Claimant Count <30	Claimant Count >30	Detection	30+31	48+37/2	58a	58b	58c	126
warren 28+29	5	5		5		1			
warren 30+31	1	1					1		
warren 45	1	1			1			1	1
warren 48+37/2	1	1						1	
warren 58a	1								
warren 58b	1								
warren 58c	1	5							
warren 126	error	error							
Tynside N 28+29	1			1		1			
Tynside N 30+31	1	1					1		
Tynside N 45	1	1			1			1	
Tynside N 48+37/2		1							
Tynside N 58a		5							
Tynside N 58b	5	1							
Tynside N 58c	1	1							
Tynside N 126	1	1							
Tynside S 28+29		1		1		1			
Tynside S 30+31	5	1					1		
Tynside S 45	5	1			1			1	1
Tynside S 48+37/2	1	1						1	1
Tynside S 58a									
Tynside S 58b									
Tynside S 58c	1	1							
Tynside S 126									
Tyndale 28+29	1	1		1		1			
Tyndale 30+31	1	1					1		
Tyndale 45	1	1			1			1	1
Tyndale 48+37/2	1	1						1	1

Tyndale 58a	1	1							
Tyndale 58b	1	1							
Tyndale 58c	1	5							
Sunderland 28+29				5		1			
Sunderland 30+31		1					1		
Sunderland 45	5	5			1			1	1
Sunderland 48+37/2									
Sunderland 58a	1	1							
Sunderland 58b	1	1							
Sunderland 58c	1	1							
Sunderland 126									
Newcastle 28+29	1	1		1		1			
Newcastle 30+31	5	5					1		
Newcastle 45	1	1			1			1	1
Newcastle 48+37/2	1	1							
Newcastle 58a	5	1							
Newcastle 58b	5	5							
Newcastle 58c	1	1							
Newcastle 126	1	1							
Alnwick 30+31	1	1					1		
Alnwick 45	1	1			1			5	5
Alnwick 58a	1	1							
Alnwick 58b	5	1							
Alnwick 58c	1	1							
Berwick 30+31	1	1					1		
Berwick 58b	1	1							
Berwick 58c	5	1							
Blyth 28+29	1	1		1		1			
Blyth 30+31	1	1					1		
Blyth 45	1	1			1			1	1
Blyth 48+37/2	1	1						1	1
Blyth 58a	1	5							
Blyth 58b	1	1							
Blyth 58c	1	1							
Castle 28+29	1	1		1		1			
Castle 30+31	1	1					1		
Castle 45	1	1			1			1	1
Castle 48+37/2	1	1						1	1

Castle 58a	1	1							
Castle 58b	1	1							
Castle 58c	1	1							
Castle 126	1	1							
Gateshead 28+29	5	1		1		1			
Gateshead 30+31		5							
Gateshead 45	1	1			1			1	1
Gateshead 48+37/2		5							
Gateshead 58a		5							
Gateshead 58b		1							
Gateshead 58c	1	1							
Gateshead 126	5	1							
Durham North 28+29	1	1		1		1			
Durham South 28+29		1				1			
Durham North 30+31	1	1					1		
Durham South 30+31	5	1					1		
Durham North 45		5			1				
Durham South 45		5			5			5	1
Durham North 48+37/2								1	5
Durham South 48+37/2		1						1	
Durham North 126	1	1							
Durham South 126	1	1							
Durham North 58a	1	1							
Durham North 58b	1	1							
Durham North 58c	5	5							
H DISTRICT 28+29		1	5	1					
M DISTRICT 28+29	1	1	1	1		1			
L DISTRICT 28+29		1							
S DISTRICT		5		1					

28+29									
H DISTRICT 30+31		1							
M DISTRICT 30+31		5	5				5		
L DISTRICT 30+31	1	1	1				5		
S DISTRICT 30+31	5	1							
H DISTRICT 45		1			1				
M DISTRICT 45	5	5	5		1			5	5
L DISTRICT 45		miss	1		5			1	5
S DISTRICT 45		1	5		1			1	1
H DISTRICT 48+37/2	1	1	5					1	
M DISTRICT 48+37/2									1
L DISTRICT 48+37/2									5
S DISTRICT 48+37/2	5	1						1	1
H DISTRICT 126	1	1	miss						
M DISTRICT 126			miss						
L DISTRICT 126	1	5	miss						
S DISTRICT 126		5	miss						
H DISTRICT 58a	1	1	1						
M DISTRICT 58a	1	1	1						
L DISTRICT 58a	1	1	1						
S DISTRICT 58a	1	1	1						
H DISTRICT 58b	1	1	1						
M DISTRICT 58b	1	miss	1						
L DISTRICT 58b	1	1	1						
S DISTRICT 58b	1	1	1						
H DISTRICT 58c	1	1	1						
M DISTRICT	1	1	1						

58c									
L DISTRICT 58c	1	1	1						
S DISTRICT 58c	5		1						

We can see that 77 of the 401 co-integrating regressions did not indicate an ADF test result on the residuals significant at five per cent or more. Therefore we can conclude that this suggests that there exists no co-integration for the 77 models and their respective variable relationships. It is interesting to note at this stage that the vast majority of the co-integrating regressions that do not suggest a co-integrating relationship are for motor vehicle crime sub-group categories. This is particularly noticeable in the major urban areas. It is also very interesting that there are three co-integrating regressions that do not show a co-integrating relationship between dwelling burglaries and criminal damage to a dwelling. All three are within the Cleveland Police area. All other geographical areas show a co-integrating relationship exists between dwelling burglaries and criminal damage to a dwelling. This is also very noticeable in the Cleveland Police area for burglaries other than a dwelling and its lack of co-integrating relationship between the crime sub-group category of criminal damage to a building other than a dwelling.

4.4 Error Correction Models, (ECM)

When you have non-stationary time series, which are integrated to the same order and the residuals from the long run ordinary least square, (OLS) regression models are stationary, then you can suggest that you have a co-integrating relationship. Having a co-integrating relationship between variables necessitates the estimation of an error correction model. We have shown that of the 401 co-integrating regressions performed 324 of them suggest that there is a co-integrating relationship in existence between the respective variables, (see Table 14).

4.4.1 Establishing an error correction model (ECM)

Using the Engle and Granger (1987) procedure we suggest that the 324 co-integrated variable relationships in Table 14, (not the 77 that are highlighted in yellow) are co-integrated based upon the first stage testing of the OLS regressions between the various dependant and explanatory variables $csc_t, cc_t \text{ and } d_t$. The residuals from the OLS regressions, (depicted byε_t), are shown to be stationary, I(0) in nature. In the second stage of this procedure the ECM is formulated by regressing the differenced variables with the lagged values of the residuals of the long run OLS regression, therefore incorporating residuals into a short run model. The process of formulating an ECM helps to secure a model which incorporates both short and long run elements of the data. This combats the effects of differencing the data at the first stage regression process, which prevents spurious regression results. However this method also results in the loss of short run information. What we hope to achieve is to show the short run fluctuations in the influence of claimant counts on property crime and to show that in the long run there is a tendency for it to return to a stable growth path.

As we have accepted that the vast majority of the variable relationships in Table 14 are co-integrated then there must be an error correction representation of the variables. This, the long run(LR)-model, is the first stage of the Engle and Granger (1987) procedure. The procedure I intend to follow for formulating an ECM will therefore be first of all to estimate LR relation (OLS) and test residuals for stationarity. Secondly to estimate ECM, LR imposed and dynamic data determined. Thirdly to test model adequacy and conduct diagnostic tests and finally to conduct some model forecasting.

4.4.2 Stage 1 – Estimate the Long run OLS regression residuals

The long run OLS models are based upon the basic crime model surrounding deterrence crime theory, as discussed in Chapter 3 and as detailed in eq. (1).

(1) Log(crime group) = α + $\beta_1$deterrence + β_2LabourMarket + u_t

Where α is the constant term

β_1 is the deterrence variable coefficient

β_2 is the labour Market variable coefficient

u_t is the error term

Based upon previously described disputed research findings surrounding the use of unemployment data and the limited research in this field based around the unemployment proxy variable of claimant counts, it was decided to use this as a proxy labour market variable. The use of the detection variable was also used as a proxy for the deterrence variable (Cleveland only). Both explanatory variables are to be initially looked at in isolation to eliminate the issues surrounding multiple co-integrating vectors in a model. As previously discussed it was also decided that crime sub-group categories would be compared against similar related crime sub-group categories to identify any significant relationships.

As we have already discussed, if certain aspects are ignored, such that the series is non-stationary of the time series data, this can lead to spurious regression results based upon OLS. Therefore the long term (co-integrating) regression(s) can be described as below, see equation (2), (3) and (4).

$$(2)\ csc_t = \beta cc_t + \mu_t$$

$$(3)\ csc_t = \beta d_t + \mu_t$$

$$(4)\ csc_t = \beta csc_t + \mu_t$$

It is important to reiterate that due to the spurious nature of these regression results, as the time series are non-stationary, we cannot rely upon the standard error estimates, (t-statistic) or R^2 estimated coefficients and therefore they will not be reported here.

The u_t residual from the long run co-integrating regression should be stationary, i.e. I(0). As we have already discussed, see previous section, we have established that most (324) are indeed I(0). If they are then we can use the μ_t residual, (lagged once) in the ECM.

If μ_t is a random walk then the expected value of $(\mu_t - \mu_{t-1})$ is zero and so the DW statistic should also be close to zero. Most of the resultant DW readings are well below 1. The DW readings that are higher and closer to 2 fail the statistical diagnostic tests. These DW calculations for the individual co-integrating regression models support the theory that the residuals are indeed stationary and therefore suggest that the respective variables are indeed co-integrated. Table 15 shows an example of residual results for the variable *residual1;* which is the residual formed when the Wansbeck 28+29 crime sub-group variable is regressed against the claimant count <30 variable.

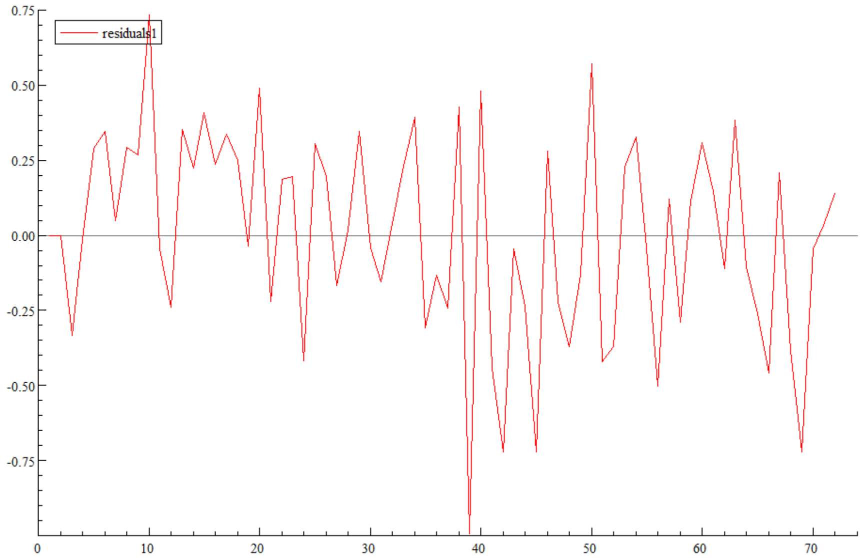
Table 15, Example residual data, residual 1 variable

0.291601
0.266396
0.735522
-0.0454
-0.2387
0.352378
0.223925
0.409833
0.23603
0.337849
0.248066
-0.03684
0.489939
-0.22073
0.18627
0.19492
-0.41751
0.305721
0.19492
-0.1662
0.016363
0.346613
-0.04215
-0.15516
0.038721
0.22883
0.393384
-0.3075
-0.13313
-0.24295
0.428323

Figure 22 also shows a graphical representation of the residual 1 variable. It indicates visually that it is stationary as previously found by use of ADF stationarity testing.

Figure 22 – Graphical representation

of variable residual 1, from PcGive (ver 12.1) software



4.4.3 <u>Stage 2 - Estimate EC, LR imposed, dynamics data determined</u>

The complete ECM will include both short run and ECM term elements within it. This restores the crime variable to its long run relationship with the respective explanatory variable, (claimant, detection or related crime sub-group category variable).

All the terms in the ECM will be required to be stationary, i.e. I(0) so that traditional regression analysis can be used for estimation and no spurious results will occur. Therefore the crime terms, as established previously as I(1) variables will need first differencing. The ECM term, ut has already been shown to be stationary and will therefore remain as it was already, i.e. I(0). Therefore the final ECMs are shown in equations (5), (6) and (7).

$$(5)\ \Delta csc_t = \beta_1 \Delta cc_t + \beta_2\,(ECM) + \varepsilon_t$$

$$(6)\ \Delta csc_t = \beta_1 \Delta csc_t + \beta_2\,(ECM) + \varepsilon_t$$

$$(7)\ \Delta csc_t = \beta_1 \Delta d_t + \beta_3\,(ECM) + \varepsilon_t$$

$$\Delta csc_t = Log\ I(Crime\ Sub - Category)$$

$$\beta_1 \Delta cc_t = Log\ I(Claimant\ Count)$$

$$\beta_2\,\Delta d_t = Log\ I(Detection\ Rate)$$

$$(ECM) = (csc_{t-1} - \beta cc_{t-1}) = \mu_t$$

ε_t is the stochastic element to the ECM equation. If this is non-zero then it suggests that it has some drift in addition to the equilibrium.

ECM will be replaced by the estimated residual μ_t lagged once, therefore it will be μ_{t-1}.

Assuming the proceeding tests were conducted correctly and the model is specified correctly all the variables and residuals should be stationary.

4.4.4 ECM Results

Using the data time series that passed the initial inspection checks and stationarity tests, (see previous Chapters) and equations (5), (6) and (7), a total of 397 ECM regression estimations were made. PcGive 12.1 software was utilised to conduct the ECM regressions. It should be noted that during the co-integrating testing stage there were 77 of the 397 models identified as not displaying properties relating to a co-integrating relationship and therefore not suitable for ECM estimation. However I made the decision to retain the 77 models in the ECM regression estimating process for two reasons. The first was for ease of overall analysis process. The second reason was based on using the 77 models as a potential checking mechanism on the ECM regression diagnostics. These 77 models are later highlighted and discussed in detail.

Table 16 shows one of the ECM regression results. The associated statistical data is presented in a standard way and although it was relatively easy to read for one individual ECM regression it was exceptionally difficult to make comparisons with the 397 ECM regressions as estimated.

Table 16 – Example ECM regression results

	Coefficient	Std.Error	t-value	t-prob	Part.R^2
Constant	0.00945736	0.02229	0.424	0.6728	0.0026
DLS Tyneside >30	1.00972	0.4598	2.20	0.0315	0.0662
residuals70_1	-0.600118	0.1091	-5.50	0.0000	0.3078

sigma	0.18573	RSS	2.34570244
R^2	0.312834	F(2,68) =	15.48 [0.000]**
log-likelihood	20.3137	DW	2.11
no. of observations	71	no. of parameters	3
When the log-likelihood constant is NOT included:			
AIC	-3.32559	SC	-3.22998
HQ	-3.28757	FPE	0.0359532
When the log-likelihood constant is included:			
AIC	-0.487711	SC	-0.392105
HQ	-0.449691	FPE	0.614061
mean(Y)	0.00286759	var(Y)	0.0480787

AR 1-2 test:	F(2,66)	=	0.79679	[0.4551]
ARCH 1-1 test:	F(1,66)	=	0.46096	[0.4995]
Normality test:	Chi^2(2)	=	3.6464	[0.1615]
Hetero test:	F(4,63)	=	0.48865	[0.7440]
Hetero-X test:	F(5,62)	=	0.55566	[0.7334]
RESET test:	F(1,67)	=	6.9005	[0.0107]*

```
DLTynside S 58c =  + 0.009457 + 1.01*DLS Tyneside >30 - 0.6001*residuals70_1
(SE)              (0.0223)    (0.46)                  (0.109)
```

The resultant ECM regression analysis resulted in 397 separate ECM regression results, as per Table 16. This made it very difficult to compare one against another and to get an overall combined feel for the results. As a result the 397 results were manually taken from the individual PcGive results sheets, they were then summarised and placed in an Excel spreadsheet, as per appendix 9. This proved to be a very time consuming process.

Auto filters were then established so that set filter conditions could be created causing the data to be filtered. Filters could specifically be set for each of the crime sub-groups, regression coefficients values or R^2 values. The models can also be selected or de-selected based upon statistical diagnostic test results. This proved to be a highly effective way of filtering out those cases that do not meet or pass certain statistical tests. A suitable range can also be placed upon some of the significant statistical estimations such as the DW and R^2 figures. The csc_tvariable can also be filtered by selecting only records that contain certain expressions, such as "28+29". This would result in only records being used for models relating to the dependent variable which is associated to the aggregated dwelling burglaries crime sub-group. I could also select and de-select crime variables based upon their respective police force areas by selecting and deselecting variables that contained the terms "district" for Cleveland and "Durham" for Durham.

Therefore using the above excel spreadsheet loaded with the ECM regression estimates results from PcGive 12.1 the following 14 result tables have been produced. These detail the relevant ECM regression parameters for specific policing areas or crime sub-group categories and also a filter statistical test results. All have been filtered additionally for models that show R^2 > 30% and pass all the statistical diagnostic tests as described later.

Table 17 – ECM regression estimates resulting in R^2 > 30%, all crime sub-groups and areas and screened statistical tests at 1% and 5% significance.

Table 18 – ECM Negative relationships

Table 19 - ECM regression estimates resulting in R^2 > 30%, all crime sub-groups and areas, claimant count <30 and screened statistical tests at 1% and 5% significance.

Table 20 - ECM regression estimates resulting in R^2 > 30%, all crime sub-groups and areas, claimant count >30 and screened statistical tests at 1% and 5% significance.

Table 21 - ECM regression estimates resulting in R^2 > 30%, all crime sub-groups, Cleveland Police area and screened statistical tests at 1% and 5% significance.

Table 22 - ECM regression estimates resulting in R^2 > 30%, all crime sub-groups, Durham Police area and screened statistical tests at 1% and 5% significance.

Table 23 - ECM regression estimates resulting in R^2 > 30%, all crime sub-groups and Northumbria Police area and screened statistical tests at 1% and 5% significance.

As R2 values cannot be used directly to compare models with different dependent variables the following tables summarise the models with the same explanatory variables.

Table 24 - ECM regression estimates resulting in R^2 > 30%, 28+29 crime sub-groups, all areas, and screened statistical tests at 1% and 5% significance.

Table 25 - ECM regression estimates resulting in R^2 > 30%, 30+31 crime sub-groups, all areas, and screened statistical tests at 1% and 5% significance.

Table 26 - ECM regression estimates resulting in R^2 > 30%, 45 crime sub-groups, all areas, and screened statistical tests at 1% and 5% significance.

Table 27 - ECM regression estimates resulting in R^2 > 30%, 48+37/2 crime sub-groups, all areas, and screened statistical tests at 1% and 5% significance.

Table 28 - ECM regression estimates resulting in R^2 > 30%, 58a crime sub-groups, all areas, and screened statistical tests at 1% and 5% significance.

Table 29 - ECM regression estimates resulting in R^2 > 30%, 58b crime sub-groups, all areas, and screened statistical tests at 1% and 5% significance.

Table 30 - ECM regression estimates resulting in R^2 > 30%, 58c crime sub-groups, all areas, and screened statistical tests at 1% and 5% significance.

Table 31 - ECM regression estimates resulting in R^2 > 30%, 126 crime sub-groups, all areas, and screened statistical tests at 1% and 5% significance.

All tables are discussed separately in detail in the following pages.

t Statistic

The statistical test associated with testing of regression coefficients is the t distribution. Using the t we can decide whether to reject the null hypothesis at a set significance level. Therefore if the calculated regression coefficient t statistic is greater than the tc (critical value) in magnitude, (sign not an issue), then we may reject the null hypothesis. The rule for acceptance of the rejection must be chosen and frequently involves the 5 per cent level of significance. If the rejection of the null is valid the model is usually accepted. PCGive 12.1 software provides the calculated t value associated with the explanatory variable regression coefficient. PCGive 12.1 also provides a further associated value, p-prob, that describes the exact significance level associated with the econometric result (t value). Therefore a p-prob value of .07 indicates a regression coefficient is statistically significant at the .07 level but not the 5 per cent level. In this case 7 per cent of the t-distribution lies outside an interval of tc standard deviations from the estimated slope parameter. For the purpose of this research I have highlighted the regression coefficients on the explanatory variable that have a significance level at the 10 per cent level. They are highlighted on the respective tables in yellow and are discussed in detail later.

As the regression coefficients have been selected based upon the 10 per cent significance level it is important to note that we would expect that approximately 1 in 10 occasions the variable would be significantly different from zero. This means that no matter how reliable the coefficient is there is always a chance that one will make incorrect inferences by relying on the regression results.

Table 17 – ECM regression estimates resulting in R^2 > 30%, all crime sub-groups

and areas and screened statistical tests at 1% and 5% significance.

csc_t	Claimant Count <30	Claimant Count >30	Detection	30+31	48+37/2	58a	58b	58c	126	ε_t	β_1	β_2	R_2	DW	t	t-prob
Tyndale 48+37/2									*	-0.0039	0.3707	-1.1519	0.6086	2.05	5.75	0
Castle 58c		*								0.0023	1.2665	-1.0755	0.5543	2.04	1.84	0.0705
Alnwick 45		*								0.011	1.3061	-1.0934	0.5493	1.99	1.51	0.136
Castle 58c	*									-0.0023	0.5415	-1.0686	0.5395	2.02	1.36	0.1774
Gateshead 58b		*								-0.0072	0.297	-1.029	0.5257	2.05	0.555	0.5809
Alnwick 45	*									0.0063	0.9124	-1.026	0.5117	1.91	1.63	0.1074
Tyndale 58a		*								-0.0058	0.4049	-1.0039	0.5099	2.08	0.496	0.6217
Alnwick 58c	*									-0.0066	-1.3416	-0.9164	0.5018	1.87	-3.18	0.0022
Alnwick 45					*					0.0026	-0.1305	-1.0034	0.5013	1.94	-1.63	0.674
Durham South 28+29		*								0.0069	1.5987	-0.8575	0.4987	1.95	3.69	0.0005
Tyndale 58c	*									0.0088	1.54	-0.9996	0.4935	1.95	2.38	0.02
warren 28+29						*				-0.006	0.6036	-0.696	0.472	2.01	4.42	0
Castle 58a		*								0.0018	0.8884	-0.9017	0.4671	2	1.17	0.2468

Alnwick 58c		*								-0.0047	0.1338	-0.9379	0.4658	1.96	0.19	0.85
Tyndale 48+37/2	*									-0.0101	-1.3192	-0.8278	0.4594	2.01	-1.76	0.0822
Alnwick 30+31		*								-0.0013	0.7798	-0.9193	0.4568	1.96	0.934	0.3537
Tyndale 48+37/2		*								-0.0103	-0.2344	-0.8961	0.4559	2.01	-0.234	0.8157
warren 30+31							*			-0.0014	0.3985	-0.7504	0.453	1.95	4.07	0.0001
Berwick 30+31	*									-0.0096	-0.9757	-0.8622	0.4522	1.88	-2.63	0.0105
Blyth 45									*	-0.0129	0.1838	-0.8617	0.4484	1.94	4.36	0
Castle 30+31		*								-0.0061	1.2487	-0.8851	0.444	2.04	1.49	0.1413
Castle 126	*									0.0039	0.8427	-0.8699	0.4424	1.99	0.894	0.3743
S DISTRICT 58b		*								0.0001	0.5173	-0.9124	0.4421	1.98	0.836	0.4059
L DISTRICT 58b		*								-0.0057	-0.637	-0.8688	0.4411	2.01	-0.966	0.3375
Castle 126		*								-0.0013	-0.8084	-0.8644	0.4359	1.95	-0.482	0.631
L DISTRICT 58b			*							-0.0019	0.0836	-0.8185	0.4355	2.01	2	0.0494
Durham South 48+37/2		*								0.0023	0.7511	-0.8312	0.431	2.1	1.22	0.2259
S DISTRICT 58b	*									-0.003	-0.2698	-0.8504	0.43	2.01	-0.426	0.6711
Alnwick 30+31	*									-0.0032	0.2326	-0.8583	0.4284	2	0.438	0.6626
Gateshead 58c		*								0.0102	1.3608	-0.6987	0.4233	1.97	3.42	0.0011
warren 45								*		-0.0065	0.4901	-0.8068	0.4197	1.98	3.15	0.0024
L DISTRICT 58b	*									-0.0027	-0.8454	-0.8371	0.4189	2.01	-1.19	0.2371
Castle 30+31							*			-0.0117	-0.1416	-0.8001	0.4188	2.12	-1.98	0.0521
Tyndale 48+37/2								*		-0.0093	0.1898	-0.8144	0.4156	2.02	1.79	0.0782
Tyndale 30+31		*								-0.0136	-1.144	-0.7123	0.4147	2.01	-1.8	0.0763
Berwick 30+31							*			-0.0095	-0.0198	-0.811	0.4141	1.94	-0.323	0.7477
warren 45									*	-0.0062	0.0975	-0.7848	0.4086	2	2.57	0.0125
Tynside N 45					*					-0.0022	0.3603	-0.6686	0.404	1.98	4.07	0.0001
Castle 30+31	*									-0.0109	0.3079	-0.7683	0.4039	2.12	0.633	0.5289
Gateshead 58b	*									-0.0081	-0.2238	-0.7707	0.4033	2.17	-0.44	0.6616
Gateshead 45									*	0.003	0.2441	-0.4459	0.4022	2.01	5.04	0
warren 45		*								-0.005	1.5025	-0.752	0.4013	1.84	1.98	0.0517

M DISTRICT 58b			*							-0.0061	0.0171	-0.7685	0.4012	2.01	0.325	0.7465
Castle 58a	*									-0.0006	0.4324	-0.7631	0.3992	2.06	0.935	0.3531
Durham North 48+37/2		*								-0.0052	-0.5657	-0.7533	0.3974	2.02	-1.25	0.2139
H DISTRICT 126		*								-0.0771	1.364	-0.7625	0.3967	2.01	1.14	0.2595
warren 48+37/2								*		-0.0048	0.5556	-0.7047	0.3918	1.94	3.57	0.0007
Blyth 45					*					-0.0123	0.1852	-0.7956	0.3874	1.85	1.8	0.0765
Sunderland 58b		*								-0.0044	-0.3786	-0.7539	0.3873	2.08	-0.701	0.4855
warren 30+31		*								-0.0042	1.2259	-0.7458	0.384	2.06	1.39	0.1701
warren 30+31	*									-0.0108	1.1977	-0.7638	0.383	2.04	1.31	0.1938
Blyth 45	*									-0.0144	-0.1863	-0.7474	0.3825	1.85	-0.272	0.7864
Blyth 48+37/2	*									-0.0058	0.9091	-0.6875	0.3822	2.19	1.42	0.1607
M DISTRICT 58b	*									-0.0052	-0.5724	-0.7247	0.3797	2.02	-0.752	0.4546
warren 45					*					-0.0067	0.1108	-0.7576	0.3785	1.95	1.13	0.2606
Castle 45		*								-0.0043	0.0079	-0.7793	0.3779	1.95	0.00868	0.9931
H DISTRICT 28+29				*						-0.007	0.3476	-0.5828	0.3758	2.12	4.39	0
Durham North 58a		*								0.0042	1.0779	-0.5828	0.3735	2.15	2.92	0.0047
warren 48+37/2	*									-0.0094	0.0339	-0.7159	0.3729	2.06	0.0428	0.966
Blyth 45								*		-0.014	0.0113	-0.7291	0.3709	1.85	0.0852	0.9323
Gateshead 58c	*									0.0036	0.81	-0.6925	0.3709	1.95	2.29	0.0252
warren 45	*									-0.0094	0.4083	-0.7668	0.3691	1.91	0.505	0.6155
Blyth 48+37/2									*	-0.006	0.0385	-0.7304	0.3681	2.11	0.93	0.3558
Tynside N 30+31							*			-0.0061	0.3101	-0.5912	0.3603	2.06	3.72	0.0004
Alnwick 58b		*								-0.0086	0.5648	-0.7331	0.3593	2.04	0.684	0.4963
Tynside N 58c		*								0.0022	0.9262	-0.728	0.3561	1.99	1.78	0.0794
Blyth 48+37/2		*								0.0009	1.461	-0.6618	0.3553	2.14	1.99	0.0508
H DISTRICT 48+37/2									*	-0.0119	0.2127	-0.4512	0.3551	1.98	4.95	0
S DISTRICT 58a		*								0.0073	0.3281	-0.6764	0.3549	1.95	0.721	0.4735
Durham North 58b	*									-0.0028	-0.5035	-0.6857	0.3541	2.08	-1.18	0.244
Durham North 58b		*								-0.003	0.0107	-0.6938	0.3533	2.05	0.0198	0.9842

Blyth 58b		*								-0.007	1.2403	-0.6791	0.3523	2.06	1.54	0.1282
Tynside N 58c	*									-0.0025	0.8667	-0.6446	0.35	1.97	1.72	0.09
Tyndale 30+31	*									-0.0072	-0.2176	-0.6596	0.348	2.01	-0.413	0.6812
Tynside N 30+31		*								-0.0038	0.8117	-0.5844	0.3452	2.04	1.58	0.1194
S DISTRICT 48+37/2								*		-0.0138	0.3519	-0.2117	0.343	2.19	4.02	0.0001
L DISTRICT 45					*					-0.0009	0.2496	-0.6668	0.3426	2.08	2.42	0.0182
L DISTRICT 30+31		*								-0.0082	-0.0495	-0.6293	0.3415	2.11	-0.101	0.9202
L DISTRICT 58a		*								0.0088	0.7722	-0.5809	0.3392	2.17	1.88	0.0649
M DISTRICT 58c			*							-0.002	0.0781	-0.6413	0.3383	2.12	1.65	0.1036
Durham South 30+31		*								-0.0003	1.0986	-0.6026	0.338	2.16	2.09	0.0404
Tynside N 45		*								-0.0054	-0.0894	-0.6537	0.3364	2.11	-0.142	0.8877
Durham North 30+31		*								-0.005	-0.4045	-0.6481	0.3363	2.1	-1.09	0.2802
Sunderland 58b	*									-0.001	-0.1796	-0.6432	0.3347	2.15	0.369	0.7134
L DISTRICT 58c		*								0.0142	1.071	-0.5675	0.3345	2.26	1.83	0.0723
Tynside N 28+29						*				-0.0065	0.468	-0.4883	0.3325	2.15	4.07	0.0001
Durham North 48+37/2								*		-0.0007	0.0674	-0.6481	0.3322	2.18	0.62	0.537
Tynside S 48+37/2									*	-0.0073	0.0969	-0.6425	0.3322	2.11	2.88	0.0054
Durham North 30+31							*			-0.003	0.1479	-0.5951	0.331	2.09	2.13	0.0365
Castle 45					*					0.0013	0.1566	-0.5834	0.3289	2.04	2.91	0.0049
S DISTRICT 58c		*								0.0158	1.0706	-0.5515	0.3286	2.15	1.98	0.0519
Blyth 28+29		*								-0.0058	-0.062	-0.6476	0.3271	2.09	-0.0657	0.9478
Blyth 48+37/2								*		-0.0041	0.1464	-0.6326	0.327	2.16	1.13	0.261
Tyndale 30+31							*			-0.0068	0.0665	-0.6228	0.3252	2.09	1.1	0.2771
Tynside N 28+29				*						-0.008	0.3399	-0.4565	0.3234	2.2	3.32	0.0014
H DISTRICT 58a			*							-0.0003	0.1072	-0.6102	0.323	2.11	2.7	0.0088
Gateshead 58a		*								0.0024	1.573	-0.5026	0.3191	2.18	3.7	0.0004
Durham North 30+31	*									-0.0035	-0.4466	-0.604	0.3168	2.12	-1.46	0.1501
S DISTRICT 58a			*							0.0035	0.1358	-0.6564	0.3142	1.99	2.24	0.0287
Blyth 58b	*									-0.0118	1.0377	-0.549	0.3117	2.19	1.4	0.1658

Durham North 28+29				*						-0.0041	0.073	-0.614	0.3117	2.08	0.522	0.6033
Durham North 48+37/2	*									-0.0032	-0.1599	-0.6232	0.3116	2.16	-0.403	0.688
Durham South 30+31	*									-0.006	0.745	-0.5249	0.3081	2.26	1.74	0.0866
Durham South 28+29	*									0.0008	0.9405	-0.54	0.307	2.11	2.35	0.0215
Durham North 28+29						*				-0.0041	-0.265	-0.5567	0.3067	2.06	-1.99	0.0505
Gateshead 45					*					0.0044	0.3175	-0.6086	0.3059	1.91	3.17	0.0023
warren 28+29	*									-0.01147	0.8245	-0.6352	0.305	2.12	0.939	0.351
Durham North 28+29	*									-0.0041	0.4163	-0.555	0.3038	2.08	0.998	0.3219
Castle 45									*	-0.0018	0.0892	-0.6279	0.3023	2.06	1.67	0.1002

The models contained within the following tables including Table 17 above, have all been filtered for diagnostic tests and passed the f distribution test, (see earlier sections for explanation). As we can see from Table 17 all the coefficients of β_2 are negative, as previously discussed. This offers some confirmation of the existence of a co-integrating relationship.

There are a total of 109 models out of 397 that have ECM regression estimates resulting in R^2 greater than 30 per cent and that pass the statistical diagnostic tests at least to the 5 per cent significance level.

At first glance a negative estimate for ε_t, as observed in a number of the models may seem surprising but it means that there is a stochastic element to the ECM equation suggesting that there is a drift in addition to the equilibrium. The value is generally low.

The values of R^2 are between 0.3023 and 0.6086 which means that less than 30 to 60 per cent of the variation of the respective crime sub-group categories can be explained by the models and the individual explanatory variables. That leaves between 70 and 40 per cent of the variation unaccounted for. This would indicate that a more complex model is required to provide a more suitable explanation of the variations in the respective crime sub-group categories. It is interesting to note at this stage that the top eight models as suggested by their respective R^2 areas are from the Northumbria police force area, all showing an above 50 per cent R^2 value for the respective models.

A lower R^2 reading may also be indicative of a large variation in the individual units of observation. This would suggest that R^2 alone may not be the most suitable measure of the extent to which a model is satisfactory. A better overall measure might be a statistic which describes the predictive power of the model in the face of new available data. This will be discussed in more detail in Chapter 6 which looks at conditional forecasting.

The 109 ECM regressions models all pass the statistical diagnostic tests. However only 51 of the models shown on Table 17, (highlighted in yellow on Table 17 and subsequent tables), indicate a t-probability value below 0.1 (10 per cent) associated to the β_1 regression coefficient. This indicates that the regression coefficient β_1 is statistically significant to the 10 per cent level. The test of the $\beta_1$coefficient was based upon the t distribution. Therefore we can say that less than 10 per cent of the t distribution lies outside an interval of $t_c$standard deviations from the estimated slope parameter. Rejection of the null hypothesis allows us to accept the two variable regression models. On examination of the t distribution values for the ECM constant regression coefficient it was found that the majority were only statistically significant up to the 90 per cent significant level and all were above the 50 per cent significance level. It was therefore decided that the constant term was statistically insignificant within the models and it will not be commented upon further.

As expected the vast majority, 82 of the 109 ECM regression models in Table 17, show a positive relationship between the sub-crime group and the explanatory variable. However it is also worthy of note that there are a 27 of ECM regressions models that do not show a positive relationship and indeed they suggest a negative relationship exists between the dependant variable and the explanatory variable. These negative relationship ECMs have been identified for the following crime sub-groups, see Table 18.

Table 18 - ECM regression estimates resulting in R^2 > 30%,

all crime sub-groups and areas, negative ECM coefficients and screened statistical tests at 1% and 5% significance.

csc_t	Claimant Count <30	Claimant Count >30	Detection	30+31	48+37/2	58a	58b	58c	126	ε_t	β_1	β_2	R_2	DW	t	t-prob
Alnwick 58c	*									-0.0066	-1.3416	-0.9164	0.5018	1.87	-3.18	0.0022
Alnwick 45					*					0.0026	-0.1305	-1.0034	0.5013	1.94	-1.63	0.674
Tyndale 48+37/2	*									-0.0101	-1.3192	-0.8278	0.4594	2.01	-1.76	0.0822
Tyndale 48+37/2		*								-0.0103	-0.2344	-0.8961	0.4559	2.01	-0.234	0.8157
Berwick 30+31	*									-0.0096	-0.9757	-0.8622	0.4522	1.88	-2.63	0.0105
L DISTRICT 58b		*								-0.0057	-0.637	-0.8688	0.4411	2.01	-0.966	0.3375
Castle 126		*								-0.0013	-0.8084	-0.8644	0.4359	1.95	-0.482	0.631
S DISTRICT 58b	*									-0.003	-0.2698	-0.8504	0.43	2.01	-0.426	0.6711
L DISTRICT 58b	*									-0.0027	-0.8454	-0.8371	0.4189	2.01	-1.19	0.2371
Castle 30+31							*			-0.0117	-0.1416	-0.8001	0.4188	2.12	-1.98	0.0521
Tyndale 30+31		*								-0.0136	-1.144	-0.7123	0.4147	2.01	-1.8	0.0763
Berwick 30+31							*			-0.0095	-0.0198	-0.811	0.4141	1.94	-0.323	0.7477
Gateshead 58b	*									-0.0081	-0.2238	-0.7707	0.4033	2.17	-0.44	0.6616
Durham North 48+37/2		*								-0.0052	-0.5657	-0.7533	0.3974	2.02	-1.25	0.2139

Sunderland 58b		*								-0.0044	-0.3786	-0.7539	0.3873	2.08	-0.701	0.4855
Blyth 45	*									-0.0144	-0.1863	-0.7474	0.3825	1.85	-0.272	0.7864
M DISTRICT 58b	*									-0.0052	-0.5724	-0.7247	0.3797	2.02	-0.752	0.4546
Durham North 58b	*									-0.0028	-0.5035	-0.6857	0.3541	2.08	-1.18	0.244
Tyndale 30+31	*									-0.0072	-0.2176	-0.6596	0.348	2.01	-0.413	0.6812
L DISTRICT 30+31		*								-0.0082	-0.0495	-0.6293	0.3415	2.11	-0.101	0.9202
Tynside N 45		*								-0.0054	-0.0894	-0.6537	0.3364	2.11	-0.142	0.8877
Durham North 30+31		*								-0.005	-0.4045	-0.6481	0.3363	2.1	-1.09	0.2802
Sunderland 58b	*									-0.001	-0.1796	-0.6432	0.3347	2.15	0.369	0.7134
Blyth 28+29		*								-0.0058	-0.062	-0.6476	0.3271	2.09	-0.0657	0.9478
Durham North 30+31	*									-0.0035	-0.4466	-0.604	0.3168	2.12	-1.46	0.1501
Durham North 48+37/2	*									-0.0032	-0.1599	-0.6232	0.3116	2.16	-0.403	0.688
Durham North 28+29						*				-0.0041	-0.265	-0.5567	0.3067	2.06	-1.99	0.0505

It is worthy of note that of the 27 negative relationship models in Table 18 only 6 of them have a statistically significant t distrubtion value for the B regression coefficient. If, on the other hand, we search the 397 ECM regressions based upon significant t distribution values at the 20 per cent significant level, assuming they also pass the statistical diagnostic tests we find that there are 9 models. At the 30 per cent t distribution significance level there are 14 models. Of these models, seven are associated with the crime sub-group category 'burglary other than a dwelling' and the closely related 'criminal damage to a building other than a dwelling' sub-group category. Of these models, five are associated to motor vehicle crime.

The above models are now going to be further broken down to police force area, claimant count category and crime sub-group type for more detailed discussion of results.

Table 19 - ECM regression estimates resulting in R^2 > 30%, all crime sub-groups and areas, claimant count <30 and screened statistical tests at 1% and 5% significance.

csc_t	Claimant Count <30	ε_t	β_1	β_2	R_2	DW	t	t-prob
Castle 58c	*	-0.0023	0.5415	-1.0686	0.5395	2.02	1.36	0.1774
Alnwick 45	*	0.0063	0.9124	-1.026	0.5117	1.91	1.63	0.1074
Alnwick 58c	*	-0.0066	-1.3416	-0.9164	0.5018	1.87	-3.18	0.0022
Tyndale 58c	*	0.0088	1.54	-0.9996	0.4935	1.95	2.38	0.02
Tyndale 48+37/2	*	-0.0101	-1.3192	-0.8278	0.4594	2.01	-1.76	0.0822
Berwick 30+31	*	-0.0096	-0.9757	-0.8622	0.4522	1.88	-2.63	0.0105
Castle 126	*	0.0039	0.8427	-0.8699	0.4424	1.99	0.894	0.3743
S DISTRICT 58b	*	-0.003	-0.2698	-0.8504	0.43	2.01	-0.426	0.6711
Alnwick 30+31	*	-0.0032	0.2326	-0.8583	0.4284	2	0.438	0.6626
L DISTRICT 58b	*	-0.0027	-0.8454	-0.8371	0.4189	2.01	-1.19	0.2371
Castle 30+31	*	-0.0109	0.3079	-0.7683	0.4039	2.12	0.633	0.5289
Gateshead 58b	*	-0.0081	-0.2238	-0.7707	0.4033	2.17	-0.44	0.6616
Castle 58a	*	-0.0006	0.4324	-0.7631	0.3992	2.06	0.935	0.3531

warren 30+31	*	-0.0108	1.1977	-0.7638	0.383	2.04	1.31	0.1938
Blyth 45	*	-0.0144	-0.1863	-0.7474	0.3825	1.85	-0.272	0.7864
Blyth 48+37/2	*	-0.0058	0.9091	-0.6875	0.3822	2.19	1.42	0.1607
M DISTRICT 58b	*	-0.0052	-0.5724	-0.7247	0.3797	2.02	-0.752	0.4546
warren 48+37/2	*	-0.0094	0.0339	-0.7159	0.3729	2.06	0.0428	0.966
Gateshead 58c	*	0.0036	0.81	-0.6925	0.3709	1.95	2.29	0.0252
warren 45	*	-0.0094	0.4083	-0.7668	0.3691	1.91	0.505	0.6155
Durham North 58b	*	-0.0028	-0.5035	-0.6857	0.3541	2.08	-1.18	0.244
Tynside N 58c	*	-0.0025	0.8667	-0.6446	0.35	1.97	1.72	0.09
Tyndale 30+31	*	-0.0072	-0.2176	-0.6596	0.348	2.01	-0.413	0.6812
Sunderland 58b	*	-0.001	-0.1796	-0.6432	0.3347	2.15	0.369	0.7134
Durham North 30+31	*	-0.0035	-0.4466	-0.604	0.3168	2.12	-1.46	0.1501
Blyth 58b	*	-0.0118	1.0377	-0.549	0.3117	2.19	1.4	0.1658
Durham North 48+37/2	*	-0.0032	-0.1599	-0.6232	0.3116	2.16	-0.403	0.688
Durham South 30+31	*	-0.006	0.745	-0.5249	0.3081	2.26	1.74	0.0866
Durham South 28+29	*	0.0008	0.9405	-0.54	0.307	2.11	2.35	0.0215
warren 28+29	*	-0.01147	0.8245	-0.6352	0.305	2.12	0.939	0.351
Durham North 28+29	*	-0.0041	0.4163	-0.555	0.3038	2.08	0.998	0.3219

There are 31 ECMs associated to Table 19. The R^2 value ranges between 54 and 30 per cent. The top ten areas are predominately made up from the Northumbria police force area and 5 of them are accounted for by the areas of Castle and Alnwick. Of these ECM regression models, 11 suggest a negative relationship exists. Again this is most noticeable within the crime sub-groups of burglary other than a dwelling and criminal damage to a building other than a dwelling.

Only nine of the models B1 regression coefficients have a statistical t distribution value at the 10 per cent or less significance level. It is worth noting that five of the nine models are from the highest rural indicator level, rural 80, see section 3.2.1. As Durham South is an aggregation of local authority areas, based upon section 3.2.1. I would estimate that the aggregated area of Durham South would fit into the rural 50 category. It also worth noting that their appears to be a difference in the crime sub-group category of criminal damage other than a dwelling based upon area type. This is shown by the two remaining models that fit both within the major urban category, see section 3.2.1. which indicate a positive relationship between claimant counts under 30 years of age and the crime sub-group of criminal damage other than a dwelling. In contrast the same crime sub-group in Alnwick and Tyndale, (both categorised as rural 80), show a significant negative relationship.

The Northumbria Police area accounts for eight of the top 10 ECM regression models, according to their respective R2 values. All except two are from areas categorised as rural 80 areas, see section 3.2.1. The other two areas, Stockton and the Redcar and Cleveland area are both categorised as large urban areas. Interestingly they both describe a negative relationship between claimant counts under 30 years of age and criminal damage to buildings other than a dwelling.

As we would expect there is also a model that suggests a significant positive relationship between dwelling burglaries and claimant counts under the age of 30.

The Durbin and Watson Statistic can be used to test for serial correlation. The DW statistic should lie in the range of 0 to 4. A low, (below 2), DW statistic indicates the presence of a positive serial correlation. A value near 2 indicates no first order serial correlation. A negative serial correlation is associated to a DW statistic above 2. This is an important statistical test as serial correlation or heteroscedasticity can lead to inefficient estimators. The DW figures give an indication that no serial correlation is present in the results tabulated. This adds comforting support to the results which have already been filtered for statistical diagnostic tests and which also look for serial correlation, as will be discussed later.

Table 20 - ECM regression estimates resulting in R^2 > 30%, all crime sub-groups and areas, claimant count >30 and screened statistical tests at 1% and 5% significant

csc_t	Claimant Count <30	Claimant Count >30	Detection	30+31	48+37/2	58a	58b	58c	126	ε_t	β_1	β_2	R_2	DW	t	t-prob
Castle 58c		*								0.0023	1.2665	-1.0755	0.5543	2.04	1.84	0.0705
Alnwick 45		*								0.011	1.3061	-1.0934	0.5493	1.99	1.51	0.136
Gateshead 58b		*								-0.0072	0.297	-1.029	0.5257	2.05	0.555	0.5809
Tyndale 58a		*								-0.0058	0.4049	-1.0039	0.5099	2.08	0.496	0.6217
Durham South 28+29		*								0.0069	1.5987	-0.8575	0.4987	1.95	3.69	0.0005
Castle 58a		*								0.0018	0.8884	-0.9017	0.4671	2	1.17	0.2468
Alnwick 58c		*								-0.0047	0.1338	-0.9379	0.4658	1.96	0.19	0.85
Alnwick 30+31		*								-0.0013	0.7798	-0.9193	0.4568	1.96	0.934	0.3537
Tyndale 48+37/2		*								-0.0103	-0.2344	-0.8961	0.4559	2.01	-0.234	0.8157
Castle 30+31		*								-0.0061	1.2487	-0.8851	0.444	2.04	1.49	0.1413
S DISTRICT 58b		*								0.0001	0.5173	-0.9124	0.4421	1.98	0.836	0.4059
L DISTRICT 58b		*								-0.0057	-0.637	-0.8688	0.4411	2.01	-0.966	0.3375
Castle 126		*								-0.0013	-0.8084	-0.8644	0.4359	1.95	-0.482	0.631
Durham South 48+37/2		*								0.0023	0.7511	-0.8312	0.431	2.1	1.22	0.2259
Gateshead 58c		*								0.0102	1.3608	-0.6987	0.4233	1.97	3.42	0.0011

Tyndale 30+31		*								-0.0136	-1.144	-0.7123	0.4147	2.01	-1.8	0.0763
warren 45		*								-0.005	1.5025	-0.752	0.4013	1.84	1.98	0.0517
Durham North 48+37/2		*								-0.0052	-0.5657	-0.7533	0.3974	2.02	-1.25	0.2139
H DISTRICT 126		*								-0.0771	1.364	-0.7625	0.3967	2.01	1.14	0.2595
Sunderland 58b		*								-0.0044	-0.3786	-0.7539	0.3873	2.08	-0.701	0.4855
warren 30+31		*								-0.0042	1.2259	-0.7458	0.384	2.06	1.39	0.1701
Castle 45		*								-0.0043	0.0079	-0.7793	0.3779	1.95	0.00868	0.9931
Durham North 58a		*								0.0042	1.0779	-0.5828	0.3735	2.15	2.92	0.0047
Alnwick 58b		*								-0.0086	0.5648	-0.7331	0.3593	2.04	0.684	0.4963
Tynside N 58c		*								0.0022	0.9262	-0.728	0.3561	1.99	1.78	0.0794
Blyth 48+37/2		*								0.0009	1.461	-0.6618	0.3553	2.14	1.99	0.0508
S DISTRICT 58a		*								0.0073	0.3281	-0.6764	0.3549	1.95	0.721	0.4735
Durham North 58b		*								-0.003	0.0107	-0.6938	0.3533	2.05	0.0198	0.9842
Blyth 58b		*								-0.007	1.2403	-0.6791	0.3523	2.06	1.54	0.1282
Tynside N 30+31		*								-0.0038	0.8117	-0.5844	0.3452	2.04	1.58	0.1194
L DISTRICT 30+31		*								-0.0082	-0.0495	-0.6293	0.3415	2.11	-0.101	0.9202
L DISTRICT 58a		*								0.0088	0.7722	-0.5809	0.3392	2.17	1.88	0.0649
Durham South 30+31		*								-0.0003	1.0986	-0.6026	0.338	2.16	2.09	0.0404
Tynside N 45		*								-0.0054	-0.0894	-0.6537	0.3364	2.11	-0.142	0.8877
Durham North 30+31		*								-0.005	-0.4045	-0.6481	0.3363	2.1	-1.09	0.2802
L DISTRICT 58c		*								0.0142	1.071	-0.5675	0.3345	2.26	1.83	0.0723
S DISTRICT 58c		*								0.0158	1.0706	-0.5515	0.3286	2.15	1.98	0.0519
Blyth 28+29		*								-0.0058	-0.062	-0.6476	0.3271	2.09	-0.0657	0.9478
Gateshead 58a		*								0.0024	1.573	-0.5026	0.3191	2.18	3.7	0.0004

Table 20 describes a total of 39 models. The R^2 value ranges between 56 and 32 per cent. Again there is a small stochastic element to the models suggesting that there is some drift in addition to the equilibrium.

With exception of 2 models the rest of the top 10 models are accounted for in the Northumbria Police force area, the R^2 value ranging from 56 to 44 per cent. It is also interesting to note that the areas of Alnwick and Castle also feature five times in the top ten. Again a number of negative relationships appear to exist and these are predominately within the crime sub-group categories of burglary, damage to buildings other than a dwelling and vehicle related crime.

However when we concentrate upon the regression parameter coefficient β_1 and look at instances when the coefficients are significant to the ten per cent level or less, (as highlighted in Table 20 in yellow) we see that there are 18 models that fit this condition. What is most noticeable is that 10 of the 18 models are from major to large urban areas and three others from the north and south Durham areas are less rural areas.

There are four models that show a positive relationship between motor vehicle damage and claimant counts over the age of 30. This positive relationship is also evident in a further three models which suggests a positive relationship between damage to dwelling burglaries and claimant counts over the age of 30. There are also three models that indicate as we would expect a positive relationship between dwelling burglaries and claimant counts over the age of 30.

The DW figures give an indication that no serial correlation is present in the results tabulated. This adds comforting support to the results which have already been filtered for statistical diagnostic tests and which also look for serial correlation as will be discussed later.

Table 21 - ECM regression estimates resulting in R^2 > 30%, all crime sub-groups, Cleveland Police area and screened statistical tests at 1% and 5% significance.

csc_t	Claimant Count <30	Claimant Count >30	Detection	30+31	48+37/2	58a	58b	58c	126	ε_t	β_1	β_2	R_2	DW	t	t-prob
S DISTRICT 58b		*								0.0001	0.5173	-0.9124	0.4421	1.98	0.836	0.4059
L DISTRICT 58b		*								-0.0057	-0.637	-0.8688	0.4411	2.01	-0.966	0.3375
L DISTRICT 58b			*							-0.0019	0.0836	-0.8185	0.4355	2.01	2	0.0494
S DISTRICT 58b	*									-0.003	-0.2698	-0.8504	0.43	2.01	-0.426	0.6711
L DISTRICT 58b	*									-0.0027	-0.8454	-0.8371	0.4189	2.01	-1.19	0.2371
M DISTRICT 58b			*							-0.0061	0.0171	-0.7685	0.4012	2.01	0.325	0.7465
H DISTRICT 126		*								-0.0771	1.364	-0.7625	0.3967	2.01	1.14	0.2595
M DISTRICT 58b	*									-0.0052	-0.5724	-0.7247	0.3797	2.02	-0.752	0.4546
H DISTRICT 28+29				*						-0.007	0.3476	-0.5828	0.3758	2.12	4.39	0
H DISTRICT 48+37/2									*	-0.0119	0.2127	-0.4512	0.3551	1.98	4.95	0
S DISTRICT 58a		*								0.0073	0.3281	-0.6764	0.3549	1.95	0.721	0.4735
S DISTRICT 48+37/2								*		-0.0138	0.3519	-0.2117	0.343	2.19	4.02	0.0001
L DISTRICT 45					*					-0.0009	0.2496	-0.6668	0.3426	2.08	2.42	0.0182
L DISTRICT 30+31		*								-0.0082	-0.0495	-0.6293	0.3415	2.11	-0.101	0.9202
L DISTRICT 58a		*								0.0088	0.7722	-0.5809	0.3392	2.17	1.88	0.0649
M DISTRICT 58c			*							-0.002	0.0781	-0.6413	0.3383	2.12	1.65	0.1036

L DISTRICT 58c		*								0.0142	1.071	-0.5675	0.3345	2.26	1.83	0.0723
S DISTRICT 58c		*								0.0158	1.0706	-0.5515	0.3286	2.15	1.98	0.0519
H DISTRICT 58a			*							-0.0003	0.1072	-0.6102	0.323	2.11	2.7	0.0088
S DISTRICT 58a			*							0.0035	0.1358	-0.6564	0.3142	1.99	2.24	0.0287

Table 21 displays a total of 20 models for the Cleveland police area. The R^2 range is from 44 to 31 per cent. Again there is a small stochastic element to the models suggesting that there is some drift in addition to the equilibrium.

The most noticeable element to the results is that 7 out of the top 10 models are from the crime sub-group category of 58b, (which is criminal damage to a building other than a dwelling) and include the top 6 which has a R^2 range of 44 to 40 per cent. It is also interesting to note that they are predominately from the L and S district areas. In addition it is also worthy of note that four of the 58b category models display a negative relationship and are predominately linked to the under 30 age claimant count explanatory variable. Interestingly the only other negative relationship that exists in the table is for L district burglaries other than a dwelling at a R^2 value of 34 per cent.

However, when we concentrate upon the regression parameter coefficient β_1 and look at instances when the coefficients are significant to the ten per cent level or less, (as highlighted in Table 21 in yellow), we see that there are 11 models that fit this condition. As we would expect there 5 models that show a significant positive relationship between detections and the respective crime-sub group.

There are three models that show a positive relationship between the other related motor vehicle crime sub-groups. As previously discussed there is a positive relationship evident in three models between damage to motor vehicles and dwelling burglaries and claimant counts over the age of 30.

The DW figures give an indication that no serial correlation is present in the results tabulated. This adds comforting support to the results which have already been filtered for statistical diagnostic tests and which also look for serial correlation, as will be discussed later.

Table 22 - ECM regression estimates resulting in R^2 > 30%, all crime sub-groups,

Durham Police area and screened statistical tests at 1% and 5% significance.

csc_t	Claimant Count <30	Claimant Count >30	Detection	30+31	48+37/2	58a	58b	58c	126	ε_t	β_1	β_2	R_2	DW	t	t-prob
Durham South 28+29		*								0.0069	1.5987	-0.8575	0.4987	1.95	3.69	0.0005
Durham South 48+37/2		*								0.0023	0.7511	-0.8312	0.431	2.1	1.22	0.2259
Durham North 48+37/2		*								-0.0052	-0.5657	-0.7533	0.3974	2.02	-1.25	0.2139
Durham North 58a		*								0.0042	1.0779	-0.5828	0.3735	2.15	2.92	0.0047
Durham North 58b	*									-0.0028	-0.5035	-0.6857	0.3541	2.08	-1.18	0.244
Durham North 58b		*								-0.003	0.0107	-0.6938	0.3533	2.05	0.0198	0.9842
Durham South 30+31		*								-0.0003	1.0986	-0.6026	0.338	2.16	2.09	0.0404
Durham North 30+31		*								-0.005	-0.4045	-0.6481	0.3363	2.1	-1.09	0.2802
Durham North 48+37/2								*		-0.0007	0.0674	-0.6481	0.3322	2.18	0.62	0.537
Durham North 30+31							*			-0.003	0.1479	-0.5951	0.331	2.09	2.13	0.0365
Durham North 30+31	*									-0.0035	-0.4466	-0.604	0.3168	2.12	-1.46	0.1501
Durham North 28+29				*						-0.0041	0.073	-0.614	0.3117	2.08	0.522	0.6033
Durham North 48+37/2	*									-0.0032	-0.1599	-0.6232	0.3116	2.16	-0.403	0.688
Durham South 30+31	*									-0.006	0.745	-0.5249	0.3081	2.26	1.74	0.0866

Table 22 displays a total of 17 ECM regression models for the Durham Police force area with a R^2 range of 50 and 30 per cent. Again there is a small stochastic element to the models suggesting that there is some drift in addition to the equilibrium.

There is a noticeable presence of the dwelling burglary crime sub-group making up 5 out of the 16 models. Again it is also worthy of note that there are five negative relationship areas in dwelling burglary, commercial burglary and in motor vehicle crime sub-groups.

Most interesting is that the dwelling burglary sub-crime category for the North Durham area which suggests a statistically significant negative relationship with that of criminal damage to a dwelling. The negative β_1 regression coefficient suggests that when there is a rise in criminal damage to a dwelling the number of dwelling burglaries drops. This model is the only one in the dwelling burglary category which shows this negative relationship to a statistically significant level. The only other two models that show this negative relationship are in the areas of South Durham and the Cleveland Police Stockton district, however they have much less statistical significance.

There are three ECM regression models that suggest a positive relationship between dwelling burglaries and claimant counts. There are however conflicting models in relation to the crime sub-category of motor vehicle theft and theft from motor vehicle and claimant counts over 30 years of age. The South of Durham shows a positive relationship and the north of Durham shows a negative relationship. A negative relationship is also evident in the north of Durham area for the same crime sub group category and the claimant count under 30 years of age variable. There is also a relatively statistically relevant negative relationship between the related criminal damage to a building other than a dwelling in the north of Durham and the under 30 years of age claimant count variable. The DW figures give an indication that no serial correlation is present in the results tabulated. This adds comforting support to the results which have already been filtered for statistical diagnostic tests and which also look for serial correlation, as will be discussed later.

Table 23 - ECM regression estimates resulting in R^2 > 30%, all crime sub-groups and Northumbria Police area and screened statistical tests at 1% and 5% significance.

csc_t	Claimant Count <30	Claimant Count >30	Detection	30+31	48+37/2	58a	58b	58c	126	ε_t	β_1	β_2	R_2	DW	t	t-prob
Tyndale 48+37/2									*	-0.0039	0.3707	-1.1519	0.6086	2.05	5.75	0
Castle 58c		*								0.0023	1.2665	-1.0755	0.5543	2.04	1.84	0.0705
Alnwick 45		*								0.011	1.3061	-1.0934	0.5493	1.99	1.51	0.136
Castle 58c	*									-0.0023	0.5415	-1.0686	0.5395	2.02	1.36	0.1774
Gateshead 58b		*								-0.0072	0.297	-1.029	0.5257	2.05	0.555	0.5809
Alnwick 45	*									0.0063	0.9124	-1.026	0.5117	1.91	1.63	0.1074
Tyndale 58a		*								-0.0058	0.4049	-1.0039	0.5099	2.08	0.496	0.6217
Alnwick 58c	*									-0.0066	-1.3416	-0.9164	0.5018	1.87	-3.18	0.0022
Alnwick 45					*					0.0026	-0.1305	-1.0034	0.5013	1.94	-1.63	0.674
Tyndale 58c	*									0.0088	1.54	-0.9996	0.4935	1.95	2.38	0.02
warren 28+29						*				-0.006	0.6036	-0.696	0.472	2.01	4.42	0
Castle 58a		*								0.0018	0.8884	-0.9017	0.4671	2	1.17	0.2468
Alnwick 58c		*								-0.0047	0.1338	-0.9379	0.4658	1.96	0.19	0.85
Tyndale 48+37/2	*									-0.0101	-1.3192	-0.8278	0.4594	2.01	-1.76	0.0822
Alnwick 30+31		*								-0.0013	0.7798	-0.9193	0.4568	1.96	0.934	0.3537
Tyndale 48+37/2		*								-0.0103	-0.2344	-0.8961	0.4559	2.01	-0.234	0.8157

warren 30+31							*			-0.0014	0.3985	-0.7504	0.453	1.95	4.07	0.0001
Berwick 30+31	*									-0.0096	-0.9757	-0.8622	0.4522	1.88	-2.63	0.0105
Blyth 45									*	-0.0129	0.1838	-0.8617	0.4484	1.94	4.36	0
Castle 30+31		*								-0.0061	1.2487	-0.8851	0.444	2.04	1.49	0.1413
Castle 126	*									0.0039	0.8427	-0.8699	0.4424	1.99	0.894	0.3743
Castle 126		*								-0.0013	-0.8084	-0.8644	0.4359	1.95	-0.482	0.631
Alnwick 30+31	*									-0.0032	0.2326	-0.8583	0.4284	2	0.438	0.6626
Gateshead 58c		*								0.0102	1.3608	-0.6987	0.4233	1.97	3.42	0.0011
warren 45								*		-0.0065	0.4901	-0.8068	0.4197	1.98	3.15	0.0024
Castle 30+31							*			-0.0117	-0.1416	-0.8001	0.4188	2.12	-1.98	0.0521
Tyndale 48+37/2								*		-0.0093	0.1898	-0.8144	0.4156	2.02	1.79	0.0782
Tyndale 30+31		*								-0.0136	-1.144	-0.7123	0.4147	2.01	-1.8	0.0763
Berwick 30+31							*			-0.0095	-0.0198	-0.811	0.4141	1.94	-0.323	0.7477
warren 45									*	-0.0062	0.0975	-0.7848	0.4086	2	2.57	0.0125
Tynside N 45					*					-0.0022	0.3603	-0.6686	0.404	1.98	4.07	0.0001
Castle 30+31	*									-0.0109	0.3079	-0.7683	0.4039	2.12	0.633	0.5289
Gateshead 58b	*									-0.0081	-0.2238	-0.7707	0.4033	2.17	-0.44	0.6616
Gateshead 45									*	0.003	0.2441	-0.4459	0.4022	2.01	5.04	0
warren 45		*								-0.005	1.5025	-0.752	0.4013	1.84	1.98	0.0517
Castle 58a	*									-0.0006	0.4324	-0.7631	0.3992	2.06	0.935	0.3531
warren 48+37/2								*		-0.0048	0.5556	-0.7047	0.3918	1.94	3.57	0.0007
Blyth 45					*					-0.0123	0.1852	-0.7956	0.3874	1.85	1.8	0.0765
Sunderland 58b		*								-0.0044	-0.3786	-0.7539	0.3873	2.08	-0.701	0.4855
warren 30+31		*								-0.0042	1.2259	-0.7458	0.384	2.06	1.39	0.1701
warren 30+31	*									-0.0108	1.1977	-0.7638	0.383	2.04	1.31	0.1938
Blyth 45	*									-0.0144	-0.1863	-0.7474	0.3825	1.85	-0.272	0.7864
Blyth 48+37/2	*									-0.0058	0.9091	-0.6875	0.3822	2.19	1.42	0.1607
warren 45					*					-0.0067	0.1108	-0.7576	0.3785	1.95	1.13	0.2606
Castle 45		*								-0.0043	0.0079	-0.7793	0.3779	1.95	0.00868	0.9931

warren 48+37/2	*									-0.0094	0.0339	-0.7159	0.3729	2.06	0.0428	0.966
Blyth 45								*		-0.014	0.0113	-0.7291	0.3709	1.85	0.0852	0.9323
Gateshead 58c	*									0.0036	0.81	-0.6925	0.3709	1.95	2.29	0.0252
warren 45	*									-0.0094	0.4083	-0.7668	0.3691	1.91	0.505	0.6155
Blyth 48+37/2									*	-0.006	0.0385	-0.7304	0.3681	2.11	0.93	0.3558
Tynside N 30+31							*			-0.0061	0.3101	-0.5912	0.3603	2.06	3.72	0.0004
Alnwick 58b		*								-0.0086	0.5648	-0.7331	0.3593	2.04	0.684	0.4963
Tynside N 58c		*								0.0022	0.9262	-0.728	0.3561	1.99	1.78	0.0794
Blyth 48+37/2		*								0.0009	1.461	-0.6618	0.3553	2.14	1.99	0.0508
Blyth 58b		*								-0.007	1.2403	-0.6791	0.3523	2.06	1.54	0.1282
Tynside N 58c	*									-0.0025	0.8667	-0.6446	0.35	1.97	1.72	0.09
Tyndale 30+31	*									-0.0072	-0.2176	-0.6596	0.348	2.01	-0.413	0.6812
Tynside N 30+31		*								-0.0038	0.8117	-0.5844	0.3452	2.04	1.58	0.1194
Tynside N 45		*								-0.0054	-0.0894	-0.6537	0.3364	2.11	-0.142	0.8877
Sunderland 58b	*									-0.001	-0.1796	-0.6432	0.3347	2.15	0.369	0.7134
Tynside N 28+29						*				-0.0065	0.468	-0.4883	0.3325	2.15	4.07	0.0001
Tynside S 48+37/2									*	-0.0073	0.0969	-0.6425	0.3322	2.11	2.88	0.0054
Castle 45					*					0.0013	0.1566	-0.5834	0.3289	2.04	2.91	0.0049
Blyth 28+29		*								-0.0058	-0.062	-0.6476	0.3271	2.09	-0.0657	0.9478
Blyth 48+37/2								*		-0.0041	0.1464	-0.6326	0.327	2.16	1.13	0.261
Tyndale 30+31							*			-0.0068	0.0665	-0.6228	0.3252	2.09	1.1	0.2771
Tynside N 28+29				*						-0.008	0.3399	-0.4565	0.3234	2.2	3.32	0.0014
Gateshead 58a		*								0.0024	1.573	-0.5026	0.3191	2.18	3.7	0.0004
Blyth 58b	*									-0.0118	1.0377	-0.549	0.3117	2.19	1.4	0.1658
Gateshead 45					*					0.0044	0.3175	-0.6086	0.3059	1.91	3.17	0.0023
warren 28+29	*									-0.01147	0.8245	-0.6352	0.305	2.12	0.939	0.351
Castle 45									*	-0.0018	0.0892	-0.6279	0.3023	2.06	1.67	0.1002

Table 23 displays a total of 72 models from the Northumbria area with a range of R^2 values between 61 and 30 per cent. 15 of the 69 models suggest a negative relationship. The negative relationships been identified in the following areas: -

58c (1), 45(2), 48+37/2(2), 30+31(5), 126(1), 58b(3) and 28+29(1)

It interesting to note again that there appears to be a significant number of negative relationships in the area of burglary other (30+31) and damage to buildings other than a dwelling (58b) crime sub-groups and also within certain vehicle crime sub-groups. In the Northumbria Police areas of Castle and Berwick the results suggest that when criminal damage to a building other than a dwelling increases the number of burglaries in a building other than a dwelling decreases. This type of negative relationship is also evident in Alnwick where theft of a motor vehicle is negatively related to the theft from a motor vehicle.

There are five ECM regression models that show significant relationships between the aggregated crime sub-group category of burglary other than a dwelling and that of its related crime sub-group category criminal damage to a building other than a dwelling. Four of the models suggest a positive relationship whilst the Castle area shows a negative relationship. This models suggests that when criminal damage to a building other than a dwelling increases there is a drop in burglaries to a building other than a dwelling. There is another model which suggests the same negative relationship however this model, from the area of Berwick, is much less statistically significant in relation to the regression coefficient β_1.

Of the 72 models, 31, have statistically significant regression coefficients, $\beta_1$in that the coefficients are significant to the ten per cent level or less, (as highlighted in Table 23 in yellow). Seven of these models are for the crime sub-group category of criminal damage to a motor vehicle, (58c) and all but one (Alnwick) show a significant positive relationship in existence between this crime sub-group and claimant counts. This suggests that when claimant counts rise then criminal damage to motor vehicles will also rise. There are a further 10 models that display this positive relationship in the Northumbria Police area although they much less statistical significance.

It is also noticeable that 28 of the top 30 Northumbria Police force area models, based upon the R^2figure, are from rural areas. The two exceptions are from the Gateshead area and are for the crime sub-group areas of criminal damage to a building other than a dwelling (58b) and criminal damage to a motor vehicle (58c) against claimant counts over 30 years of age. This finding is also reflected in the statistical significance of the regression coefficient where we can see that 21 out of 33 models are from the rural areas of Northumbria. The DW figures give an indication that no serial correlation is present in the results tabulated. This adds comforting support to the results which have already been filtered for statistical diagnostic tests and which also look for serial correlation, as will be discussed later.

Table 24 - ECM regression estimates resulting in R^2 > 30%, crime sub-group 28+29 and

All areas and screened statistical tests at 1% and 5% significance.

csc_t	Claimant Count <30	Claimant Count >30	Detection	30+31	48+37/2	58a	58b	58c	126	ε_t	β_1	β_2	R_2	DW	t	t-prob
Durham South 28+29		*								0.0069	1.5987	-0.8575	0.4987	1.95	3.69	0.0005
warren 28+29						*				-0.006	0.6036	-0.696	0.472	2.01	4.42	0
H DISTRICT 28+29				*						-0.007	0.3476	-0.5828	0.3758	2.12	4.39	0
Tynside N 28+29						*				-0.0065	0.468	-0.4883	0.3325	2.15	4.07	0.0001
Blyth 28+29		*								-0.0058	-0.062	-0.6476	0.3271	2.09	-0.0657	0.9478
Tynside N 28+29				*						-0.008	0.3399	-0.4565	0.3234	2.2	3.32	0.0014
Durham North 28+29				*						-0.0041	0.073	-0.614	0.3117	2.08	0.522	0.6033
Durham South 28+29	*									0.0008	0.9405	-0.54	0.307	2.11	2.35	0.0215
Durham North 28+29						*				-0.0041	-0.265	-0.5567	0.3067	2.06	-1.99	0.0505
warren 28+29	*									-0.01147	0.8245	-0.6352	0.305	2.12	0.939	0.351
Durham North 28+29	*									-0.0041	0.4163	-0.555	0.3038	2.08	0.998	0.3219

There are only 11 models for the crime sub-group 28+29 which display a R^2 figure between 30 and 50 per cent, see Table 24. It is worth noting that 5 of the 11 are from the Durham force area and that 3 of them suggest a positive relationship between dwelling burglaries and claimant counts under the age of 30. All but 2 of the models suggest a positive relationship between the explanatory variables and dwelling burglaries. As previously highlighted there appears to be a very interesting negative β_1 variable that suggests approximately 30 per cent of the variation of the dwelling houses burglaries in the north of Durham are accounted for by the variation of the damage to dwelling premises.

The most interesting point is that the results for the North of Durham suggest that the relationship is a negative one in that when damage to dwelling properties rises, the number of burglary dwellings decreases. This relationship is the only one of its kind with a R^2 value above 30 per cent. It is also worth pointing out that the regression parameter coefficient, t, indicates that it is statistically significant to approximately the 5 per cent level. This negative relationship is also noticeable when there is an increase in male claimant counts over 30 years of age then there would a suggested decrease in dwelling burglaries. Although it is clear that there is a very low statistical significance attached to the regression parameter in this case, (approximately 95 per cent in favour of null). It is also noticeable in three of the models that there is a positive relationship between dwelling burglaries and commercial burglaries, suggesting that when commercial burglaries rise then dwelling burglaries will rise too. The DW figures give an indication that no serial correlation is present in the results tabulated. This adds comforting support to the results which have already been filtered for statistical diagnostic tests and which also look for serial correlation, as will be discussed later.

Table 25 - ECM regression estimates resulting in R^2 > 30%, 30+31 crime sub-groups, all areas, and screened statistical tests at 1% and 5% significance.

csc_t	Claimant Count <30	Claimant Count >30	Detection	30+31	48+37/2	58a	58b	58c	126	ε_t	β_1	β_2	R_2	DW	t	t-prob
Alnwick 30+31		*								-0.0013	0.7798	-0.9193	0.4568	1.96	0.934	0.3537
warren 30+31							*			-0.0014	0.3985	-0.7504	0.453	1.95	4.07	0.0001
Berwick 30+31	*									-0.0096	-0.9757	-0.8622	0.4522	1.88	-2.63	0.0105
Castle 30+31		*								-0.0061	1.2487	-0.8851	0.444	2.04	1.49	0.1413
Alnwick 30+31	*									-0.0032	0.2326	-0.8583	0.4284	2	0.438	0.6626
Castle 30+31							*			-0.0117	-0.1416	-0.8001	0.4188	2.12	-1.98	0.0521
Tyndale 30+31		*								-0.0136	-1.144	-0.7123	0.4147	2.01	-1.8	0.0763
Berwick 30+31							*			-0.0095	-0.0198	-0.811	0.4141	1.94	-0.323	0.7477
Castle 30+31	*									-0.0109	0.3079	-0.7683	0.4039	2.12	0.633	0.5289
warren 30+31		*								-0.0042	1.2259	-0.7458	0.384	2.06	1.39	0.1701
warren 30+31	*									-0.0108	1.1977	-0.7638	0.383	2.04	1.31	0.1938
Tynside N 30+31							*			-0.0061	0.3101	-0.5912	0.3603	2.06	3.72	0.0004
Tyndale 30+31	*									-0.0072	-0.2176	-0.6596	0.348	2.01	-0.413	0.6812
Tynside N 30+31		*								-0.0038	0.8117	-0.5844	0.3452	2.04	1.58	0.1194
L DISTRICT 30+31		*								-0.0082	-0.0495	-0.6293	0.3415	2.11	-0.101	0.9202

Durham South 30+31		*								**-0.0003**	**1.0986**	**-0.6026**	**0.338**	**2.16**	**2.09**	**0.0404**
Durham North 30+31		*								-0.005	-0.4045	-0.6481	0.3363	2.1	**-1.09**	**0.2802**
Durham North 30+31							*			-0.003	0.1479	-0.5951	0.331	2.09	**2.13**	**0.0365**
Tyndale 30+31							*			**-0.0068**	**0.0665**	**-0.6228**	**0.3252**	**2.09**	**1.1**	**0.2771**
Durham North 30+31	*									-0.0035	-0.4466	-0.604	0.3168	2.12	**-1.46**	**0.1501**
Durham South 30+31	*									**-0.006**	**0.745**	**-0.5249**	**0.3081**	**2.26**	**1.74**	**0.0866**

There are 21 models in Table 25 with a R^2 value between 30 and 46 per cent. All but 8 of the 21 models display a positive relationship. All models display a small stochastic element, suggesting some drift in the model in addition to the equilibrium. Of the 8 models 6 are negative relationship models that are linked to claimant counts. The remaining 2 models suggest a negative relationship exists, (at a R^2 figure of around 41 per cent), between commercial burglaries and commercial criminal damage. This suggests that when commercial criminal damage goes up, the commercial burglaries go down. There are six areas that show a significant link, R^2 above 30 per cent, between commercial premises burglaries and commercial premises damage. Most interesting is that two of them show a negative correlation in that they suggest when commercial criminal damage goes up it results in a decline in commercial burglaries. Six out of the 15 models above for claimant counts also show R^2 above 30 per cent. Again most interestingly six out the 15 display a negative relationship between the variables; 3 from the less than 30 claimant count variable and 3 from the over 30 claimant count age group. It is also worth noting that the top 14 models (displaying the highest R^2 figures) are all from the Northumbria police force area. It also noticeable that the areas of Alnwick and Castle have 2 models each in the top 6 models.

The DW figures give an indication that no serial correlation is present in the results tabulated. This adds comforting support to the results which have already been filtered for statistical diagnostic tests and which also look for serial correlation, as will be discussed later.

Table 26 - ECM regression estimates resulting in R^2 > 30%, 45 crime sub-groups,

all areas, and screened statistical tests at 1% and 5% significance.

csc_t	Claimant Count <30	Claimant Count >30	Detection	30+31	48+37/2	58a	58b	58c	126	ε_t	β_1	β_2	R_2	DW	t	t-prob
Alnwick 45		*								0.011	1.3061	-1.0934	0.5493	1.99	1.51	0.136
Alnwick 45	*									0.0063	0.9124	-1.026	0.5117	1.91	1.63	0.1074
Alnwick 45					*					0.0026	-0.1305	-1.0034	0.5013	1.94	-1.63	0.674
Blyth 45									*	-0.0129	0.1838	-0.8617	0.4484	1.94	4.36	0
warren 45								*		-0.0065	0.4901	-0.8068	0.4197	1.98	3.15	0.0024
warren 45									*	-0.0062	0.0975	-0.7848	0.4086	2	2.57	0.0125
Tynside N 45					*					-0.0022	0.3603	-0.6686	0.404	1.98	4.07	0.0001
Gateshead 45									*	0.003	0.2441	-0.4459	0.4022	2.01	5.04	0
warren 45		*								-0.005	1.5025	-0.752	0.4013	1.84	1.98	0.0517
Blyth 45					*					-0.0123	0.1852	-0.7956	0.3874	1.85	1.8	0.0765
Blyth 45	*									-0.0144	-0.1863	-0.7474	0.3825	1.85	-0.272	0.7864
warren 45					*					-0.0067	0.1108	-0.7576	0.3785	1.95	1.13	0.2606
Castle 45		*								-0.0043	0.0079	-0.7793	0.3779	1.95	0.00868	0.9931
Blyth 45								*		-0.014	0.0113	-0.7291	0.3709	1.85	0.0852	0.9323
warren 45	*									-0.0094	0.4083	-0.7668	0.3691	1.91	0.505	0.6155
L DISTRICT 45					*					-0.0009	0.2496	-0.6668	0.3426	2.08	2.42	0.0182

Tynside N 45		*								-0.0054	-0.0894	-0.6537	0.3364	2.11	-0.142	0.8877
Castle 45					*					0.0013	0.1566	-0.5834	0.3289	2.04	2.91	0.0049
Gateshead 45					*					0.0044	0.3175	-0.6086	0.3059	1.91	3.17	0.0023
Castle 45									*	-0.0018	0.0892	-0.6279	0.3023	2.06	1.67	0.1002

There are 19 models in Table 26 showing a R^2 value of between 30 and 51 per cent. All but 3 of the cases suggest a positive relationship exists. The 3 models that show a negative relationship are from 3 separate areas. All but one of the models are from the Northumbria police force area, the only other area being in L district in the Cleveland Police force area. Worth mentioning that 6 of the areas show a positive relationship between the 45 crime sub-group categories and that of the related 48 + 37/2 aggregated crime sub-group.

The DW figures give an indication that no serial correlation is present in the results tabulated. This adds comforting support to the results which have already been filtered for statistical diagnostic tests and which also look for serial correlation, as will be discussed later.

Table 27 - ECM regression estimates resulting in R^2 > 30%, 48+37/2 crime sub-groups,

all areas, and screened statistical tests at 1% and 5% significance.

csc_t	Claimant Count <30	Claimant Count >30	Detection	30+31	48+37/2	58a	58b	58c	126	ε_t	β_1	β_2	R_2	DW	t	t-prob
Tyndale 48+37/2									*	-0.0039	0.3707	-1.1519	0.6086	2.05	5.75	0
Tyndale 48+37/2	*									-0.0101	-1.3192	-0.8278	0.4594	2.01	-1.76	0.0822
Tyndale 48+37/2		*								-0.0103	-0.2344	-0.8961	0.4559	2.01	-0.234	0.8157
Durham South 48+37/2		*								0.0023	0.7511	-0.8312	0.431	2.1	1.22	0.2259
Tyndale 48+37/2								*		-0.0093	0.1898	-0.8144	0.4156	2.02	1.79	0.0782
Durham North 48+37/2		*								-0.0052	-0.5657	-0.7533	0.3974	2.02	-1.25	0.2139
warren 48+37/2								*		-0.0048	0.5556	-0.7047	0.3918	1.94	3.57	0.0007
Blyth 48+37/2	*									-0.0058	0.9091	-0.6875	0.3822	2.19	1.42	0.1607
warren 48+37/2	*									-0.0094	0.0339	-0.7159	0.3729	2.06	0.0428	0.966
Blyth 48+37/2									*	-0.006	0.0385	-0.7304	0.3681	2.11	0.93	0.3558
Blyth 48+37/2		*								0.0009	1.461	-0.6618	0.3553	2.14	1.99	0.0508
H DISTRICT 48+37/2									*	-0.0119	0.2127	-0.4512	0.3551	1.98	4.95	0
S DISTRICT 48+37/2								*		-0.0138	0.3519	-0.2117	0.343	2.19	4.02	0.0001
Durham North 48+37/2								*		-0.0007	0.0674	-0.6481	0.3322	2.18	0.62	0.537
Tynside S 48+37/2									*	-0.0073	0.0969	-0.6425	0.3322	2.11	2.88	0.0054
Blyth 48+37/2								*		-0.0041	0.1464	-0.6326	0.327	2.16	1.13	0.261

Durham North 48+37/2	*								-0.0032	-0.1599	-0.6232	0.3116	2.16	-0.403	0.688

There are total of 15 models in Table 27 showing a R^2 value of between 61 and 31 per cent. All put 4 of the models suggest a positive relationship. The 4 models that display a negative relationship are all related to either the Durham North area or the Northumbria police force area of Tyndale. This higher band of R^2 figures for this crime sub-group category appear to be specific to particular areas, such as Tyndale (4 counts), Blyth (4 counts) and Durham North (3 counts). All areas but one show a small stochastic element to them suggesting that the ECM has a drift in addition to the equilibrium.

The DW figures give an indication that no serial correlation is present in the results tabulated. This adds comforting support to the results which have already been filtered for statistical diagnostic tests and which also look for serial correlation, as will be discussed later.

Table 28 - ECM regression estimates resulting in R^2 > 30%, 58a crime sub-groups,

all areas, and screened statistical tests at 1% and 5% significance.

csc_t	Claimant Count <30	Claimant Count >30	Detection	30+31	48+37/2	58a	58b	58c	126	ε_t	β_1	β_2	R_2	DW	t	t-prob
Tyndale 58a		*								-0.0058	0.4049	-1.0039	0.5099	2.08	0.496	0.6217
Castle 58a		*								0.0018	0.8884	-0.9017	0.4671	2	1.17	0.2468
Castle 58a	*									-0.0006	0.4324	-0.7631	0.3992	2.06	0.935	0.3531
Durham North 58a		*								0.0042	1.0779	-0.5828	0.3735	2.15	2.92	0.0047
S DISTRICT 58a		*								0.0073	0.3281	-0.6764	0.3549	1.95	0.721	0.4735
L DISTRICT 58a		*								0.0088	0.7722	-0.5809	0.3392	2.17	1.88	0.0649
H DISTRICT 58a			*							-0.0003	0.1072	-0.6102	0.323	2.11	2.7	0.0088
Gateshead 58a		*								0.0024	1.573	-0.5026	0.3191	2.18	3.7	0.0004
S DISTRICT 58a			*							0.0035	0.1358	-0.6564	0.3142	1.99	2.24	0.0287

There are only 9 models that have a R^2 value between 31 and 51 per cent, see Table 28. The most noticeable point is that they all display a positive relationship and that 6 of the 9 models are associated with the >30 age group claimant count variable. It is also worth noting that all 3 police force areas are in this group. The areas of Tyndale and Castle exhibit the highest R^2values.

The DW figures give an indication that no serial correlation is present in the results tabulated. This adds comforting support to the results which have already been filtered for statistical diagnostic tests and which also look for serial correlation, as will be discussed later.

Table 29 - ECM regression estimates resulting in R^2 > 30%, 58b crime sub-groups,

all areas, and screened statistical tests at 1% and 5% significance.

csc_t	Claimant Count <30	Claimant Count >30	Detection	30+31	48+37/2	58a	58b	58c	126	ε_t	β_1	β_2	R_2	DW	t	t-prob
Gateshead 58b		*								-0.0072	0.297	-1.029	0.5257	2.05	0.555	0.5809
S DISTRICT 58b		*								0.0001	0.5173	-0.9124	0.4421	1.98	0.836	0.4059
L DISTRICT 58b		*								-0.0057	-0.637	-0.8688	0.4411	2.01	-0.966	0.3375
L DISTRICT 58b			*							-0.0019	0.0836	-0.8185	0.4355	2.01	2	0.0494
S DISTRICT 58b	*									-0.003	-0.2698	-0.8504	0.43	2.01	-0.426	0.6711
L DISTRICT 58b	*									-0.0027	-0.8454	-0.8371	0.4189	2.01	-1.19	0.2371
Gateshead 58b	*									-0.0081	-0.2238	-0.7707	0.4033	2.17	-0.44	0.6616
M DISTRICT 58b			*							-0.0061	0.0171	-0.7685	0.4012	2.01	0.325	0.7465
Sunderland 58b		*								-0.0044	-0.3786	-0.7539	0.3873	2.08	-0.701	0.4855
M DISTRICT 58b	*									-0.0052	-0.5724	-0.7247	0.3797	2.02	-0.752	0.4546
Alnwick 58b		*								-0.0086	0.5648	-0.7331	0.3593	2.04	0.684	0.4963
Durham North 58b	*									-0.0028	-0.5035	-0.6857	0.3541	2.08	-1.18	0.244
Durham North 58b		*								-0.003	0.0107	-0.6938	0.3533	2.05	0.0198	0.9842
Blyth 58b		*								-0.007	1.2403	-0.6791	0.3523	2.06	1.54	0.1282

Sunderland 58b	*									**-0.001**	**-0.1796**	**-0.6432**	**0.3347**	**2.15**	**0.369**	**0.7134**
Blyth 58b	*									**-0.0118**	**1.0377**	**-0.549**	**0.3117**	**2.19**	**1.4**	**0.1658**

The most noticeable finding with this crime sub-group is the negative B coefficient sign. This indicates a negative relationship between the explanatory and dependant variable which appears to be significant in the eight of the models. It is important to note however that only one of the models indicates a regression coefficient that is statistically significant below the ten per cent significance level and this suggests, as we would suspect, a positive relationship between the detection rate and this crime sub-group category in the Cleveland police L district area. The negative relationships models show regression coefficients, t, of much less statistical significance indicating between 23 and 71 per cent significance level.

There are 14 models in Table 29 showing a R^2 value of between 31 and 53 per cent. All bar one of the <30 age group for claimant counts suggest a negative relationship against the commercial criminal damage crime sub-group. On examination of the other models that were filtered for this table we find a further model for 58b against <30 age claimant counts. It passed the statistical diagnostic tests but had a R^2 figure under the set 30 per cent significance value. It is interesting that a further seven models, despite failing a number of the statistical diagnostic tests displayed a negative relationship between 58b and <30 age claimant counts. If the latter are to be believed it would suggest that 14 out of the 17 areas displayed negative relationships in this area. In contrast it is worth noting that 5 of the 7 models associated to the >30 age claimant count variable appear to display a positive relationship. Again all but one model displays a small negative stochastic element to it suggesting that some drift is present in the model in addition to the equilibrium. The 14 models are across all 3 police force areas and Cleveland account for 7 of the top 10 models for this particular crime sub-group.

Table 30 - ECM regression estimates resulting in R^2 > 30%, 58c crime sub-groups,

all areas, and screened statistical tests at 1% and 5% significance.

csc_t	Claimant Count <30	Claimant Count >30	Detection	30+31	48+37/2	58a	58b	58c	126	ε_t	β_1	β_2	R_2	DW	t	t-prob
Castle 58c		*								0.0023	1.2665	-1.0755	0.5543	2.04	1.84	0.0705
Castle 58c	*									-0.0023	0.5415	-1.0686	0.5395	2.02	1.36	0.1774
Alnwick 58c	*									-0.0066	-1.3416	-0.9164	0.5018	1.87	-3.18	0.0022
Tyndale 58c	*									0.0088	1.54	-0.9996	0.4935	1.95	2.38	0.02
Alnwick 58c		*								-0.0047	0.1338	-0.9379	0.4658	1.96	0.19	0.85
Gateshead 58c		*								0.0102	1.3608	-0.6987	0.4233	1.97	3.42	0.0011
Gateshead 58c	*									0.0036	0.81	-0.6925	0.3709	1.95	2.29	0.0252
Tynside N 58c		*								0.0022	0.9262	-0.728	0.3561	1.99	1.78	0.0794
Tynside N 58c	*									-0.0025	0.8667	-0.6446	0.35	1.97	1.72	0.09
M DISTRICT 58c			*							-0.002	0.0781	-0.6413	0.3383	2.12	1.65	0.1036
L DISTRICT 58c		*								0.0142	1.071	-0.5675	0.3345	2.26	1.83	0.0723
S DISTRICT 58c		*								0.0158	1.0706	-0.5515	0.3286	2.15	1.98	0.0519

There are 11 models in Table 30 which display a R^2 figure between 33 and 55 per cent. All but one of the above crime sub-group categories display a positive relationship between the claimant counts and damage variable. It is worth noting at this point that there were a large number of these models rejected as a result of statistical diagnosis testing and showing a below 30 per cent R^2 value. Given the results in the previous tables it is also worth highlighting that the Northumbria Police force areas of Castle, Alnwick and Tyndale feature in the top 5 models with this particular crime sub-group category. There is a mixture of both positive and negative stochastic elements in the ECM, albeit small in value. This again suggests that there is some drift present in the model in addition to the equilibrium.

The DW figures give an indication that no serial correlation is present in the results tabulated. This adds comforting support to the results which have already been filtered for statistical diagnostic tests and which also look for serial correlation, as will be discussed later.

Table 31 - ECM regression estimates resulting in R^2 > 30%, 126 crime sub-groups,

all areas, and screened statistical tests at 1% and 5% significance.

csc_t	Claimant Count <30	Claimant Count >30	Detection	30+31	48+37/2	58a	58b	58c	126	ε_t	β_1	β_2	R_2	DW	t	t-prob
Castle 126	*									0.0039	0.8427	-0.8699	0.4424	1.99	0.894	0.3743
Castle 126		*								-0.0013	-0.8084	-0.8644	0.4359	1.95	-0.482	0.631
H DISTRICT 126		*								-0.0771	1.364	-0.7625	0.3967	2.01	1.14	0.2595

This crime sub-group category suffered in the early stages of analysis with some of the statistical procedures and tests. This is believed to be due to the low number of crimes given the areas concerned, resulting in a low variance of the data. Despite this, three models survived the tests and showed a R^2 figure of between 40 and 44 per cent, see Table 31. Once more the Northumbria Police force area of Castle accounts for the top 2 models. It is interesting to note that the Castle area model displaying a suggested negative relationship is associated with the explanatory variable >30 claimant count and the positive relationship model is associated to its counterpart <39 claimant count variable in the same area of Castle.

The DW figures give an indication that no serial correlation is present in the results tabulated. This adds comforting support to the results which have already been filtered for statistical diagnostic tests which also look for serial correlation, as will be discussed later.

4.4.5 ECM validation

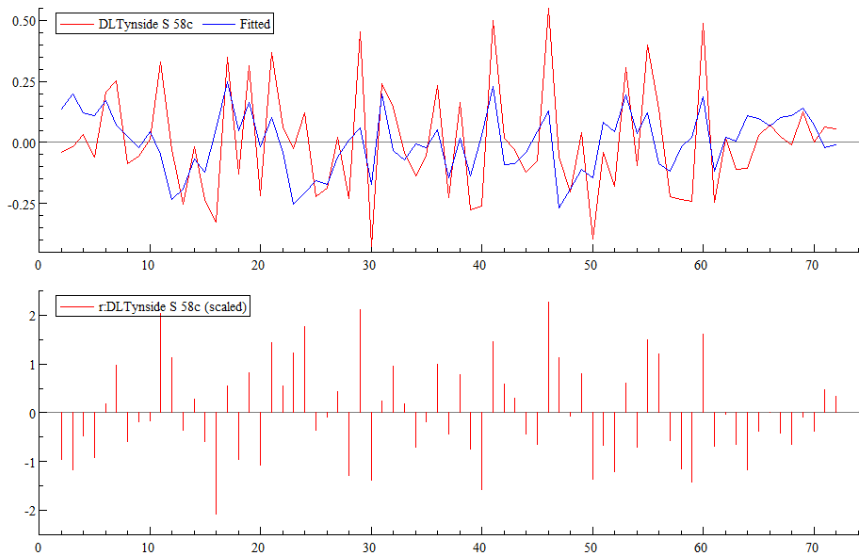
4.4.5.1 Confirmation of co-integration

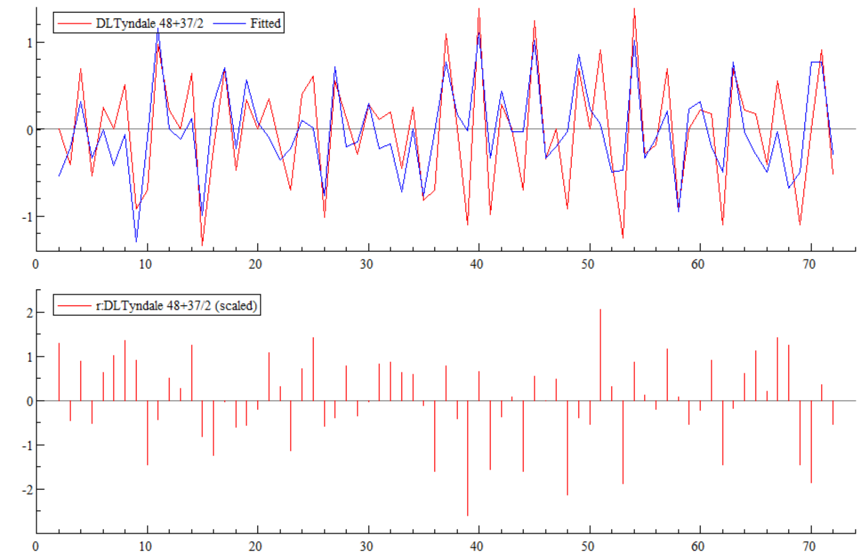
As the Engle and Granger approach to error correction modelling requires the existence of co-integration between variables, which suffers from the use of ADF testing, (potential misinterpretation and misspecification), in the first stages it would be useful to confirm the existence of co-integrating relationships. Failing to establish a statistical co-integrating relationship between the two variables would mean that we could not use an ECM and therefore we would have to revert back to the short run OLS model. This would mean that we would have to use the first difference of the time series to combat the stationarity of the same and therefore this would result in long term loss of information. The very process of ECM estimation will help us to confirm or disprove that a co-integrating relationship exists, in particular by examination of the resultant ECM regression coefficient, β_2 . The ECM regression coefficient should be between -1 and 0 and therefore should always be negative. This negative coefficient estimate is an indication in their role to correct for any deviation away from the long run equilibrium. As we can see from Appendix 9, all models show negative ECM coefficients between -1 and 0 and therefore support the findings of the earlier co-integration ADF test results. This is even despite a number of regressions failing their respective statistical diagnostic tests.

Despite the above finding we need to remind ourselves that 77 of the 397 models, based upon the co-integrating regression analysis of their residuals, did not suggest that a co-integrating relationship existed and they were added as a potential checking mechanism. There are a number of studies, Hale and Sabbagh (1991) and Beki, Zeelenberg and Montfort (1999) that did not find co-integrating relationships between certain data types. In particular Osborn (1995) was unable to find any long run relationships between crime sub-group categories and unemployment data. This research both supports this finding, based upon 77 models and disagrees with it, based upon 324 models.

Although the R^2 value does not tell us that the explanatory variable is the true cause in the changes of the dependent variable, or that the correct regression was used or indeed that the most appropriate variable was used, it does give us an initial validation of the models. As such we would expect that all the R^2 values for the models to be between the range of 0 and 1, therefore they should all be positive in value. As can be seen from appendix 9 all the R^2 figures for all 397 models, (even including ones that fail statistical diagnostic tests), are positive in value and are in the expected range of 0 to 1. A further model validation technique could be graphical residual analysis if there are any further doubts. See Figure 23 showing two residual graphs that suggest stationary residuals following co-integration regression analysis for the variables Tynside 58C and Tyndale 45.

Figure 23 – ECM regression residual plots





ECM Statistical Diagnostic tests

Approximately half of the models failed some of the statistical validation tests. These statistical tests are based upon the fundamental assumptions required for linear regression. Only 210 out of the 397 models passed all 6 statistical tests. The below table summarizes the number of models that failed each of the statistical tests. Some of the models failed a number of the tests.

Table 32 – Summary of error correction modelling statistical test fails

Statistical Test	Number of models failing test
AR1-2	106
ARCH 1-1	14
NORMALITY	69
HETERO	20
HETERO X	20
RESET	31

Normality Test

We can see from Table 32 that 69 models are rejected for the normality test. From appendix 7 we can see that on several the null hypothesis of normal disturbances is rejected strongly, (two asterisks show that this conclusion can be rejected even at the one per cent significance level). A number of models, 47, are rejected on the five per cent confidence limit and 22 on the one per cent confidence limit. This could be an indication of a number of important factors in the modelling process. If the residuals are not normally distributed, then the dependent variable or at least one explanatory variable may have the wrong functional form, or important variables may be missing. This would give support to the requirement of a motivational and deterrence variable in the model.

Heteroscedasticity using squares and cross-products

White (1980) suggested this test, (called the hetero-x test in the PcGive 12.1 software). This is a general test for heteroscedastic errors; H_0 is that the errors are homoscedastic or, if heteroscedasticity is present, it is unrelated to the *x*s. Unfortunately, Monte Carlo simulations of its behaviour suggest it should not form part of the test battery in model selection, even in relatively large samples. Godfrey and Orme (1994) also show that this test does not have power against omitted variables. As a result this statistical diagnostic result was ignored.

The assumption of a constant variance for the disturbance term (homoskedasticity) must also be rejected in favour of the alternative of heteroskedasticity. There may be reason to believe that the error terms associated to bigger policing areas will potentially have greater variance than those associated in smaller policing areas.

When we remove the filters associated to the above statistical diagnostic tests we find that the following models, (see Table 33) are also included in the results, based upon filtering for R^2 value above the 30 per cent significance level. Although several models fail other statistical tests and are below the R^2 value of 30 per cent.

Table 33 - ECM regression estimates resulting in R^2 > 30%, diagnostic filters removed

csc_t	Claimant Count <30	Claimant Count >30	Detection	30+31	48+37/2	58a	58b	58c	126	ε_t	β_1	β_2	R_2	DW	AR 1-2	Arch 1-1	Normality	Hetero	Hetero-x	RESET
Alnwick 45		*								0.011	1.3061	-1.0934	0.5493	1.99				*	**	
Berwick 58c		*								-0.0057	0.3193	-0.7496	0.3801	2.01			*	*	*	
H DISTRICT 48+37/2									*	-0.0119	0.2127	-0.4512	0.3551	1.98				*		
H DISTRICT 58c	*									0.0065	2.4	-0.7589	0.4351	2.08			**	*	*	
L DISTRICT 45								*		-0.0021	-0.1661	-0.5587	0.295	2.09				*		
L DISTRICT 48+37/2		*								-0.0061	1.194	-0.4385	0.224	2.03				**	*	*
L DISTRICT 48+37/2								*		-0.0145	0.0976	-0.3765	0.2054	2.17	*			*		
M DISTRICT 28+29		*								-0.011	0.5331	-0.3908	0.1726	2.04				*	*	
M DISTRICT 45					*					-0.0148	0.1647	-0.3538	0.2076	2.01			*	**	**	
M DISTRICT 45									*	-0.0127	0.2583	-0.2805	0.2373	2.11				**	**	
S DISTRICT 30+31							*			-0.009	0.3414	-0.2431	0.2494	2.44	**			*	**	
S DISTRICT 48+37/2	*									-0.0088	0.2148	-0.261	0.133	2.25				*	**	
Durham North 58b	*									-0.0028	-0.5035	-0.6857	0.3541	2.08				**	**	
Tyndale 28+29	*									-0.0005	-0.2975	-0.444	0.197	2.5	**			*		**
Tyndale 45	*									0.0024	-0.3658	-0.8467	0.448	2.04			**	*	**	
Tyndale 45									*	0.0029	0.2313	-0.846	0.4241	2.04			**	*		

Alnwick 58b	*									-0.0113	-0.2409	-0.7333	0.343	2.04		*		**	**	
Tynside N 126	*									-0.054	-0.1646	0.049	0.0053	2.79	**	*		*		
Tynside N 58c		*								0.0022	0.9262	-0.728	0.3561	1.99				*		
Tynside S 126	*									-0.0397	-0.1076	-0.3029	0.1358	2.49	**	**	**	*	*	

Test for linearity, using Ramsey's RESET test

The null hypothesis is that there is a linear relationship between the dependent variable and the explanatory variable. This was an assumption made at the start of the research. If the assumption of linearity is rejected, as is the case in a number of the 397 models estimated, then it could be due to nonlinearity or be the consequence of a missing explanatory variable. The RESET test is considered as a general test for model misspecification.

Auto-Regressive Conditional Autocorrelation Heteroscedasticity, (ARCH)

ARCH is a test for autocorrelelation in the residual process. The null hypothesis is no ARCH process. A significant ARCH test result signals a misspecified model. This may be another indication of a missing explanatory variable in the model.

Testing the regression equation

One way of testing the existence of a linear relationship is to make use of the f distribution statistic. We would expect a strong statistical relationship between two variables to result in a large ratio of explained to unexplained variance. The f statisitic can be used for measuring this.

The value of the f distribution statistic will be zero only when the explained variance in the regression is zero. Therefore we can associate a low value with a weak (linear) relationship and a high value with a strong (linear) relationship. The f (1,N-2) and therefore for our models will be denoted by f (2,68).

The f distribution statistic from the models should therefore be higher than the figure of approximately 4.9 based upon f statistics from the tables in Biometrika, vol. 33, p.73, 1943, where f (2,60) has a value of 4.98 and f (2,120) has a value of 4.79 at the f distribution at 1 per cent significance. Alternatively at the 5 per cent significance level when f (2,60) has a value of 3.15 and f (2,120) has a value of 3.07. PcGive 12.1 actually highlights the relevant f statistics significance levels on the results ECM regression results.

Table 34 – Error correction models that are significant at the 1 per cent significant level for the f distribution test.

Dependant variable	Explanatory variable	f Distribution value
Tyndale 45	48+37/2	2.068
Tynside 58a	<30CC	2.56
Tynside 58b	<30CC	3.057
Warren 48+37/2	126	0.7117
LDistrict28+29	<30	0.3748
LDistrict28+29	>30	0.3824
LDistrict28+29	DLdet28/29	1.655
SDistrict28+29	<30	2.687
SDistrict28+29	DSdet28/29	3.097
MDistrict48+37/2	<30	2.417
LDistrict28+29	58a	1.188
SDistrict28+29	58a	1.92
Gateshead28+29	<30	3.733
Sunderland28+29	<30	2.121
Sunderland48+37/2	>30	2.857
Sunderland58c	>30	0.9915
Tynside126	30>	0.4785
Tynside126	<30	0.1833

A total of 18 out of 397 models fail the f distribution test, see Table 34 above. It is worth noting that of the 77 models that failed to display a co-integrating relationship during the co-integrating regression tests 14 of them have been picked up by this test, (see those highlighted as yellow in Table 30). Although the crime sub-group category (which is highlighted in red) fails the f distribution test here, it passed the ADF testing during the co-integrating regression analysis stage. Although only to the five per cent significance level and not the one per cent. Therefore those models that passed at the five per cent level could be treated with extra caution. A further 21 only pass the f distribution test at the 5 per cent significance level, (see Table 35 below for details) and f distribution test figures. As we can see there are a further 11 models (in yellow) that were rejected at the co-integrating regression stage and have been highlighted by the f distribution test results.

There are also three models that are highlighted here (in red) that again only passed the co-integrating regression stage at the five per cent significance level. We can therefore reject the null hypothesis of no relationship between the dependent and explanatory variable at the 1 per cent significance for 379 of the 397 models. We can also reject the null hypothesis of no relationship for a further 21 of the 397 models at the 5 per cent significance level by looking up the appropriate critical value of the f distribution. If the value calculated from the regression is larger than the critical value we reject the null hypothesis that there is 'no relationship' at the 5 per cent level. It is interesting to note at this stage that there are four models that fail the f distribution tests for dwelling burglaries against the claimant count under 30 year of age variable, based upon the areas of Gateshead, Sunderland, Stockton and Langbaurgh. All with the exception of the Gatehead variable, (passed co-integrating regression test at five per cent significance level), did not pass the co-integrating regression tests. There is also an additional four models that fail the f distribution test at the 1 and 5 per cent significance level for dwelling burglaries against dwelling damage, hinting at the possibility of no significant relationship between the variables. However two of these models are models that did not pass the co-integrating regression tests. The remaining two models have been identified as being from major urban areas.

Table 35 – Error correction models that are significant at the 5 per cent significant level for the f distribution test.

Dependant variable	Explanatory variable	f Distribution value
Tydale28+29		4.089
SDistrict30+31	Det30+31	4.455
HDistrict45	<30	4.739
MDistrict45	<30	3.609
MDistrict45	>30	3.632
SDistrict45	<30	4.604
SDistrict45	Det45	4.709
MDistrict48+37/2	<30	2.417
MDistrict48+37/2	Det48+37/2	3.758
MDistrict126	>30	3.981
HDistrict28+29	58a	3.472
HDistrict45	58c	3.408
HDistrict58c	>30	3.436
Gateshead28+29	58a	3.733
Gateshead48+37/2	<30	4.794
Gateshead48+37/2	58c	4.034
Newcastle45	<30	4.722
Newcastle45	48+37/2	3.876

Newcastle45	126	3.638
Newcastle45	<30	3.948
Sunderland28+29	>30	4.068
Sunderland28+29	58a	4.602

5 Forecasting

Forecasting of data models is a complex area of statistics. This chapter will essentially look at a period of time which is advanced beyond our modelling sample period but is also in the past. Therefore we will conduct an ex-post forecast. This has a forecast period such that all values of the dependant and explanatory variable are known. This allows for ex-post forecasts to be checked against actual data and provide a direct means of evaluation. Use of standard error of forecast (SEF) can then be used as a measure of the successfulness of the model.

I have selected seven models from the ECM results section. All models are from the Durham and Cleveland Police force areas due to the ease of access to crime data. All seven models are based upon crime sub-group and claimant count relationships and show a relatively significant respective $R^2\ and\ t$ value. The seven models, along with the ECM regression coefficients are detailed in Table 36. The seven models can be algebraically written as follows (based upon the regression coefficients of the sampling period):-

$$\Delta(Durham\ South\ 28+29)_t\ =\ 0.0069\ +\ 1.5987\Delta CC(>30)_t -\ 0.8575ECM$$

$$\Delta(Durham\ North\ 58a)_t\ =\ 0.0042\ +\ 1.0779\Delta CC(>30)_t -\ 0.5828ECM$$

$$\Delta(Durham\ South\ 28+29)_t\ =\ 0.0008\ +\ 0.9405\Delta CC(<30)_t -\ 0.5.4ECM$$

$$\Delta(Durham\,South\;30+31)_t \;=\; -0.0003 \;+\; 1.0986\Delta CC_t -\; 0.6026ECM$$

$$\Delta(S\,District\;58c)_t \;=\; 0.0158 \;+\; 1.0706\Delta CC(>30)_t -\; 0.5515ECM$$

$$\Delta(L\,District\;58a)_t \;=\; 0.0088 \;+\; 0.7722\Delta CC(>30)_t -\; 0.5809ECM$$

$$\Delta(L\,District\;58c)_t \;=\; 0.0142 \;+\; 1.071\Delta CC(>30)_t -\; 0.5675ECM$$

Where the $ECM = ((Durham\,South\;28+29) - \;\beta CC(>30))_{t-1}$

I have obtained the relevant claimant count data and crime sub-group data for an additional 16 month period, (April 2008 to July 2009), beyond our initial modelling period, (April 2002 to March 2008 inclusive) for the specified model areas. I can therefore predict the crime levels based upon the known claimant count data for the above period and using the error correction models compare them to the actual crime levels recorded by the police. It is worthy of note that the above additional period is very significant and it includes a significant turning point in the economy, namely the start of the 2008 recession which is reported as starting in September 2008. This could have an impact upon the modelling process and should be borne in mind prior to the results being considered.

If this is to prove useful then this could lead onto the conditional forecasting techniques which would include a procedure for predicting the explanatory variable claimant counts into the future. This is an area that could also benefit from further research, particularly in the field of time lagged variables. This could result in the use of lagged variables in the modelling process therefore reducing the need to predict the variable far into the future.

Table 36 – Models used for ex-post forecast

csc_t	Claimant Count <30	Claimant Count >30	Detection	30+31	48+37/2	58a	58b	58c	126	ε_t	β_1	β_2	R_2	DW	t	t-prob
Durham South 28+29		*								0.0069	1.5987	-0.8575	0.4987	1.95	3.69	0.0005
Durham North 58a		*								0.0042	1.0779	-0.5828	0.3735	2.15	2.92	0.0047
Durham South 28+29	*									0.0008	0.9405	-0.54	0.307	2.11	2.35	0.0215
Durham South 30+31		*								-0.0003	1.0986	-0.6026	0.338	2.16	2.09	0.0404
S DISTRICT 58c		*								0.0158	1.0706	-0.5515	0.3286	2.15	1.98	0.0519
L DISTRICT 58a		*								0.0088	0.7722	-0.5809	0.3392	2.17	1.88	0.0649
L DISTRICT 58c		*								0.0142	1.071	-0.5675	0.3345	2.26	1.83	0.0723

I have for the purpose of the ex-post forecasting period assumed that the data series are I(1), (stationary at the 1st difference) and co-integrated as previously established with the original sampling period. Therefore the respective claimant count data will be log transformed and then the first difference taken. Figures 24 and 25 shows the crime counts, (monthly reported crimes by crime sub-group and area) for the additional 16 month period (Apr 2008 to Jul 2009) and the claimant counts for the same area and period respectively.

Figure 24 – Monthly Claimant Counts April 2008 to July 2009

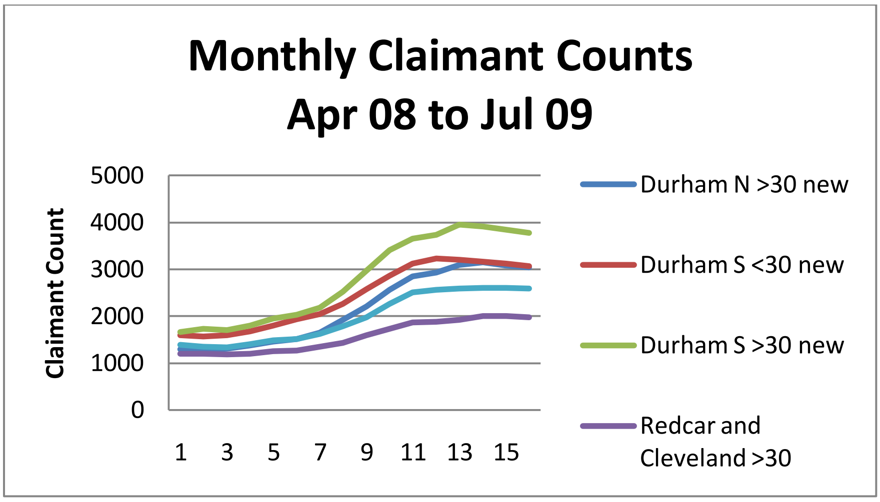
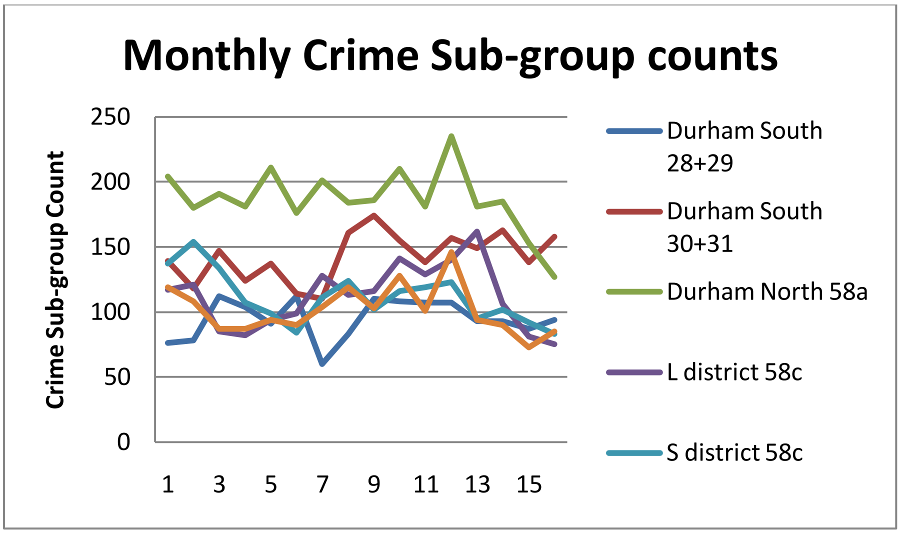


Figure 25 – Monthly Crime Sub-group Counts

April 2008 to July 2009



The use of additional known data can help to improve the model when allowing the model parameter estimates (coefficients) to be updated. However a significant change in the model coefficients may suggest that the model could be improved.

Therefore I have recalculated the ECM models with the addition of the new sampling period. For the purpose of this we will assume that the data remains I(1) in nature and continues to be co-integrated. Table 37 summaries the updated ECM model coefficients and key statistics. When we compare the original ECM results in Table 36 with that of the ECM results in Table 37, which include the additional data period, we can see that there are a number of significant changes. It is obvious that the R2 and t-prob figures are not as significant on the ex-post forecast results. The DW figure has moved towards the suggestion that there is positive serial correlation. The model coefficients have changed significantly and in particular the worrying change in the sign of the two coefficients and thus signifying the change in relationship direction between the variables.

The auto regressive test at the first difference (AR1) for many of these models suggests that serial correlation is present in the data, this giving support to the increased DW figures found. This could be explained by the sudden structural change in the claimant count data as a result of the impact of the recession change in September 2008. Due to the serial correlation we would also expect that the ECM regression coefficients would change to attempt to compensate for this problem. We can see from the results that this is the case with the ECM regression coefficients. As a result the R2, DW and t-prob figures also weaken, (see Tables 36 and 37). The changes in the coefficients may suggest that the model could be improved and could also highlight that careful consideration needs to be given when there are clear structural breaks in the explanatory variables being considered.

Table 37 – Models used for ex-post forecast (updated ECM)

csc_t	Claimant Count <30	Claimant Count >30	Detection	30+31	48+37/2	58a	58b	58c	126	ε_t	β_1	β_2	R_2	DW	t	t-prob
Durham South 28+29		*								-0.0020	0.4594	-0.4903	0.267	2.15	1.13	0.2628
Durham North 58a		*								-0.00455	0.6005	-0.4509	0.257	2.17	1.61	0.1119
Durham South 28+29	*									-0.0056	0.4342	-0.5066	0.2699	2.23	1.57	0.1199
Durham South 30+31		*								-0.0005	0.2049	-0.4489	0.2422	2.4	0.5	0.6181
S DISTRICT 58c		*								0.3404	-0.04603	-0.481	0.2643	2.29	-0.411	0.6820
L DISTRICT 58a		*								0.2786	-0.039	-0.3766	0.1909	2.37	-0.344	0.7313
L DISTRICT 58c		*								0.2954	-0.0409	-0.482	0.2555	2.22	-0.282	0.7788

As a result of the shortfalls encountered in allowing the ECM regression parameters to update themselves I decided to use another method for forecasting. The new method still requires the use of post-model data. However it is based upon the use of the same coefficients as in the original ECM but involves replacement of the EC variables values for the additional forecast period with the original ECM estimation sample means. Thus the new model does not exhibit equilibrium-correcting behaviour in the forecasting period, but in all other respects it matches the EC model.

All seven models were completed and are represented graphically in Figures 26 to 32 inclusive. For the purpose of this procedure I also assumed that the data remains I(1) in nature and continues to be co-integrated. The ECM regression coefficients are not tabulated here as they by the nature of this procedure are the same as in Table 36.

Figure 26 – Durham South (28+29) crime sub-group against Claimant Counts over 30 ECM model predictions for April 2002 to March 2008. Also 1 step-forecast from April 2008 to July 2009.

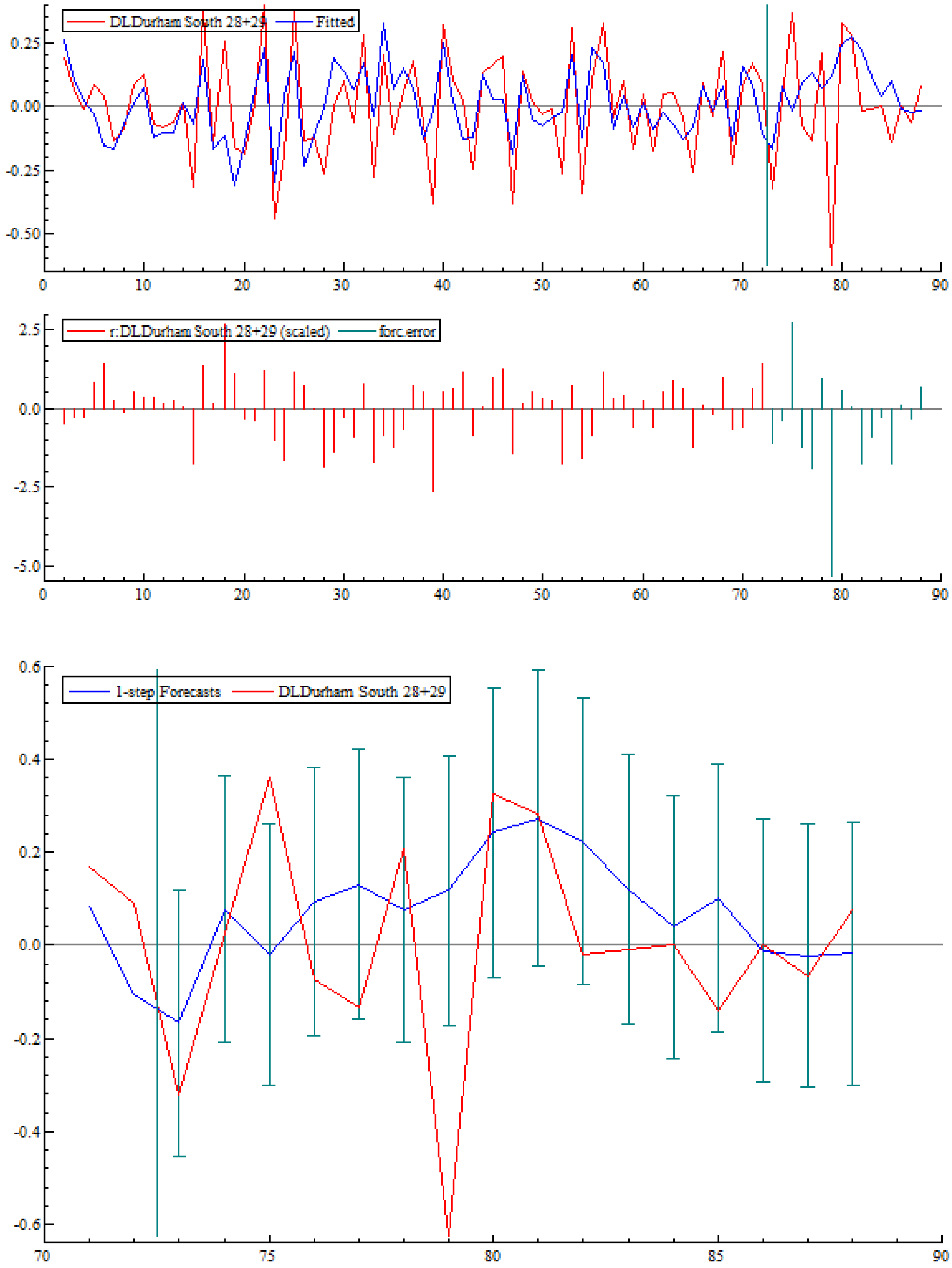


Figure 27 – Durham South (28+29) crime sub-group against Claimant Counts under 30 ECM model predictions for April 2002 to March 2008. Also 1 step-forecast from April 2008 to July 2009.

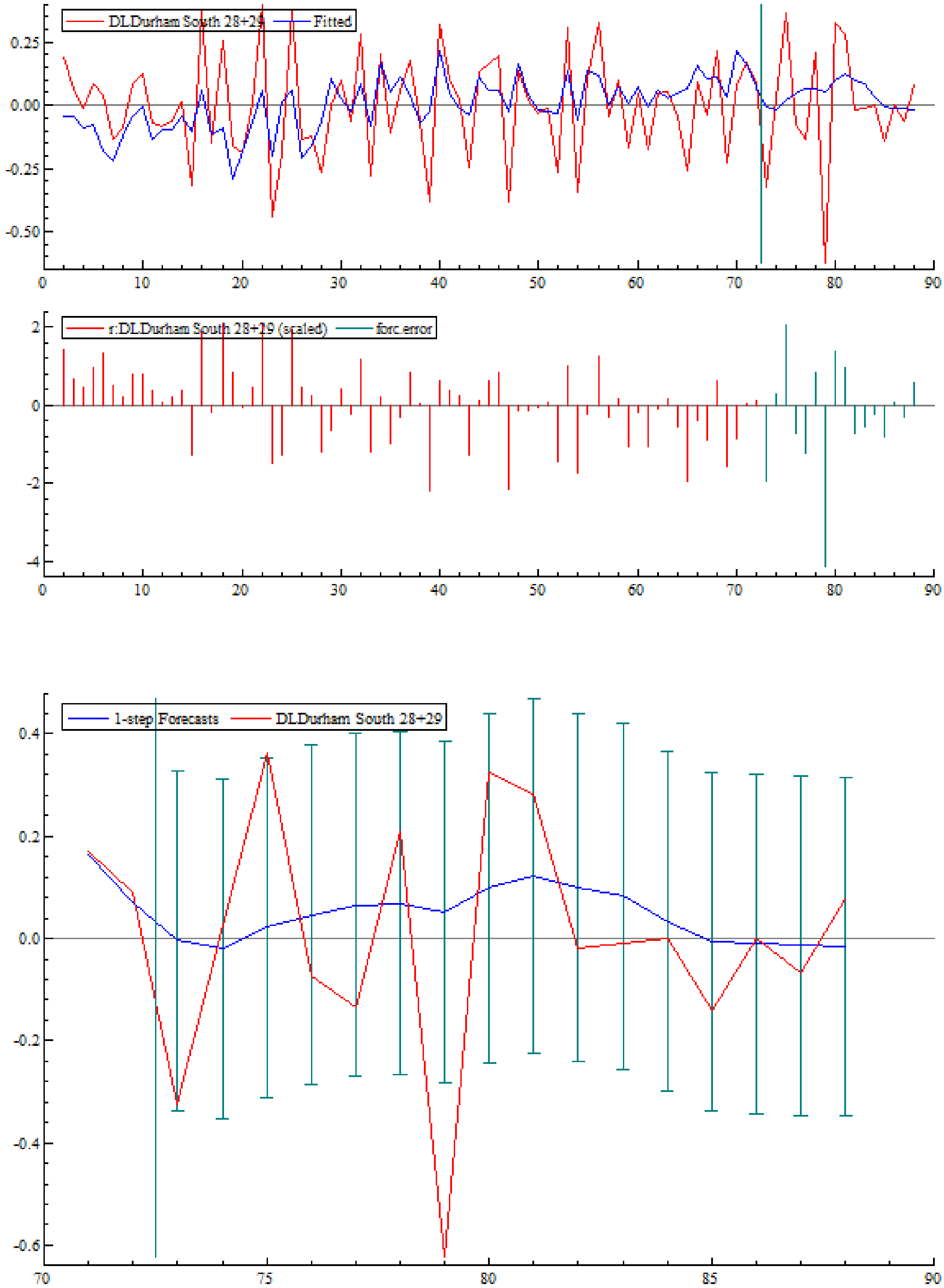


Figure 28 – Durham South (30+31) crime sub-group against Claimant Counts over 30 ECM model predictions for April 2002 to March 2008. Also 1 step-forecast from April 2008 to July 2009

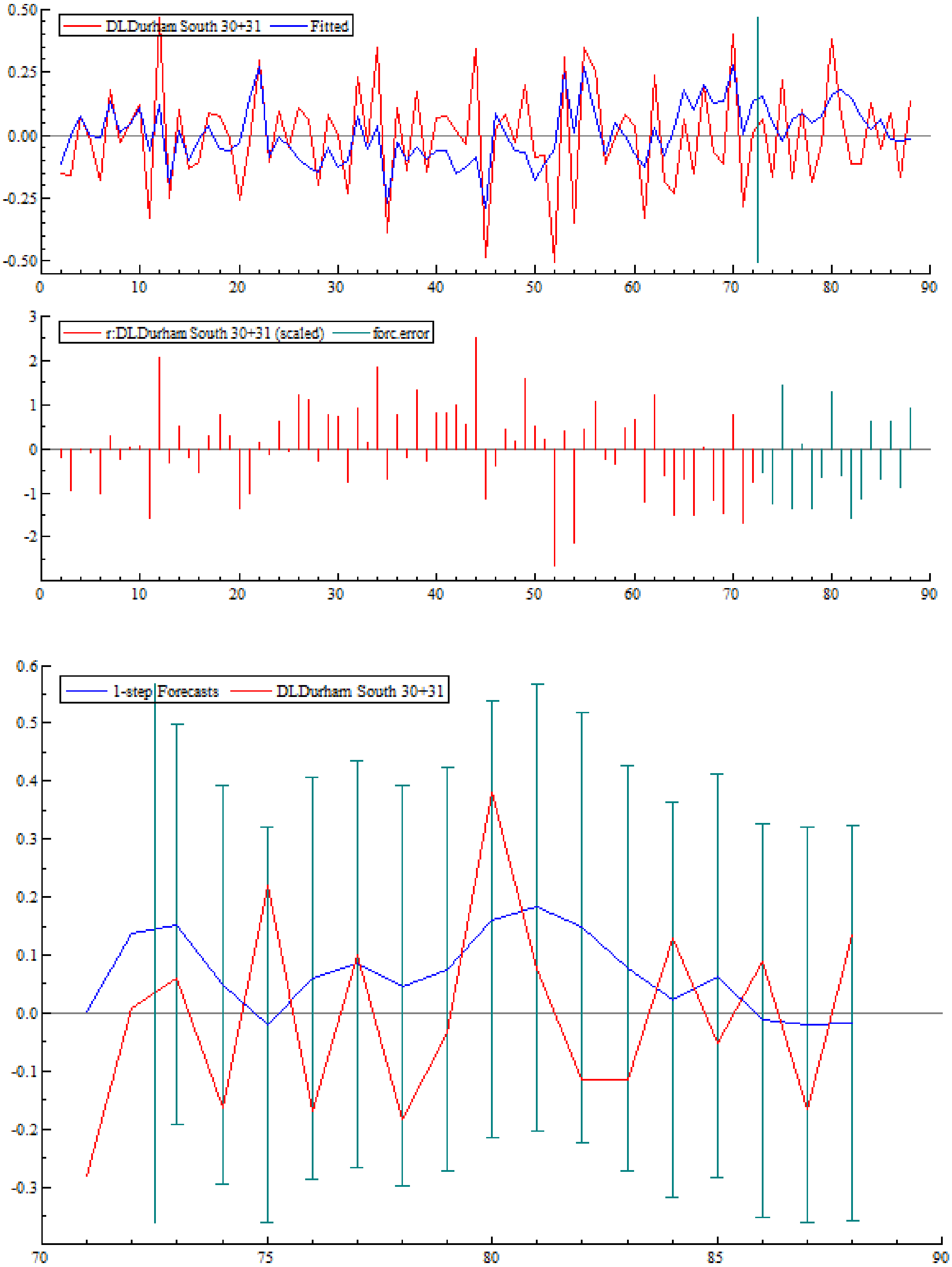


Figure 29 – Durham North (58a) crime sub-group against Claimant Counts over 30 ECM model predictions for April 2002 to March 2008. Also 1 step-forecast from April 2008 to July 2009.

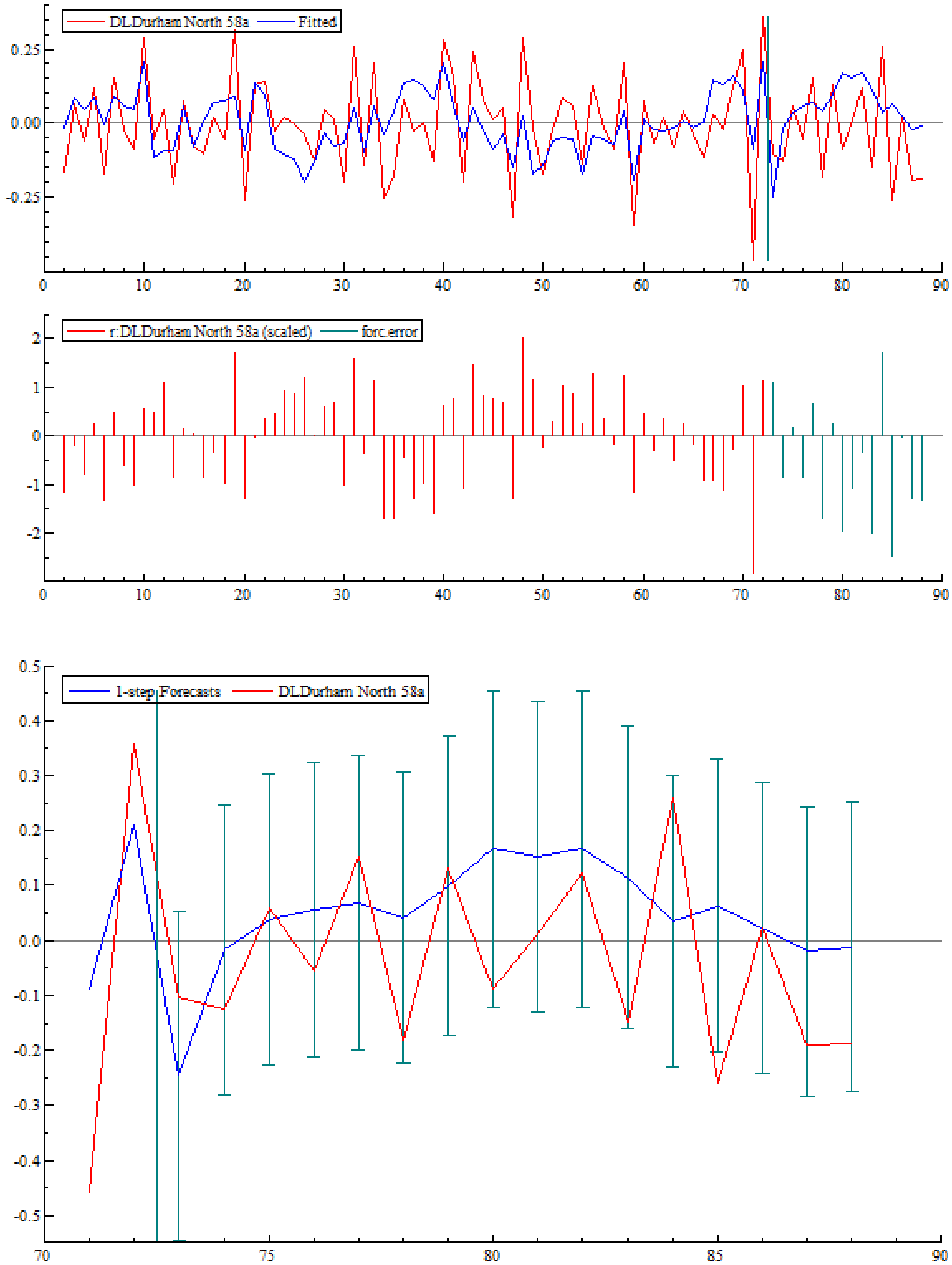


Figure 30 – Redcar and Cleveland (58c) crime sub-group against Claimant Counts over 30 ECM model predictions for April 2002 to March 2008. Also 1 step-forecast from April 2008 to July 2009.

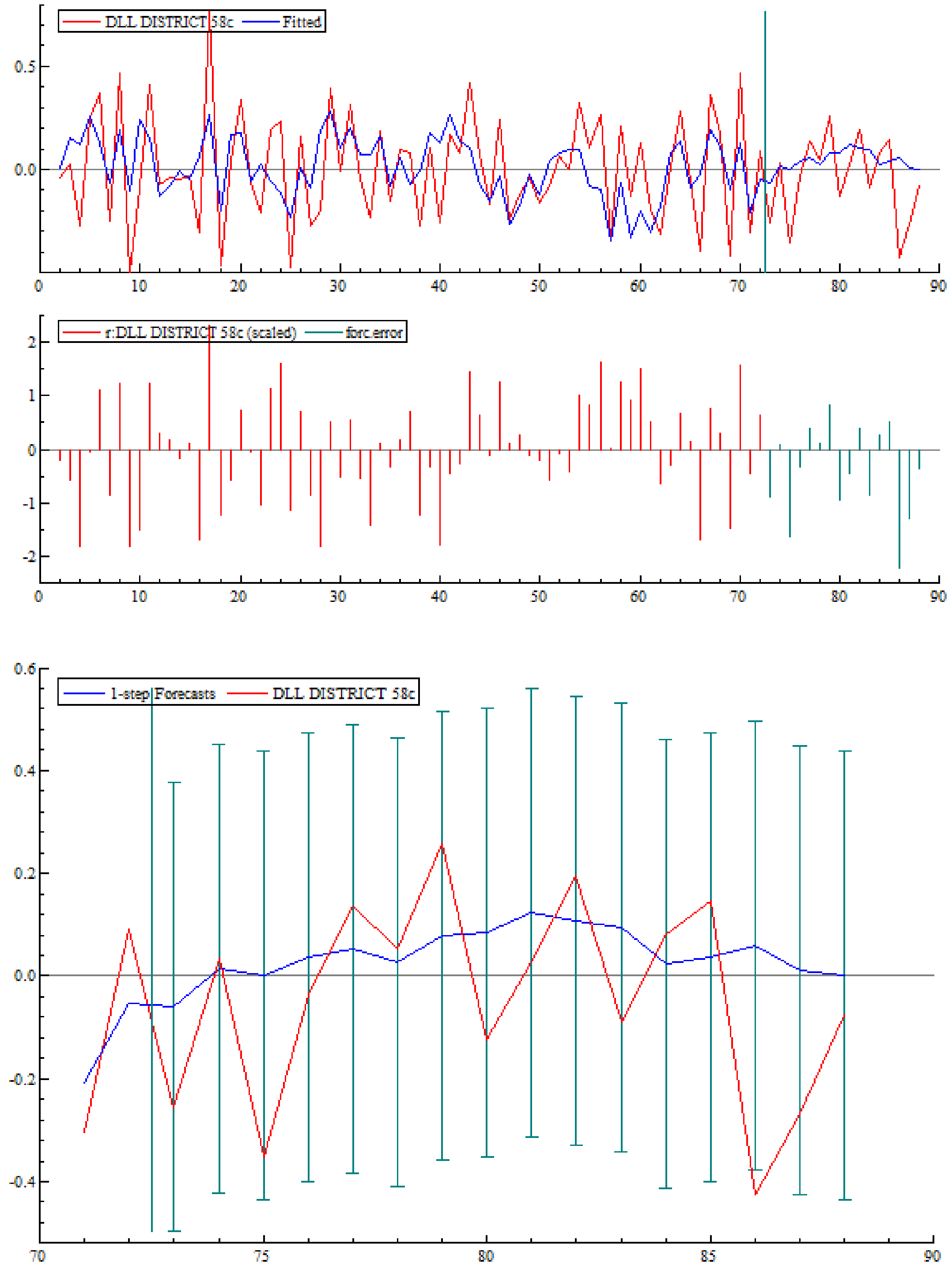


Figure 31 – Stockton (58c) crime sub-group against Claimant Counts over 30 ECM model predictions for April 2002 to March 2008. Also 1 step-forecast from April 2008 to July 2009.

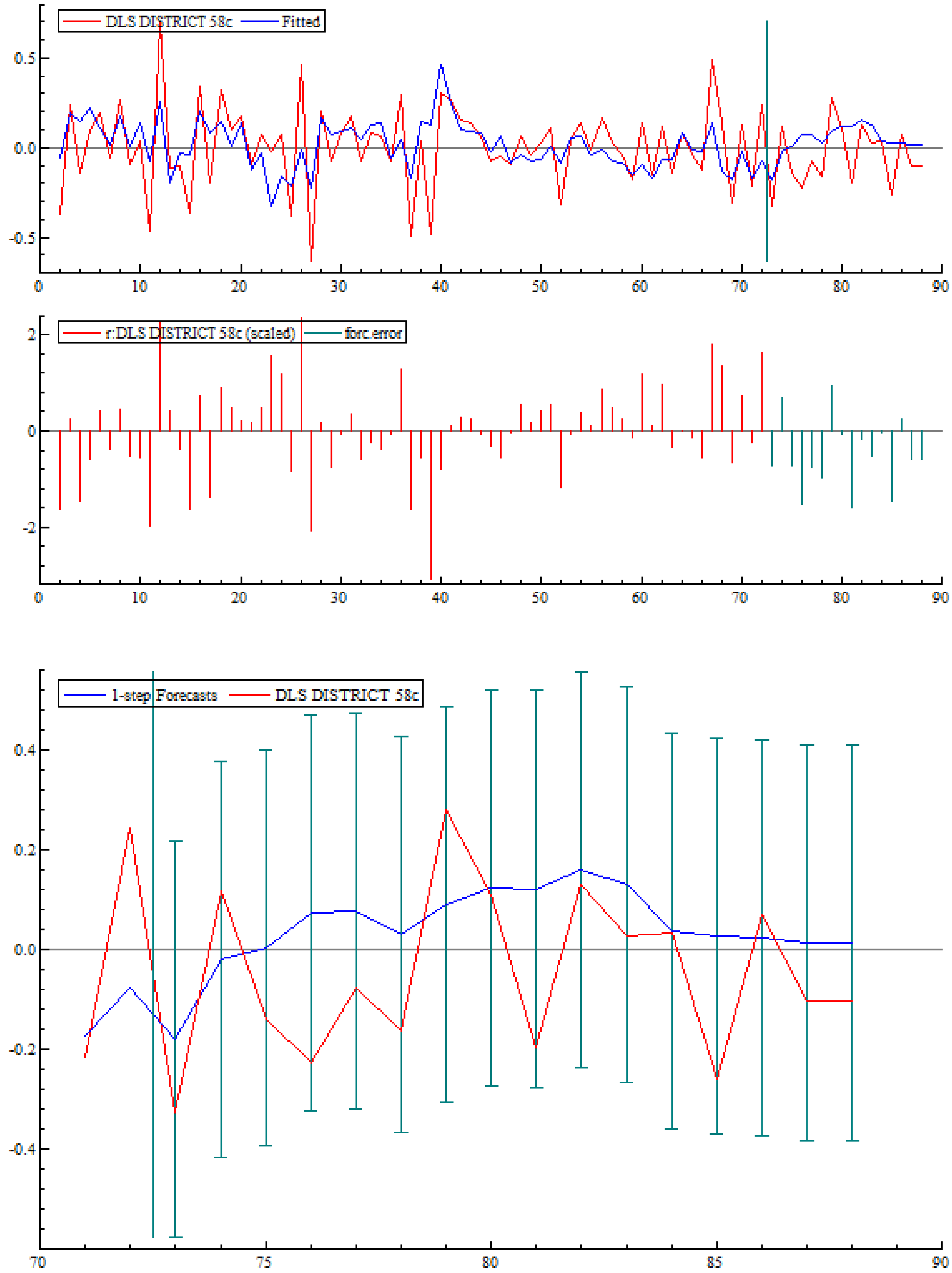


Figure 32 – Redcar and Cleveland (58a) crime sub-group against Claimant Counts over 30 ECM model predictions for April 2002 to March 2008. Also 1 step-forecast from April 2008 to July 2009.

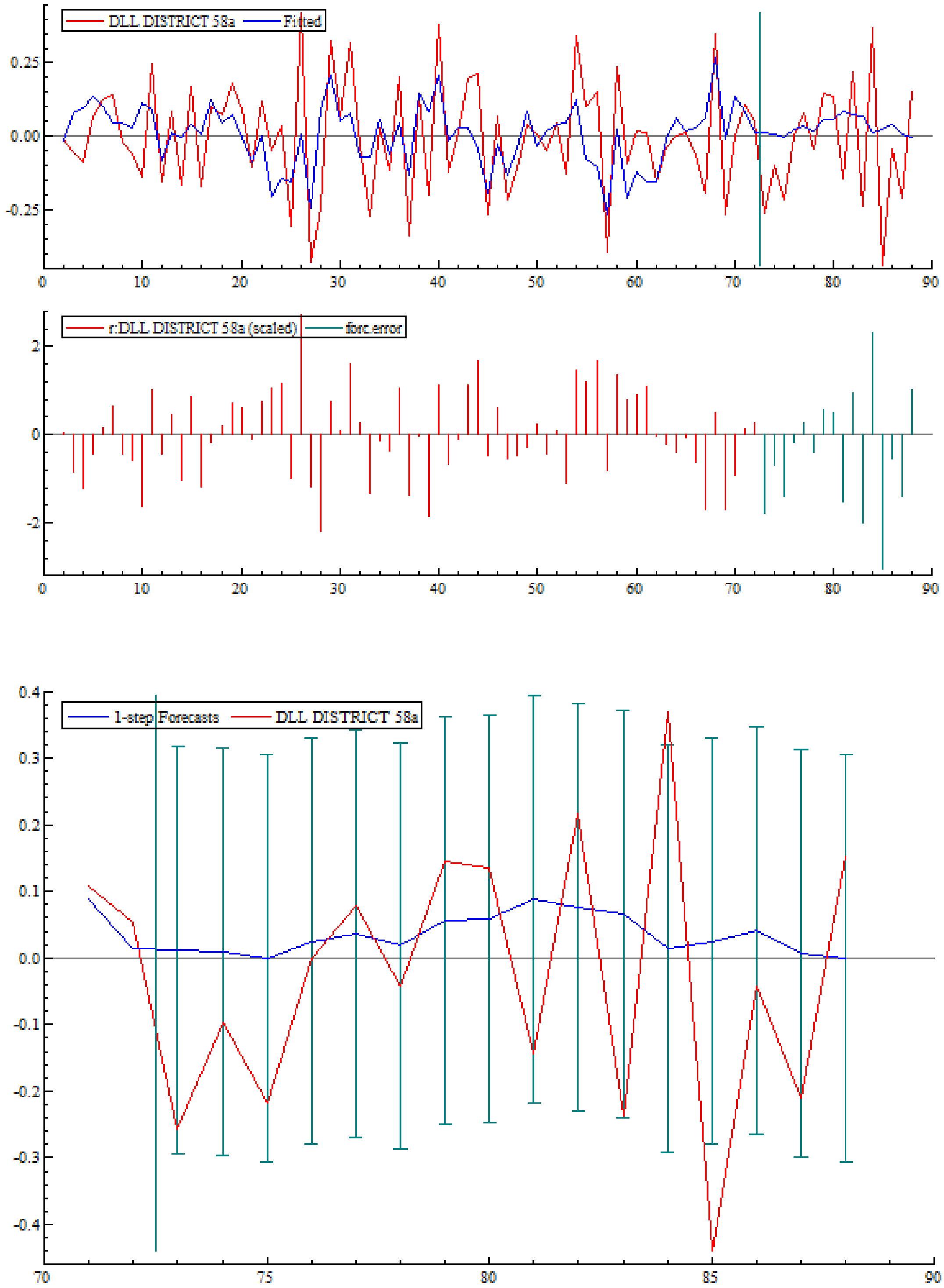


Figure 26 details the logged difference of the actual crime variable Durham (28+29) over the initial model period April 2002 to March 2008 inclusive, (72 months). The figure also includes the post-model period of April 2008 to July 2009 inclusive (16months). The later period is also depicted in more detail in the second pane of Figure 26. Both panes also include the fitted data from the model in question in both initial and post modelling periods. The first observation with regards to Figure 26 is that the graphical representation for the pre-forecast period shows a visibly good fit between actual data, (in red) and fitted data, (in blue). The second observation is that the actual real data in the ex-post forecast period from April 2008 onwards, (as detailed in pane 2 of Figure 26) appears to mainly fit within two standard deviations of the forecasted fitted data. The departure from the confidence limits in this case is explained by an unusual 50 per cent drop in crime count of this aggregated sub-crime category at the time. This is believed to have occurred as a result of a targeted crime operation in this area at the time.

We can also see from the forecasting graphs (see Figures 27 to 32) that although the forecasts are somewhat suppressed in their nature, (probably due to taking the mean of the ECM element from the sampling period) the actual logged differenced crime figures fit within two standard deviations of the predicted figures as generated by the models. It is important to note that the graphs represent the logged difference of the predicted and actual crime sub-group counts.

It is also important to note that these forecasts will include an error element to them, made up from, model specification, conditioning error

(Claimant count rounding error), sampling error (model parameters based upon sample period April 2002 to March 2008) and a random error element.

In the main the observations from Figures 26 to 32 inclusive show that the ex-post forecast period appear to fit within their individual confidence bars. Therefore we can accept to some degree the consistency of those individual models and therefore the potential predictability of them. The degree of variation could also be evidence that suggests that a more sophisticated model is required to provide improved forecasting capability. It is also worthy of note that out-of-sample forecast performance is not a reliable indicator of the validity of an empirical model, nor therefore of the crime theory on which the model is based.

6 Discussion

In this study monthly disaggregated crime groups were used against claimant count figures in sub-police force areas in the North East of England. The individual data series were examined for stationarity by use of the augmented Dickey Fuller test and graphical examination of the residuals. The time series were then declared stationary or not. Single equation regression analysis was then used and careful consideration was given to the potential for the data to be co-integrated. Co-integration was found in many of the models and as a result error correction models were developed and examined. The research adds to the ECM work of Deadman (2000) in that it explores more localised research as suggested by Deadman (2003). I have broken my discussion down into two distinct areas, the modelling process itself and the research findings.

6.1 Modelling Process

Careful consideration was made for this research in the selection of geographical areas, time span and crime sub-groups to minimise the number of legislative and procedural changes by predominately focusing upon a post-NCRS period of time. The impact of potential ‘under reporting’ of crime was also considered. Crime group areas that are shown by the British Crime Survey to be a better reflection of actual crime levels were selected for the research. The vast majority of research in crime modelling has been conducted using national data. Very little research has been conducted at sub-police force level and in particular in the North East of England.

Unemployment data is based upon localised surveys that add estimating error to the research. Claimant count data was selected as a proxy variable for overall unemployment levels. This decision was based upon claimant counts providing a more accurate count, (although there is a small rounding error). Claimant count figures also have the added benefit of being published on a month by month basis. The comparison of the effects of the two labour market measures, (official unemployment and claimant count figures) for the purpose of crime modelling would assist future modelling research. It is worth noting that claimant count data not only provides the data by a breakdown of age but also provides data on the length of time of person has been claiming. This could have a huge effect on the potential motivation of an offender. Further work in this area could prove to be beneficial for future research.

Masih (1995) and Britt (2001) suggested that the relationship between unemployment and crime seems to be dependent on crime type and demographic properties of individuals (age and gender). This research has attempted to reduce these effects by focusing upon specific crime sub-groups within the area of property crime and to focus upon males in two distinct age bands within the claimant count explanatory variable.

The decision to conduct the research for a period of time that was post-NCRS was a huge influencing factor in the formulation of the research. Although by the very use of this period of time we did reduce the potential for recording errors in the official crime statistics used and its exposure to legislative alterations we effectively placed a requirement on the research to be based upon data that was of a monthly frequency. The use of monthly data in this research has added value to crime modelling research as previous studies have predominately concentrated upon annual data. The use of monthly data has however not been without its problems.

The first issue was the limited access to crime data from a single point of source. Direct contact was made to three separate police force areas and although individually excellent in their respective assistance, it was provided to me in very much different ways. This made it a particularly difficult job in collecting crime data from three separate forces as it was presented in slightly different formats. As a result there was a huge amount of effort involved in formatting the 72 months worth of data into a workable format. Research of this type would certainly benefit in the future by a more consistent availability of police force data and in a much more disaggregated format. Although this has now started to become available to the general public via police force websites at the geographical ward level, (a much smaller area than talked about here). It does not provide historical data in the quantity required for research. I believe police forces would benefit from allowing academic researchers more free access to crime data at more disaggregated levels. Much time was also required when it came to the cleaning of the data into a standard format so that it could be used in the subsequent computer software packages for analysis.

The above procedure was aggravated by the decision to use crime sub-group categories in the research. However Levitt (2001) suggests that national time series data may fail to indicate the unemployment and crime relationship as they do not clearly show the variation in local data to an adequately significant level. This research has specifically used data at a sub-police force level to help reduce the national aggregation effect on the data and to build upon the suggestions of Levitt (2001). My research also suggested, in some cases, that monthly data for sub-police force areas is compromised by a lower data variance which results in reduced accuracy of any potential modelling. This was seen in particular with the crime sub-group 126, which depicts vehicle tampering and interference. As a result of monthly data being used, the use of smaller geographical areas and a relatively low offending rate crime sub-group the data series data variance for the sub-group 126 was very low. In particular, the crime sub-group, category of 126 in the areas of Alnwick and Berwick were shown to be stationary in nature in their raw time series. On reflection it is believed that this was due to its low data variance. Therefore careful consideration has to be given to data variance when considering future research studies that are at the sub-police force level, based on monthly crime counts and at a crime sub-group level.

There needs to be a trade off between disaggregation of areas, time-span and breakdown of the crime area under investigation. This model balancing should be a careful consideration in future research, in particular when looking at small geographical areas at higher time frequency and at a below crime category level. Therefore there may be merit in using a higher level of disaggregated crime data in modelling of crime, or greater geographical area for particular types of sub-group category crime. This low data variance effect was also identified by this research which highlighted the use of aggravated crime sub-group categories as a similar potential problem.

Coupled with a higher time sampling frequency and smaller geographical areas the variance in the crime data is very low and results in a time series of very little value. This further resulted in the crime sub-group categories and their respective aggravated crime sub-group categories being aggregated up into a single crime sub-group category for the purpose of this research.

Given the fact that the research used data that was based on a lower level of disaggregation of time, data and area, it not only had a direct bearing on model and explanatory variable selection but also impacted on the resultant analysis process. In particular it led to a large number of regression models being analysed and results having to be complied manually into another computer package to assist in the interpretation of them.

This research looked at a total of 397 individual models. This observation does support the need for a careful balance during model planning and provides some justification for limiting the disaggregation of time, geographical area and crime groups. The number of crime sub-groups to be used in the research is also an important decision as this again can have a huge impact on the number of resultant models generated during the analysis phase. This identified issue and the fact that previous research has focused around more aggregated time, geographical area and crime groups, acts as a warning for future researchers who wish to consider more disaggregated data in this field. A review of the crime data used in this research at police force and regional level and for combined crime sub-group categories could result in improvement of the model results. Although, as we will discuss later the geographical type for the area is important and this itself could be lost if aggregated area data is considered.

More time could have been spent examining the time series for seasonality, outliers, mistakes etc which all have a potential influence on the resultant research and conclusions. Research focusing on a particular sub-police force level area would allow for a more detailed examination of these areas and also for the careful consideration of crime substitution and crime recording manipulation.

Following on from the initial examination of the 328 data time series, removing problem series and aggregating crime sub-group categories with their respective aggravated crime sub-group categories, a total of 199 time series were presented for unit root testing, (this included crime and claimant count data). The research concluded that of the 199 time series 197 of them were found to be I(1), i.e. only need differencing once to make stationary. Although this research is based upon sub-police force areas and has used monthly data at sub-group category level, it offers support to the findings of Hale (1998), Hale and Sabbagh (1991) and Osborn (1995), who also show crime variables as being I(1). This adds further doubt to the findings of Pyle and Deadman (1994) that describe theft offences as I(2).

This is an important stage in the process of building a crime model and it dictates the direction required to take dependent upon whether the data is stationary or not. Again the process of testing for stationarity was not straight forward and was hampered by the high volume of ADF tests required to draw a conclusion on this matter. A total of 796 ADF tests were conducted and interpreted. This again highlights the need for careful consideration at the research planning phase as to the quantity of time series to be considered.

As a result of 197 time series being considered as I(1) a total of 401 co-integrating relationships were examined. There are a number of studies, (Hale and Sabbagh 1991 and Beki, Zeelenberg and Montfort 1999) that did not find co-integrating relationships between certain data types. In particular Osborn (1995) was unable to find any long run relationships between crime sub-group categories and unemployment data. Although this research uses claimant counts as a proxy variable for unemployment it does suggest that co-integrating relationships exists between crime sub-group categories and claimant counts and would tend to dispute the findings of Osborn (1995). This research also suggests evidence that supports the existence of co-integrating relationships between crime sub-group categories and therefore draws an alternative conclusion than that suggested by Hale and Sabbagh (1991) and Beki, Zeelenberg and Monfort (1999). The identification of a number of co-integrating relationships between crime sub-groups and claimant counts suggests that they have comparable long-run properties. However my research also identifies 77 of the 401 models that suggest co-integrating relationships do not exist between crime sub-group categories and claimant counts and other crime sub-group categories.

As discussed above there were a significant number of models (77) in the analysis that did not show that a co-integrating relationship existed. Many of these models (31) were from relationships regarding claimant counts (under the age of 30) and motor vehicle related crime sub-groups. The most interesting finding to note (with regards to the models that do not show the existence of a co-integrating relationship), is the fact that virtually all 77 models come from geographical areas that are classified as various levels of urban areas. There are only 7 models that come from rural areas and these are within crime sub-group areas that potentially have low data variance as previously discussed. The list below breaks down the crime sub-group categories against claimant count relationships that do not show a co-integrating relationship and counts them against their respective geographical area type. They are grouped by descending geographical rural area type, as described in section 3.2.1.

Rural 50	2
Significant rural	3
Other urban	4
Large urban	14
Major urban	21

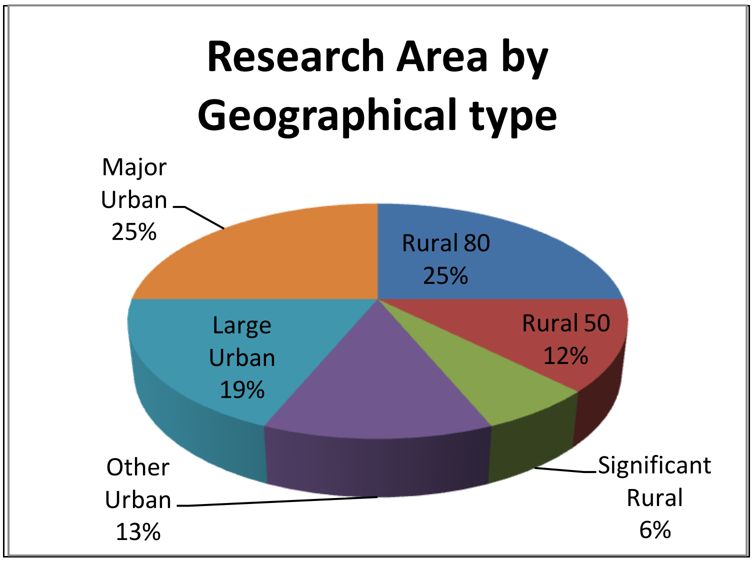
Although very rudimentary, when we break down the claimant count co-integration failures it is apparent that it suggests as an area becomes more urban there is an increase in the number of co-integrating relationship failures. This suggests that a more complex crime model is required for geographical areas that are more urban in their respective natures. This was supported by the research of Wiles and Costello (2000) who suggest that rural areas that border urban areas are of higher risk of offender movement towards them. This therefore suggests that offender movement from within urban areas is more significant than that of rural areas. This could indicate that the true reflection of urban based offenders is not fully reflected in their respective localised crime counts. However on the contrary you would also expect that the rural areas would also be affected by this movement. Based on the research by Wiles and Costello we would therefore expect to see the areas of Berwick, Alnwick, Warren, Tyndale, Blyth and Castle as models showing a higher degree of correlation, as they are rural areas themselves and they only boarder predominately rural geographical areas. Therefore there should be a reduced 'movement of offenders effect observed'. This improving the reliability of the crime data and improving one of the fundamental assumptions of my research that localised crimes are committed by local offenders and as suggested by Wiles and Costello (2000). This will be discussed in more detail later.

It is also apparent that there is a breakdown in the co-integrating relationships between various crime sub-group categories in more urban areas. In this research we identified 18 models that suggested no co-integrating relationship existed between crime sub-groups and related crime sub-groups. As we can see in the list below, as an area becomes more urban there is an increase in the likelihood of crime sub-groups not displaying a co-integrating relationship with related crime sub-groups.

Rural 50	1
Significant Rural	1
Other urban	2
Large urban	5
Major urban	9

Both these findings, although basic in their formulation, do appear to suggest that there is a significance given that the rural/urban ratio in the north east of England is about 43/57 per cent respectively, see Figure 33.

Figure 33 – Research area by geographical type



There could however be an alternative underlying reason due to this geographical link. The alternative reason could be purely related to the differences in data variance given the type of geographical area concerned. If we refer back to the original time series graphs, as in appendix 3, we can see that generally the more rural the areas the lower the crime counts.

The most noticeable research finding relating to crime sub-group relationships is highlighted in three separate geographical areas that did not show a co-integration relationship between burglary dwellings and criminal damage to a dwelling. This is despite all other areas (a further 14) showing the existence of a relationship. There are also a further three areas that display no relationship between burglaries other than dwellings and the related criminal damage to buildings other than a dwelling. There are two other areas that only show that a co-integrating relationship exists at the five percent level for the burglaries other than a dwelling and criminal damage to a building other than a dwelling relationship. The most interesting point is that all but one of the eight models is from the Cleveland Police area.

Should it be the case that no relationship exists between burglary and criminal damage to properties (either commercial or dwelling)? I did make the assumption at the start of this research that there was such a relationship and this is the basis of one of my research hypothesis, (the level of property crime sub-groups are affected by other related property crime sub-groups). The research does show many crime sub-group relationships exist. On first glance you would expect theoretically that burglary figures should not be influenced by criminal damage figures, although Mawby (2001) suggests that higher rates of burglary are found in areas, or close to areas, with socially disadvantaged housing, (these areas being traditionally linked to higher levels of criminal damage). Therefore, using this assumption we should conclude that the models that do not show a significant co-integrating relationship in existence for burglary to criminal damage are influenced by another factor. This could be an indication of crime substitution by the offender, successful crime intervention techniques or localised crime recording manipulation. This could also be as a result of the unique geographical make up of the Cleveland Police force area, (all urban) and its surrounding rural setting.

It is also interesting to note that the more statistically significant co-integration models tend to come from the more rural areas. Although there are a number of the more statistically significant models associated with major urban areas based upon crime sub-group relationships.

The recent British Crime Survey 2009 highlights that the risk of becoming a victim of burglary is dependent upon the type of area you live in. This research does support the important role that geographical area type plays in crime. Wilkstron (1991) also displayed the importance of geographical area consideration when residential dwelling burglaries were shown to occur disproportionately in areas of high socio-economic status and especially near to high offending rate areas.

As a result of the identification of 324 separate co-integrating relationships, the research focused upon the formulation of individual error correction models. The failed 77 co-integrating models were included in this stage as a checking mechanism. Only 220 of the total 397 ECM relationship models, (failed co-integrated models included), passed the statistical diagnostic tests that form the fundamental assumption of linear regression. Given this and the fact that this research focused on individual relationships this suggests that a more complex model is required and indicates that there are potentially significant missing explanatory variables in the model. This supports some of the suggestions of Field (1999) and Hale (2001) and also more complicated crime theories. It could also be indicative of the lower data variance used as a result of area, time sampling and crime sub-groups considerations. This could also suggest that a more complex non-linear relationship exists between some crime sub-groups and explanatory variables. Most of the 77 failed co-integrated models were included in the failed error correction models.

The identification of 220 separate error correction models in this research does support the findings of Hansen and Machin (2003) that modelled crime at police force level and concluded that single equation ECMs to model burglary were justified on the basis of co-integration. They also conclude that unemployment had a role to play in crime modelling.

6.2 Findings

The research finds that in the majority of cases the crime sub-group categories and claimant count data were as expected, non-stationary. Confirmation of this is important as use of this data in its basic state results in it being difficult to represent a crime model by a simple algebraic formula and would lead to a spurious regression result. Following further analysis on the non-stationary data by use of ADF testing my research findings suggest further support to the confrontational findings of Hale (1998) supporting the argument that crime is integrated of the order one, I(1). This has been shown to be the case across a number of crime sub-group categories and aggregated crime sub-group categories. Claimant count data is also shown to integrated to the order one, I(1) in nature.

The results do appear to suggest that the more rural the area is, the better the statistical relationship between crime sub-groups and claimant counts is. This could be evidence, given that the rural areas tend to be much bigger geographical areas, to support the theory that people only travel a short distance to commit types of crime thus generally remaining in the same area. Offenders who travel similar distances in compact urban areas may cross into other administrative areas. Specifically the areas of Castle, Alnwick(x2), Durham South, Tyndale (x2) and Berwick account for the top seven crime sub-group/claimant count relationships based upon the highest $R^2$and statistically significant regression coefficients. Based on the research by Wiles and Costello (2000) as previously discussed, I stated that I would expect to see the areas of Berwick, Alnwick, Warren, Tyndale, Blyth and Castle as models showing a higher degree of correlation as they only boarder predominately rural geographical areas. Therefore we should observe a reduced movement of offenders effect. We can conclude that this appears to be the case as described above and therefore this research supports the conclusions of Wiles and Costello (2000).

The research did look at whether co-integrating relationships exist between closely related crime sub-groups. On the whole there appeared to a positive relationship that existed between related crime sub-groups. However there were also findings that suggest the opposite. As the research was based upon property crime many of the crime sub-groups were related and this was concentrated upon to establish the relationship between closely related crime sub-group categories and any potential issues around crime recording manipulation or crime substitution by the offender. As many other crime groups were eliminated from this research due to other issues, such as recording error, there was little focus on the potential effects of crime substitution by offenders. This was recently looked at by Jantzen (2008) who concludes that there are many co-integrating relationships in existence between crime groups. He found interestingly that burglaries move counter to other crime areas, such as violent crime and motor vehicle (auto theft) crimes. As we will show later, as Jantzen (2008) used aggregated burglary data, (both dwelling and non-dwelling crime sub-groups), this provided a basic finding. This research gives some indication, as will be discussed later, that the crime sub-groups of burglary in a dwelling and burglary in a building other than a dwelling move in separate directions when modelled against claimant counts. Crime substitution is a research area that has had little work conducted upon it particularly the disaggregated level. Steffersmeir (1999) showed a substitution effect existed between burglary and motor vehicle crime. This is an area that requires more research and in particular with the additional consideration of localised crime recording practices. A better understanding of this area, with the added focus of crime sub-group categories, could help to produce a more sophisticated crime model for future research.

Boroeah & Collins (1995) describes a positive relationship between unemployment and crime and show that police crime clear up, (detection counts) as factors which helps to deter offenders from crime. In particular they identify a strong and positive relationship between unemployment and burglary rates. This, as with many other research studies has concentrated upon the aggregated crime group of burglary, which obviously includes the sub-categories of crime of dwelling burglaries and commercial burglaries. This previous focus upon the aggregated crime groups may account for the different findings in relation to crime and unemployment relationships such as Pyle and Deadman (1994) and Field (1990) who conclude dubious links between unemployment and crime. It is worth noting that the majority of these studies use annual data which is based around aggregated areas and over much longer periods of time, which encapsulates a wider range of legislative changes in relation to the measurement of unemployment, crime and crime recording standards.

This research suggests that there is a benefit to look at crime in a more disaggregated form, thus looking at the problem in more detail. The downside to this is the potential to reduce the data variance to such a level that it becomes impractical to work with and therefore careful consideration must be given to other data specification factors such as the geographical area of study and sampling frequency.

Hale (1998) re-examined the research of Field(1990) and Pyle and Deadman (1994) and concludes that burglary is positively related to unemployment. Thomas (1927) showed that there was a definite rise in burglary and robbery in periods of a business depression. Willis (1983) in one of the first police force level research studies, showed that for a one per cent increase in unemployment a small rise in theft occurred. This research breaks this down even further and supports the findings of Hale (1998) in that there is evidence to suggest a positive relationship between dwelling burglaries and also that there is evidence to suggest a negative relationship between commercial burglaries and claimant counts, (a proxy variable for unemployment). Boroeah and Collins (1995) also suggest a positive relationship between dwelling burglaries and unemployment. This research also supports the findings of the recent Home Office statistics report (2009) that reports a downturn in commercial premises burglaries despite seeing an overall increase in property crime. My research suggests for some geographical areas that an increase in claimant counts would result in a decrease in burglaries to a building other than a dwelling (commercial) and the related crime sub-categories of criminal damage to a building other than a dwelling. Although it does need to be highlighted that there is a statistical significance level in play here. The link to between burglaries to a building other than a dwelling and damage to buildings other than a dwelling is I suggest linked to the consumption of alcohol. Recent research shows strong links to alcohol consumption and violent crime. As with the Hale (1998) review of previous research work my work focuses upon the crime groups of violent crime, burglary and theft. It omits the property crime group of criminal damage. As we have seen in this research there are some important co-integrating relationships in existence here and I would therefore suggest that this should be included in future research work to provide a better overall understanding of crime dynamics. Alcohol consumption might be an important predicator of violent crime and should not be omitted. Raphael and Winter-Blomer (2001) and Field (1990) also found a positive effect for alcohol consumption on violent crime. There are theories that suggest that alcohol consumption is associated with violent behaviour (Seto 1995 and Collins 1981). Could this be the reason that commercial criminal damage reduces during times of higher unemployment (higher claimant counts), could it be a suggestion that in times when more people have less money the night time economy reduces and hence the level of commercial property damage. Poutrara and Prikis (2007) suggest there is a substitution effect between property crime and violent crime. Given the potential link between property crime and alcohol and the additional link of violent crime to alcohol, future research could be developed around a more complete crime picture that is more interlinked, thus taking account of crime substitution and offender motivational effects. This interlinking of crime is supported by my research which suggests a number of co-integrating relationships within the broad band of property crime. This type of research would I suggest benefit from more aggregated geographical data sets due to its complexity but it would allow for a model that would show a fuller dynamic crime model for a given area.

The BCS survey suggests that there is a short fall in official crime statistics in that a 'dark figure' exists and that not all crimes are reported. However the survey explains further that the 'dark figure' is different for various crime categories. The BCS suggest, (based on 2007 report) that only 93 per cent of motor vehicle theft, 81 per cent of burglary (with loss), 55 per cent of burglary (without loss), 43 per cent theft from motor vehicle and 32 per cent of vandalism crimes are reported by the public. We would therefore expect, (assuming the claimant count has an effect on crime), to see theft of motor vehicle to show a better level of relationship between the two separate claimant count variables. Although these crime areas are broader than the areas in this research study, my research does provide some indirect supporting evidence of this sliding scale of crime reporting behaviour. My research shows 11 out of 15 of the top claimant count and crime sub-group category models are based upon motor vehicle crime. However only 3 of them are for theft of motor vehicle offences category. The other 8 are for criminal damage to a motor vehicle and theft from a motor vehicle. Although the BCS suggest a 'dark figure' exists in crime reporting it would appear that research into this area has only looked at it at a crime category level. It would be hugely beneficial to crime modelling researchers to have the 'dark figure' broken further down into crime sub-group categories. I would suggest that the crime sub-group categories of theft of motor vehicle and criminal damage of motor vehicle, although hidden in the BCS figures above, will also have a high reporting ratio. If this is not the case then these findings could potentially suggest that although motor vehicle thefts, (which include attempt thefts of motor vehicle), are being reported they are being recorded as alternative motor vehicle crimes, such as theft from or criminal damage of motor vehicle. This would lead onto the suggestion of crime recording manipulation. Clearly the issue surrounding under-reporting and the more accurate measurement of the 'dark figure' would prove to be a useful piece of research for future advancements in crime modelling.

This research does show a statistically significant positive link (in most cases) between property crime and the number of claimant counts in a given sub-police area (district or BCU). This finding is supported by Raphel and Winter-Eboner (1999) who suggest a highly significant effect between unemployment and property crime. Therefore it is fair to suggest that as this is based upon the assumption that crime is generally committed by localised offenders then this research offers some indirect support of the findings of Wilks and Costello (2000), who suggest evidence that shows localised criminal behaviour.

Chiricos (1987) states that opportunity is related to the current level of employment and motivation is also linked as it takes a while for the unemployment to start to generate financial stresses. This would support the requirement of further research in the area of time lagging. Time lagged variables could also be a significant help when it comes to forecasting.

We would expect to see that the claimant count rate is positively related to the property crime sub-group categories as concluded by Wolpin (1975) and Pyle (1989). Chiricos (1987) also identifies that this positive relationship is more evident in studies that used post-1970s data and that have concentrated upon property related crime studies. Batharom and Habibullah (2008) results indicate that unemployment has a meaningful relationship with both aggregated and disaggregated crime. They suggest that crime has a positive relationship with crime, (except for violent crime) which shows a negative relationship. Papps and Winklelman (1999) found some evidence of significant effects of unemployment on crime both for total crime and for sub-categories of crime in 16 regions in New Zealand. Although it is interesting to note here that domestic burglaries and motor vehicle crime were the main areas of concentration.

This research does support the above findings by identifying a positive relationship between crime sub-groups and claimant counts. This was identified predominately by positive coefficients in the ECM regressions, as evidenced by 49 of the top 70 crime to claimant count relationship models. However it is noticeable that there was a relatively high number of ECM regressions that displayed a negative coefficient. This indicates a negative relationship exists between certain crime sub-groups and claimant counts, as evidenced in 21 of the top 70 models. Most striking is that two thirds of these are linked to the crime sub-group category of burglaries other than a dwelling and their associated criminal damage to a building other than a dwelling sub-crime category.

This finding appears to support the recent Home Office BCS (2009) report regarding property crime. The report states that between the years of 2007/8 and 2008/9 at a national level there has been a one per cent increase in domestic burglaries and a two per cent fall in non-domestic burglaries. Obviously the BCS report includes a significant economical turning point (recession) which has largely been reported as occurring around September 2008. This is interesting given that there has been an overall increase in property crime. This research would appear to be significant given that the models were based on a time period that was economically strong and did not include the recent turn in the economic climate. It is also worthy of identifying a possible link between commercial style property crime and violent crime, as there appears to be empirical grounds in this and previous research (Batharom and Habibullah 2008) to suggest that they too follow a similar negative relationship with unemployment levels. Hansen and Machin suggest that disaggregation of crime (burglary) proved unimportant, however Deadman (2003) disagrees with this finding. This research also supports the findings of Deadman (2003) and suggests that there could be a significant difference, dependant on geographical area regards to different burglary sub-groups. This difference is only identified if data is disaggregated and could be a reason why previous research has concluded dubious links between crime and unemployment. This common relationship or inter-crime sub-group relationship would certainly benefit from further research and assist in future modelling in this crime area.

Although the model does take account of age it keeps this relatively simple. Age breakdown is suggested by Cohen (2005) and suggests that there are individual crime age relationships. This research does suggest a slightly higher relationship between property crime sub-groups and claimant counts for the above 30 age band, however this is only slight and is believed to be statistically insignificant due to data variance as a result of a higher age band. This area of crime modelling, particular at the sub-force geographical level and sub-crime group level, could benefit from further research. Additionally a better understanding of localised age-crime relationships would help to refine the crime modelling procedure. At the start of the research the age band split was considered to be important due to previous age-crime research and the results do support the findings of Timbrell (1988), who showed some evidence of an unemployment and crime link when it is considered by unemployment age groups as opposed to more generalised research such as Long and Witte (1981) and Freeman (1989), who show the link between unemployment and crime to be moderate. This may be an indication of the importance of refining a crime-unemployment relationship to specific age bands. Further research could be focused upon the deciphering of unemployment age breakdown and its crime theory effects, such as motivation and guardianship.

There is some evidence in the research that related crime sub-group categories show a high correlation with each other. This would be expected, however there are a couple of relationships that show low and high relationships levels dependant on what geographical area they are based upon, e.g. vehicle crime against vehicle damage. Why are some crime sub-group categories showing a strong relationship in areas as you would expect and other areas do not show these relationships? Could this be an indication of crime recording manipulation, local choice in crime preference or substitution in offending. This could also be indicative of good crime prevention initiatives. Further research needs to be conducted in this field to help to understand the dynamics of the crime recording and inter-relationships between crime sub-group categories that are both directly related and not related at disaggregated levels of crime modelling. The impact of all this could be reduced by reverting back to national, annual and crime group type modelling as in previously discussed research.

7.1 Conclusion

This research is distinguished from previous research studies by focusing on disaggregated police force areas in the North East of England, crime sub-group categories, the use of monthly sampling period frequency and by its use of claimant count data. This research used a post NCRS sampling period to reduce the effects of procedural and legislative change. The relationships between disaggregated crime and claimant count data were explored as were relationships between related crime sub-group categories. Both these explored relationships formed the basis of the research hypotheses and the following conclusions can be drawn as a result:-

1. This research identifies the difficulties in obtaining and analysing disaggregated data in crime modelling and highlights the needs for careful pre-research planning.

2. Support was found for previously disputed research that crime data is integrated to the order one, I(1). This research also shows that this is the case even down to crime sub-group category level. Claimant count data is also shown as integrated to the order one I(1).

3. The results of this research do tend to suggest that property crime sub-groups, claimant counts and related property crime sub-groups

variables are co-integrated therefore offering some supporting evidence to the crime theory of routine activity theory.

4. Statistical coefficients and diagnostics tests suggest that a more complex model may exist.

5. The research provides supporting evidence to show a positive relationship exists between certain crime sub-group categories and claimant counts.

6. The research also identifies the importance of using crime sub-group categories in modelling. This is evidenced by the identification of a negative relationship between burglary other than a dwelling and claimant counts.

7. This research suggests that the type of geographical area plays a big role in the successfulness of a crime model. I suggest that offender movement between geographical areas (in support of previous research) or data variance (as identified by statistical tests) is the cause.

8. Some areas were identified as not displaying the same crime sub-group category co-integrating relationships that other areas displayed, suggesting that additional influential factors existed. Crime substitution and recording practices have been suggested as possible causes.

9. Use of a post NCRS sampling period led to the use of monthly data which reduced the availability of explanatory variables and potentially led to lower data variance when coupled with smaller geographical areas and crime sub-group categories.

10. There was some evidence found to support the under reporting of crime, evidenced by the top performing error correction models.

11. The sourcing and resultant analysis process involving disaggregated data impacted upon the ability to forecast more models in this research.

12. The forecasting process was also hampered by large economic changes.

The basic crime model selection based upon the established crime theory of routine activity theory is relatively straight forward. The difficulty arises when the decision is focused upon time period, crime data and explanatory data selection. Previous research has highlighted some of the significant issues surrounding the use of official crime statistics and some of the influential changes that have taken place over time, which affect the relative ease of making statistical comparisons over time. Explanatory variables suffer similar problems which also include issues around recording and estimating errors. This has to be a huge balancing act in relation to data time period and frequency selection so that some of these errors can be kept to a minimum. However as I have found with this research, if you focus too much on this then you seriously limit yourself in terms of available data for analysis. Although on this research I used a higher frequency of data it seriously impacted upon developing a more complete model. This disaggregation of model elements is also noticeable when you use sub-crime groups and sub-police force areas. Perhaps future research should concentrate upon only disaggregation of one dimension only, not time, crime and area.

However this research has produced some significant findings and suggests that the level of property crime is affected by claimant counts and that there are significant relationships between related crime sub-group categories. I hope that this research helps to fuel future interest in this field as previous research did me.

7.2 Suggested Future Research

This research identifies a number of areas that would benefit from further research:-

1. Further research at a sub-police force level (crime management level) to quantify crime substitution and reporting manipulation between crime sub-groups.

2. Further research is required to explore the dynamic relationship between crime sub-group categories.

3. Further research into crime modelling quantifying the effects of geographical area types.

4. Research in the field of time lagging of claimant counts.

5. Research into cross border movement of offenders.

6. The comparison of the effects of the two labour market measures, (official unemployment and claimant count figures) for the purpose of crime modelling.

7. Further research into unemployment age and length of time unemployed. Consideration of motivational effects and guardianship.

8. Further research into the relationship between property crime sub-groups and violent crime sub-groups?

9. A more accurate measurement of the BCS ‘dark figure’ would prove to be a useful piece of research for future advancements in crime modelling particular down to the official crime recording level of crime sub-groups.

Bibliography

Allen, C. (2005). The Links between heroin, crack cocaine and crime. *British Journal of Criminology , 45*, 355-372.

Baharom, A., & Habibullah, M. (2008). *Is crime cointegrated with income and unemployment?*

Barr, R., & Pease, K. (1990). Crime Displacement. In M. Tonry, & N. Morris, *Crime and Justice.* Chicago: University of Chicago Press.

becker, G. (1968). Crime and Punishment: An Economic Approach. *Journal of Political Economy , 76*, 169-217.

Beki, C., Zeelenberg, K., & Montfort, K. (1999). An analysis of the crime rate in the Netherlands 1950-93. *British Journal of Criminology* , 401-415.

Bennett, T. (2000). *Drugs and Crime: The Results of the Second Development Stage of the NEW ADAM Programme.* London: Home Office.

Bennett, T., & Holloway, K. (2005). *Understanding Drugs, Alcohol and Crime.* Maidenhead: Open University Press.

Best, D., Strang, J., Beswick, T., & Gossop, M. (2001). Assessment of a concentrated, High-profile Police Operation: No Discernible Impact on Drug Availability, Price or Purity. *British Journal of Criminology* , 738-45.

Borooah, V. H., & Collins, G. (1995). *Unemployment and Crime in the Regions of Britain: A Theoretical and Emperical Analysis.* Co. Antrim: University of Ulster.

Bottomley, A. K., & Coleman, K. (1981). *Understanding crime rates: Police and public roles in the production of official statistics.* Gower.

Bottoms, A. E. (2007). Place, Space, Crime and Disorder. In M. Maguire, R. Morgan, & R. R, *The Oxford Handbook of Criminology* (pp. 528-574). New York: Oxford University Press.

Bowers, K., Johnson, S., & Hirschfield, A. (2004). The measurment of crime prevention intensity and its impact on levels of crime. *British Journal of Criminology , 44*, 1-22.

Bowling, B., & Foster, J. (2002). Policing and the police. In M. Maguire, R. Morgan, & Reiner, *The Oxford Handbook of Criminology.* Oxford: Oxford University Press.

Box, S. (1971). *Deviance, Reality and Society.* London: The Macmillan Press.

Box, S. (1987). *Recession, Crime and Punishment.* London: MacMillian.

Britt, C. (2001). Testing theory and the analysis of time series. *Journal of Quantitative Criminology , 17* (4), 343-357.

Burrows, J., Tarling, R., Mackie, A., Lewis, R., & Taylor, G. (2000). *Review of police forces crime recording practices.* London: Home Office.

Charemza, W. W., & Deadman, D. F. (1992). *New Direction in Econometric Practice.* England: Edward Elgar.

Chiricos, T. (1987). Rates of Crime and Unemployment: An analysis of Aggregate Research Evidence. *Social Problems , 34*, 187-212.

Clarke, R., & Hough, M. (1984). *Crime and Police Effectiveness.* London: Home Office.

Clements, M. P., & Hendry, D. F. (2003). *Evaluating a model by forecast performance.* Oxford.

Cloward, R., & Ohlin, L. (1957). *Delinquency and Opportunity.* Glencoe: Free Press.

Cohen, E. G. (1990). Weather and Crime. *british Journal of Criminology , 30*, 51-64.

Cohen, L. E., & Felson, M. (1979). Social change and crime rate trends: a routine activity approach. *American Sociological Review , 44*, 588-608.

Cohen, L. (2005). *The cost of crime and justice.* Routledge.

Cohen, L., Felson, M., & Land, K. (1980). Property crime rates in the US: A macrodynamic Analysis 1947-1977. *American Journal of Sociology* , 90-118.

Coleman, C., & Moynihan, J. (1996). *Understanding crime data.* Open University Press.

Collins, J. (1981). *Drinking and Crime: Perspectives on the Relationships Between Alcohol Consumption and Criminial Behaviour.* New York: The Guilford Press.

Craglia, M., & Costello, A. (2005). A model of offenders in England. *AGILE (Association Geographic Information Laboratories Europe).* Lisbon: Universidade Nova de Lisboa.

Danziger, S., & Wheeler, D. (1975). The Economics of Crime: Punishment of Income Redistribution. *Review of Social Economy , 33*, 113-31.

Deadman, D. (2000). Forecasting Residential Burglary. *International Journal of Forecasting* , 2-18.

Deadman, D. (2003). *Modelling crime and offending: recent developments in England and Wales.* London: Home Office.

Deadman, D. (2004). Offenders as victims of crime?:An investigation into the relationship between criminal behaviour and vicitimization. *Journal Statistics in Society* , 53-67.

Deadman, D., & Pyle, D. (1997). Forecasting recorded property crime using a time-series econometric model. *British Journal of Criminology* , 437-445.

Defronzo, J. (1984). Climate and Crime: Tests of an FBI Assumption. *Environment and Behaviour , 16*, 185-210.

Dhiri, S. B. (1999). *Modelling and prediciting property crime trends in England and Wales.* London: Home Office.

Dickenson, D. (1995, 2). Crime and Unemployment. *New Economy* .

Easterlin, R. (1968). *Population, Labor Force, and long swings in economic growth.* New York: Columbia University Press.

Engle, R., & Granger, C. (1987). Co-integration and error correction: Estimation and testing. *Econometrica* , 251-276.

Ezell, M. E., & Cohen, L. (2005). *Desisting from Crime: Continuity and Change in Long Term Crime Patterns of Serious Chronic Offenders.* Oxford: Oxford University Press.

Fabricant, R. (1979). The distribution of criminals in an urban environment: A spatial analysis of criminal spillovers and juvenile offenders. *American Journal of Economics and Sociology* , 31-47.

Farrell, G., & Pease, K. (1994). Crime Seasonality: Domestic Disputes and Residential Burglary in Merseyside 1988-90. *British Journal of Criminology , 34*, 487-498.

Farrington, D. P., & Burrows, J. N. (1993). Did Shoplifting Really Decrease? *British Journal of Criminology* , 57-69.

Farrington, D. (1995). The Development of Offending and Anti-Social Behaviour from Childhood: Key findings from the Cambridge Study in Delinquent Development. *Journal of Child Psychology and Psychiatry , 360*, 929-64.

Farrington, D., & Langan, P. (1998). *Crime and Justice in the Unitied States and England and Wales 1981-96.* Washington: Bureau of Justice Statistics.

Farrington, D., Loeber, R., Elliott, D., Hawkins, J., Kandel, D., Klein, M., et al. (1990). Advancing knowledge about the onset of delinquency and crime. *Advances in Clinical Psychology* .

Feldman, H. S., & Jarmon, R. G. (1979). Factors Influencing Criminal Behaviour in Newark: A Local Study in Forensic Psychiatry. *Journal of Forensic Science , 24*, 234-9.

Felson, M., & Clarke, R. (2004). *Opportunity makes a thief.* Police Research Papers.

Field, S. (1999). *Modelling and predicting property crime trends in England and Wales.* London: Home Office Research Studies.

Field, S. (1992). The Effect of Temperature on Crime. *British Journal of Criminology , 32*, 340-351.

Field, S. (1990). *Trends in crime and their interpretation: A Study of recorded crime in post-war England and Wales.* London: HMSO.

Field, S. (1998). *Trends in crime revisited.* London: Home Office.

Flood-Page, C., Campbell, S., Harrington, V., & Miller, J. (2000). *Youth Crime: Findings from the 1998/99 Youth Lifestyles Survey.* London: Home Office.

Forrester, D., Chatterton, M. R., & Pease, K. (1988). *The Kirkholt Burglary Prevention Demonstration Project, Rochdale.* London: Home Office.

Fowles, R., & Merva, M. (1996). Wage inequality and Criminal Activity: An extreme Bounds Analysis for the United states. *Criminology , 34*, 163-82.

Freeman, R. B. (1983). Crime and Unemployment. In J. Q. Wilson, *Crime and Public Policy* (pp. 89-106).

Genn, H. (1988). Multiple Victimisation. In Maguire, & Ponting, *Victims of crime:A real deal.* Open University Press.

Gottfredson, M., & Hirschi, T. (1986). The True Value of Lambda Would Appear to be Zero: An Essay on Career Criminals, Criminal Careers, Selective Incapacitation, Cohort Studies, and Related Topics. *Criminology , 24*, 213-233.

Gould, E., Weinberg, B., & Mustard, D. (2002). Crime Rates and Local Labour MArket Opportunities in the Unitied States: 1979-1995. *Review of Economics and Statistics* , 45-61.

Graham, J., & Bowling, B. (1995). *Young People and Crime.* London: Home Office.

Green, s. (1991). *How many subjects does it take to do a regression analysis? Multi-variate behavioural research.*

Greenberg, D. F. (1977). Delinquency and the Age Structure of Society. In S. L. Messinger, & E. Bittner, *Criminology Review Yearbook.* California: Sage.

Greenberg, D. F., & Kessler, R. C. (1983). The effect of police employment on Crime. *Criminology* , 375-394.

Hakim, S. (1979). Interjurisdictional spillover of crime and police expenditure. *Land Economics* , 200-212.

Hale, C. (1998). Crime and the Buisness Cycle in Post-War Britain Revisited. *British Journal of Criminology , 38*, 681-698.

Hale, C., & Sabbagh, D. (1991). Testing the relationship between unemployment and crime a methodological comment and empirical analysis using time series data from England and Wales. *Journal of research in crime and delinquency* , 400-415.

Hamilton-Smith, N. (2004). *The Reducing Burglary Intiative: Design, Development and Delivery.* London: Home Office.

Hansen, B. E. (1992). *Regression with Non-stationary Variances.* University of Rochester.

Hansen, K. (2003). *A quantitative analysis of crime and the labour market (PHD).* London School of Economics.

Hansen, K., & Machin, S. (2001). Crime and the minimum Wage forthcoming. *Quantitative Journal of Criminology* .

Hanson, K. (2003). Eductaion and the Crime-Age profile. *British Journal of Criminology , 43*, 141-168.

Heaton, R. (2000). The prospects for intelligence led policing: Some historical and quantitative considerations. *Policing and Society* , 337-56.

Heller, N. B., & Markland, R. E. (1970). A Climatological Model for Forecasting the Demand for Police Service. *Journal of Research in Crime and Delinquency , 7*, 167-76.

Hird, C., & Ruparel, C. (2007). *Seasonality in recorded crime: premliminary findings.* London: Home Office.

Hirschfield, A. (2004). *The impact of the Reducing Burglary Intiative in the North of England.* London: Home Office.

Hirschi, T., & Gottfredson, M. (1983). Age and the Explanation of Crime. *American Journal of Sociology , 91*, 22-7.

Hirshi, T. (1969). *Causes of Delinquency.* Berkley: University of California Press.

Houchin, R. (2005). *Social Exclusion and Imprisonment in Scotland.* Glasgow: Glasgow Caledonian University.

Hough, M., & Mayhew, P. (1983). *1983 The British Crime Survey.* London: HMSO.

Hoyle, C., & Zedner, L. (2007). Victims, Victimization and Criminal Justice. In M. Maguire, & R. Morgan, *The Oxford Handbook of Criminology* (pp. 461-95). New York: Oxford Univrsity Press.

Ilston, G. (2008, September). Credit crunch could fuel rise in crime says Home Office. *Police Professional* .

Jantzen. (2008). *Dynamics of New York City Crime.*

Jarvis, G., & Parker, H. (1989). Young Heroin Users and Crime. *British Journal of Criminology , 29*, 175-185.

Jones, T., & Newburn, T. (1998). *Private Security and Public Policing.* Oxford: Oxford University Press.

Kelling, G., Pate, A., Dieckman, D., & Brown, C. (1974). *The Kansas City Preventive Patrol Experiment: Technical report.* Washington: Police Foundation.

Kershaw, C., Chivite-MAthews, N., Thomas, C., & Aust, R. (2001). *The 2001 British Crime Survey, First Results, England and Wales.* London: Home Office.

Kershaw, C., Nicholas, S., & Walker, A. (2008). *Crime in England and Wales 2007/08.* London: HMSO.

Laub, J. H., & Sampson, R. J. (2001). Understanding Desistence from Crime. In M. Tonry, *Crime and Justice: A Review of Research* (pp. 1-70).

Levitt, S. (2001). Alternative strategies for identifying the link between unemployment and crime. *Journal of Quantitative Criminology* , 377-390.

Levitt, S. (1998). Juvenille Crime and Punishment. *Journal of Political Economy* , 1156-1185.

Levitt, S. (1997). Using Electoral Cycles in Police Hiring to Estimate the Effect of Police on Crime. *American Economic Review* , 270-290.

Lombroso, C. (1911). *Crime: Its Causes and Remedies.*

Long, S. K., & Witte, A. D. (1981). Current Economic Trends:Implications for Crime and Criminal Justice. In K. N. Wright, *Crime and Criminal Justice in a Declining Economy* (pp. 69-143).

Machin, S., & Meghir, C. (2000). *Crime and Economic Incentives.* University of Chicago Press.

Mackinnion, J. B. (1991). Critical values for co-integration tests. In R. F. Engle, & W. J. Granger, *Long run economic relationships.* Oxford: Oxford University Press.

Maguire, M. (2000). Policing by risks and targets: Some dimensions and implications of intelligence led social control. *Policing and Society* , 315-37.

Marsh, I. (2006). *Theories of Crime.* London.

Mash, R. (1995). Modelling the dynamic interactions covering crime, detterence and socio-economic variable: evidence from a vector error-correction model. *Mathematics and computer simulations , 39*, 411-416.

Masih, R. (1995). A fractional cointegration approach to empirical tests of PPP. *Weltwritschafiliches Archive* , 673-94.

Mathews, R., & Young, J. (1986). *Confronting Crime.* London.

Mawby, R. I. (2001). *Burglary, Cullomptom, Devon.* Willian.

Mayhew, P., Maung, N. A., & Mirless-Black, C. (1993). *The 1992 British Crime Survey.* London: Home Office.

McCord, J. (1982). A longitudinal view of the relationship between parental abscence and crime. In J. Gunn, & D. P. Farrington, *Abnormal Offenders, Delinquency and the Criminal Justice System.* Chichester: Wiley.

Mehay, S. L. (1977). Interjurisdictional spillovers of urban police services. *Southern Economic Journal* , 1352-1359.

Merton, R. (1957). *Social Theory and Social Structure.* New York: Free Press.

Miles, J. N., & Shevlin, M. (2001). *Applying regression and correlation: a guide for students and researchers.* London: Sage Publications.

Morgan, R., & Newburn, T. (1997). *The Future of Policing.* Oxford: Oxford University Press.

Neale, B., & Evans, M. (2003). *Repeat Victimisation Domestic Burglary Project.* London: Home Office.

Newburn, T. (1995). *Crime and Criminal Justice Policy.* London: Longman.

Nicholas, S., Kershaw, C., & Walker, A. (2007). *Crime in England and Wales 2006/07.* London: Home Office.

Nicholas, S., Povey, D., Walker, A., & Kershaw, C. (2005). *Crime in Engalnd and Wales 2004/2005.* London: Home Office.

Office, H. (2009). *British Crime Survey.*

Osborn, D. R., & Tseloni, A. (1995). *The Distribution of Household Property Crimes.* Discussions Paper Series, no. 9530, University of Manchester, School of Economic Studeis.

Papps, K., & Rainer, W. (1999). *Unemployment and crime: New Evidence for an old question.* University of Canterbury.

Papps, K., & Winkelmann, R. (1999). *Unemployment and crime: New evidence for an old question.* London.

Parsons, T. (1937). *The Structure of Social Action.* New York: McGraw-Hill.

Pate, T., Ferrar, A., Bowers, R. A., & Lorence, J. (1976). *Police Response Time: Its determinants and Directs.* Washington DC: Police Foundation.

Patterson, E. B. (1991). Poverty, Income Inequality and Community Crime Rates. *Criminology , 29*, 755-76.

Perron, P. (1990). Testing for a unit root in a time series with a changing mean. *Journal of Buisness and Economic Statistics* , 153-162.

Perry, J. D., & Simpson, M. E. (1978). Violent Crimes in a City: Environmental Determinants. *Environment and behaviour , 19*, 77-90.

Pollack, O. (1961). *The criminality of women.* New York: A.S. Barnes.

Polvi, N., Looman, T., Humphris, C., & Pease, K. (1990). Repeat Break and Enter Victimisation: Time Course and Crime Prevention Opportunity. *Journal of Police Science and administration , 17*, 8-11.

Pudney, S., Deadman, D., & Pyle, D. (2000). The relationship between crime, punishment and economic conditions: is reliable inference possible when crimes are under-recorded? *Journal of the Royal Statistical Society* , 81-97.

Pyle, D. a. (1994). Crime and the Buisness Cycle in Post-War Britain. *British Journal of Criminology , 34*, 314-324.

Pyle, D. a. (1994). Crime and Unemployment in Scotland : Some Further Results. *Scottish Journal of Political Economy , 41*, 314-324.

Raistrick, D., Hodgson, R., & Ritson, B. (1999). *Tackling Alcohol Together: The Evidence Base for a UK Alcohol Policy.* London: Free Association Books.

Raphael, S., & Winter-Ebmer, R. Identifying the Effect of Unemployment on Crime. In *2001.*

Raphael, S., & Winter-Ebmer, R. (1999). *Identifying the Effect of Unemployment on Crime.* University of Linz.

Reilly, B., & Witt, R. (1996). Crime, Deterrence and Unemployment in England and Wales:An empirical analysis. *Bulletin of Economic Research* , 137-159.

Rice, K. J., & Smith, W. R. (2002). Socioecological Models of Automotive Theft: Integrating Routine Activity and Social Disorganization Approaches. *Journal of Research in Crime and Delinquency , 39*, 304-336.

Rowe, A., & Tittle, C. (1988). Two Empirical Regularities (Maybe) in Search of an Explanation: Commentary on the Age/Crime debate. *Criminology , 26*, 75-85.

Rutter, M. (1979). *Fifteen Thousand Hours.* Cambridge: Harvard University Press.

Sampson, R. J., & Wooldredge, J. (1987). Linking the Micro- and Macro-level Dimensions of Lifestyle - Routine Activity and Opportunity Models of Predatory Victimisation. *Journal of Quantitative Criminology , 3*, 371-393.

Saridakis, G. (2008). *Violent crime and incentives in the long-run: Evidence from England and Wales.* Loughborough University.

Seddon, T. (2002, 14 Autumn). Five Myths about Drugs and Crime. *Safer Society* .

Seto, M. (1995). The role of alcohol in sexual aggression. *Clinical Psychology Review* , 545-566.

Sherman, L., & Berk, R. A. (1984). The Specific Deterrent Effects of Arrest for Domestic Assault. *American Sociological Review* , 261-72.

Simmons, J. (2001). *An initial analysis of police recorded crime data to end of March 2001 to establish the effects of the introduction of the ACPO National Crime Recording Standard.* London: Home Office.

Soothill, K., Francis, B., & Fligelstone, R. (2002). *Patterns of Offedning Behaviour: A New Approach.* London: Home Office.

Sparks, R. F., Glenn, H., & Dodd, D. J. (1977). *Surveying Victims.* London: Wiley.

Statitics, O. o. (2008). *How exactly is unemployment measured?*

Steffensmeier, D. J., & Harer, M. D. (1987). Is the crime rate really falling? An 'aging' US population and its impact on the nations crime rate 1980 - 1984. *Journal of Research in Crime and Delinquency* , 23-48.

Steffensmeier, D., Allan, E., Harer, M., & C, S. (1989). Age and the Distrubution of Crime. *American Journal of Sociology , 23*, 803-31.

Stockdale, J., & Gresham, P. (1995). *Combating Burglary: An Evaluation of Three Strategies.* London: Home Office.

Stockdale, J., & Gresham, P. (1998). *Tackling Street Robery: A Comparative Evaluation of Operational Eagle Eye.* London: Home Office.

Sutherland, E. (1947). *Principles of Criminology.* Philadelphia: Lippincott.

Tarling, R. (1982). *Crime and Unemployment.* Home Office. London: HMSO.

Tarling, R. (1982). *Crime and Unemployment.* London: HMSO.

Thaler, R. (1977). An Econometric Analysis of Property Crime. *Journal of Public Economics* , 37-51.

Thomas, D. S. (1927). *Social Aspects of The Buisness Cycle.* New York: Gordon and Breach.

Thornberry, T., Moore, M., & Christenson, R. L. (1985). The Effect of Dropping Out of High School on Subsequent Criminal Behaviour. *Criminology , 23*, 3-18.

Timbrell, M. (1988). *Does Unemployment Lead to Crime.* Department of Economics. Exeter: University of Exeter.

Trickett, A., Osborn, D. R., Seymour, J., & Pease, K. (1992). What is different about high crime areas? *British Journal of Criminology , 32*, 81-89.

Tseloni, A. (2002). Fear walking alone in one's neighbourhood: regression and multilevel analysis. In C. Zarafontitou, *Fear of crime* (pp. 156-207). Athens: Sakkoulas.

Wadsworth, M. (1979). *Roots of delinquency.* London: Robertson.

Walker, A., Flatley, J., & Kershaw, C. (2009). *Crime in England and Wales 2008/09.* London: HMSO.

Wells, J. (1995). *Mitigating the effects of unemployment: Crime and unemplyment.* House of Commons Select Committee on employment.

Wells, L. E., & Rankin, J. H. (1991). Families and delinquency: a meta-analysis of the impact of broken homes. *Social Problems , 38*, 71-93.

Wikstrom, P.-O. H. (1991). *Urban Crime, Criminals and Victims: The Swedish Experience in an Anglo-American Comparative Perspective.* New York: Springer-Verlag.

Wikstrom, P.-O. H., & Loeber, R. (2000). Do disadvantaged neighbourhoods cause well-adjusted children to become adolescent delinquents?: a study of male serious juvenile offending, individual risk and protective factors and neighborhood context. *Criminology , 38*, 1109-42.

Wiles, P., & Costello, A. (2000). *The 'Road to Nowhere': the Evidence for Travelling Criminals.* London: Home Office.

Willis, K. G. (1983). Spatial variations in crime in England and Wales: Testing an economic model. *Regional Studies* , 261-272.

Witt, R., Clarke, A., & Fielding, N. (1999). Are Higher Long-Term Unemployment Rates Associated with Higher Crime. *British Journal of Criminology* , 391-400.

Witt, R., Clarke, A., & Fielding, N. (1999). Crime and economic activity: a panel data approach. *British Journal of Criminology* , 391-400.

Witt, R., Clarke, A., & Fielding, N. (1998). Crime, Earnings Inequality and Unemployment in England and Wales. *Applied Economics Letters* (5), 265-67.

Witte, A. D., & Witt, R. (2001). *Crime Causation: Economic Theories.*

Wolpin, K. (1978). An economic analysis of crime and punishment in England and Wales. *Journal of Political Economy* , 815-40.

Young, M. (1991). *An Inside Job: Policing and Police Culture in Britain.* Oxford: Oxford University Press.

Appendix 1

Data Sources

Dependant (Crime data)

Variable	28 Burglary in a dwelling 29 Aggravated burglary in a dwelling 30 Burglary in a building other than a dwelling 31 Aggravated burglary in a dwelling other than a dwelling 37.2 Aggravated vehicle taking 45 Theft from m/v 48 Theft or unauthorised taking of m/v 126 Interfering with a m/v (inc tampering) 58A Criminal damage to building 58B Criminal damage to building other than dwelling 58C Criminal damage to vehicle 58E Racially/religiously aggravated criminal damage to a dwelling 58F Racially/religiously aggravated criminal damage to a building other than dwelling 58G Racially/religiously aggravated criminal damage to a vehicle Total Burglary (28+29+30+31) Total M/V Crime (37.2+45+48+126) Total Criminal Damage (58A to 58G) Total (Selected property crime areas)
Data Description	Official police recorded crime statistics
Data Source	Cleveland Police, Northumbria Police and Durham Con.
Date Range	2002 to 2008
Frequency	Monthly
Geography	Force, BCU
Cleaned data format	

Explanatory Variables

Variable	**Population**
Data Description	Mid-Year population estimates (Broken down to sex and age groups). The estimated resident population of an area includes all people who usually live there, whatever their nationality. Members of UK and non-UK armed forces stationed in the UK are included and UK forces stationed outside the UK are excluded. Students are taken to be resident at their term time address. The methodology used to update the population estimates accounts for flows of long-term international migrants. A long-term international migrant is defined as somebody who changes his or her country of usual residence for a period of at least one year.
Data Source	NOMIS
Date Range	1998 to 2006

Frequency	Annual
Geography	Regional and District
Cleaned data format	Year, sex, (district by age group)

Variable	**Gross Disposable Household Income (GDHI)**
Data Description	Gross Disposable Household Income (GDHI) is the balancing item of the secondary distribution of income account, and can be compared with the concept of income as generally understood in economics, where income is often defined as the maximum amount that a household can consume without reducing its real worth. The UK level estimate can also be found in Table 6.1.4 of the UK National Accounts (the Blue Book). The UK and sub national GDHI figures are published annually.
Data Source	Office of National Statistics, (ONS)
Date Range	1998 to 2006
Frequency	Annual
Geography	Regional, Sub-region (NUTS3)
Cleaned data format	

Variable	**Gross Value Added (GVA)**
Data Description	Gross Value Added (GVA) represents the incomes generated by economic activity within the UK economy. GVA data presented in the Regional Accounts uses the income approach or GVA(I) and comprises: • compensation of employees (wages and salaries, national insurance contributions, pension contributions, redundancy payments etc); • gross operating surplus (self-employment income, gross trading profits of partnerships and corporations, gross trading surplus of public corporations, rental income etc).
Data Source	Office of National Statistics, (ONS)
Date Range	1998 to 2006
Frequency	Annual
Geography	Regional, Sub-region (NUTS3)
Cleaned data format	

Variable	**Police Strength**
Data Description	Police Strength includes regular police officers (rank breakdown), special constables and police community support officers, (PCSO).
Data Source	Home Office (HO) Statistical Bulletin
Date Range	1998 to 2008
Frequency	Annual
Geography	Police Force
Cleaned data format	

Variable	**Crime Clearup Rates**
Data Description	In England, Wales and Northern Ireland, following an arrest the police may release the suspect without further action; issue a caution, either formally or informally; or make a charge. Offences are said to be

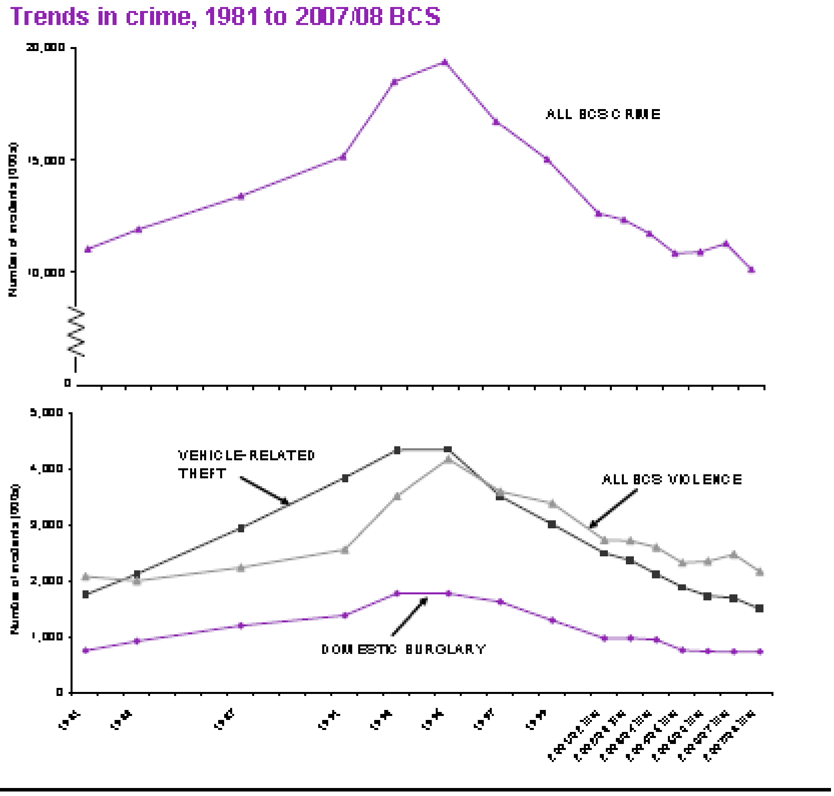
	cleared-up by primary means (for example, those where someone is cautioned, charged or summoned to appear in court) or by secondary means (for example, when a prisoner admits to further offences). The new counting rules were introduced on 1 April 1998 for clear-up rates for notifiable offences.
Data Source	Cleveland Police, Northumbria Police and Durham Con.
Date Range	1998 to 2008
Frequency	Monthly
Geography	Force, BCU
Cleaned data format	

Variable	**Sentence Lengths**
Data Description	Court level data by area, court type and offence type.
Data Source	Sentencing Guidelines Secretariat
Date Range	1999 to 2005?
Frequency	Annual
Geography	Court level
Cleaned data format	

Variable	**Claimant Count (age and duration)**
Data Description	The Jobseeker's Allowance (JSA) is a working-age benefit entitled to those who are: • under 65 (for men) or under 60 (for women) • out of work, or working on average less than 16 hours a week • available for work for at least 40 hours a week • actively seeking work • capable of working The number of people claiming JSA is measured by the monthly claimant count. This is compiled by the Office for National Statistics from the administrative records of Jobcentre Plus local offices. Claimant count data are published monthly in the labour market statistics First Release, Labour Market Trends and on Nomis®.
Data Source	NOMIS
Date Range	Apr 1998 to Jul 2008
Frequency	Monthly
Geography	Region and District
Cleaned data format	

Appendix 2

National Crime Graphs

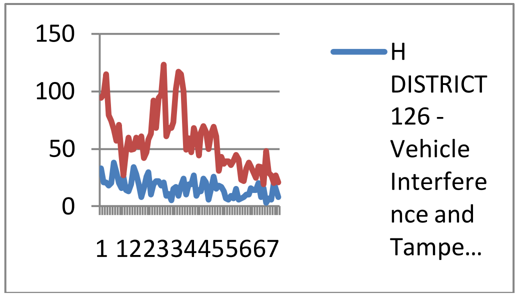


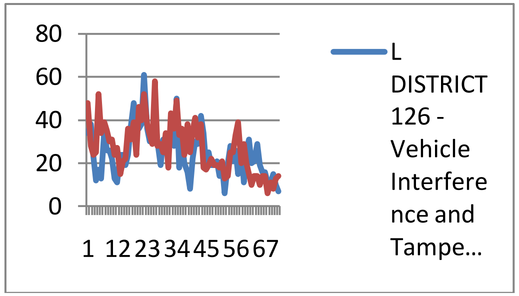
(Nicholas et al, 2007)

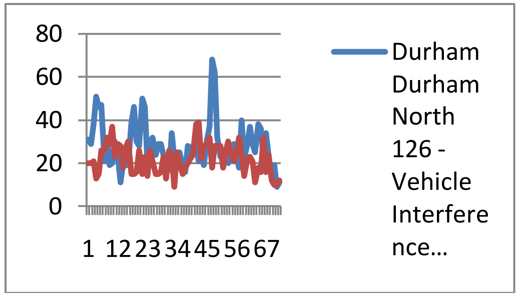
Appendix 3

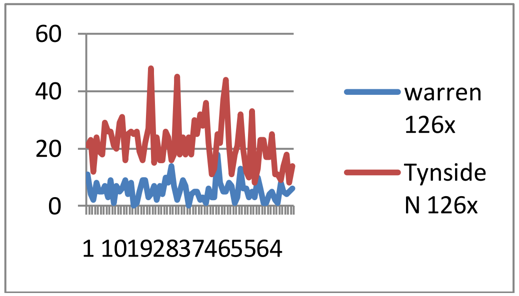
Data Graphs

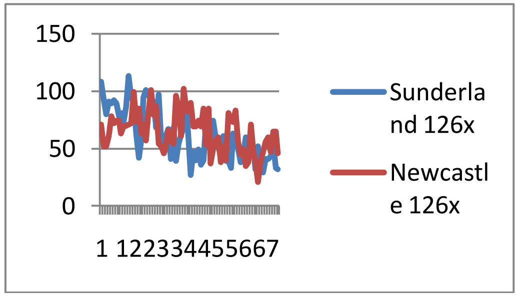
Crime Sub-Group Category 126

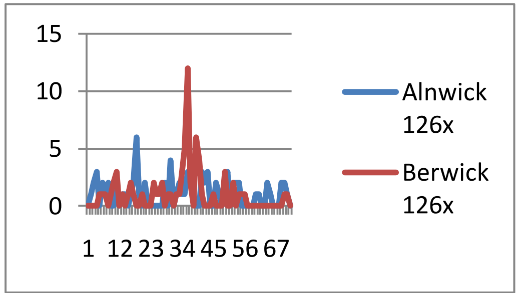


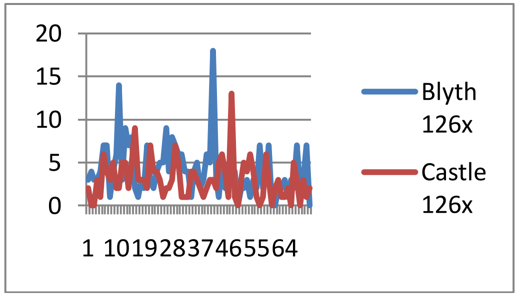


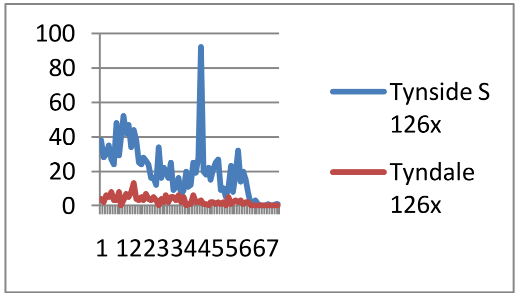


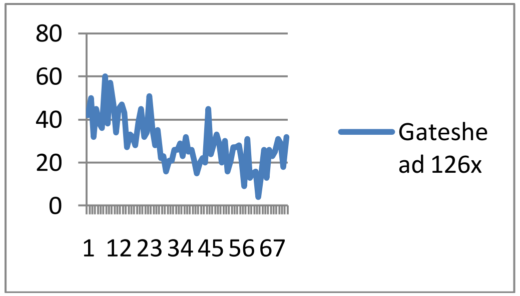




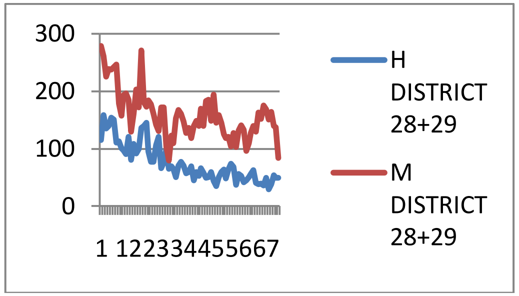


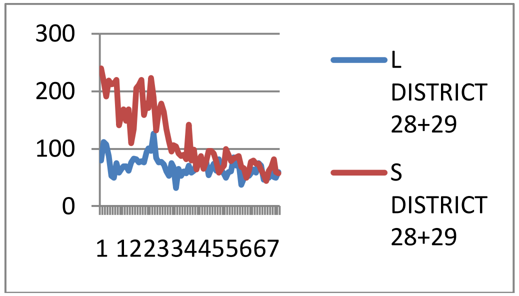

20
15
10
5
0
1 10192837465564
Blyth 126x
Castle 126x

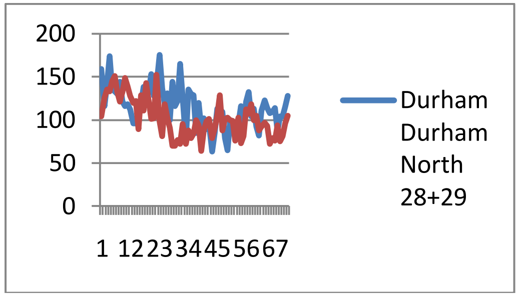

100
80
60
40
20
0
1 122334455667
Tynside S 126x
Tyndale 126x

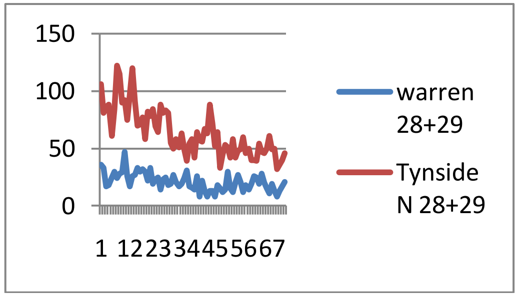

80
60
40
20
0
1 12 23 34 45 56 67
Gateshe ad 126x

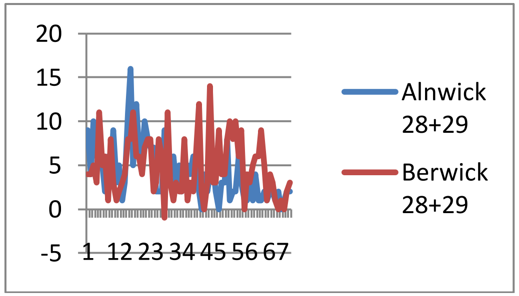
Crime Sub-Group Category 28 + 29

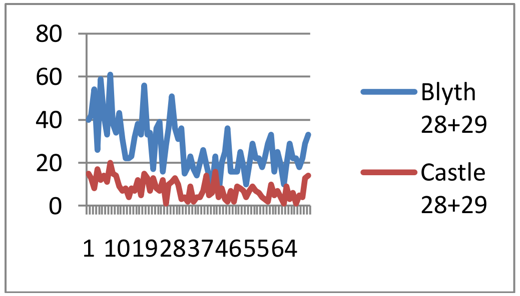


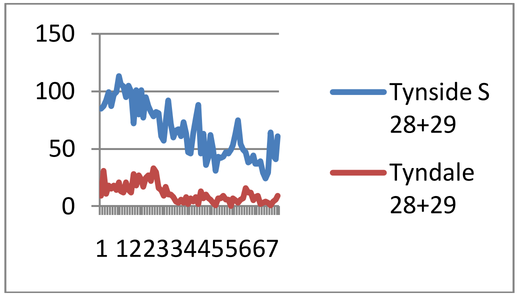


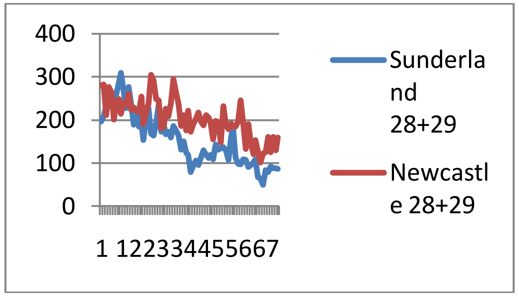


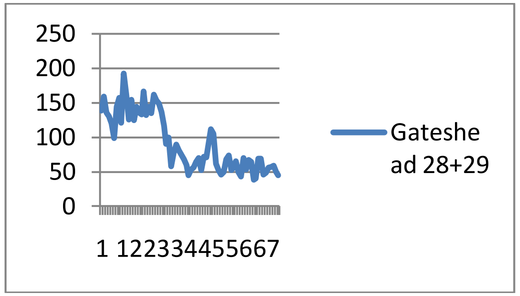




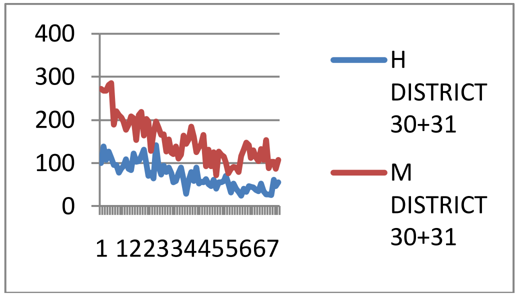


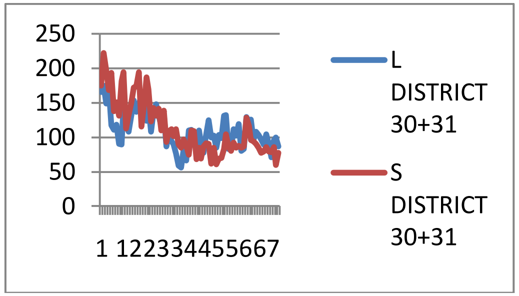


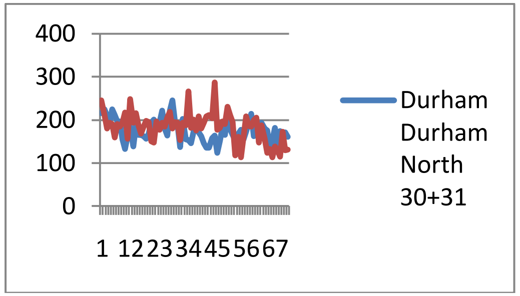


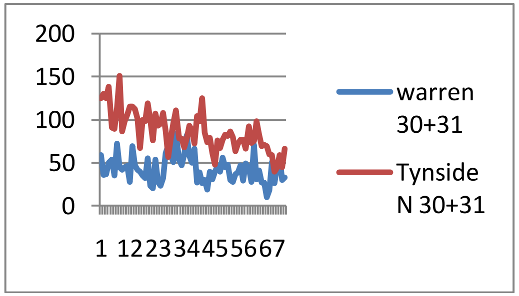


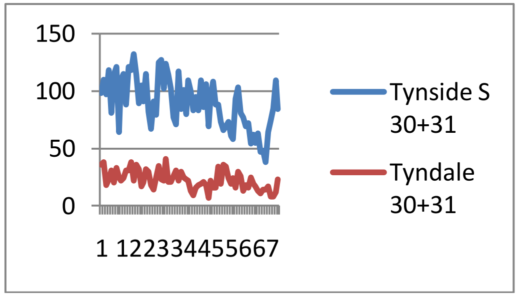
Crime Sub-Group Category 30 +31

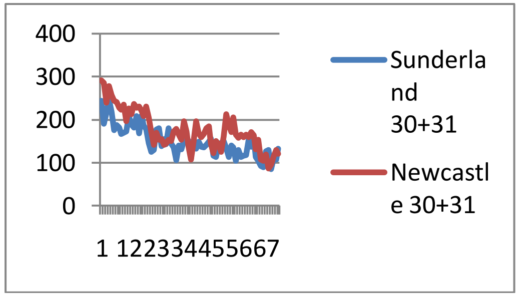


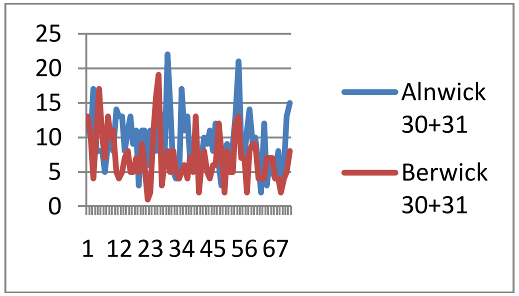


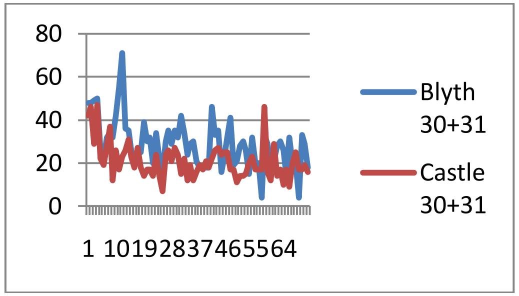


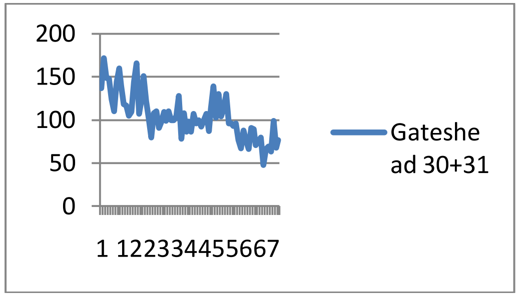




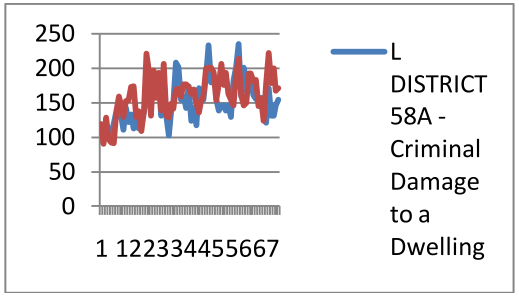


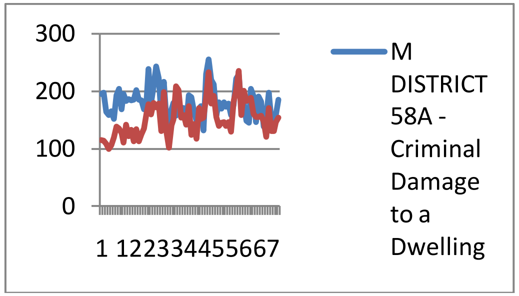


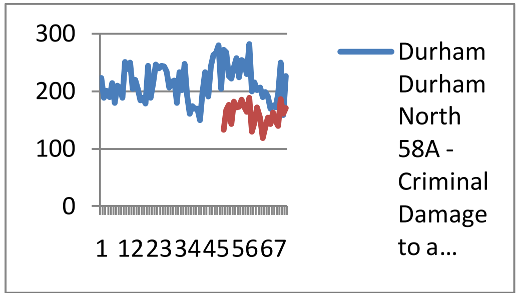


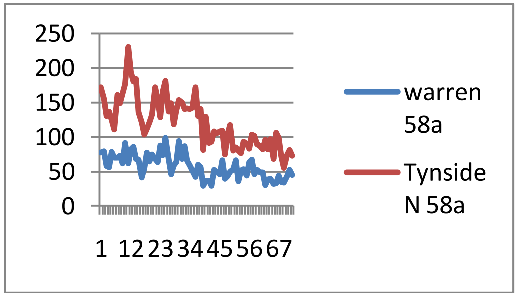


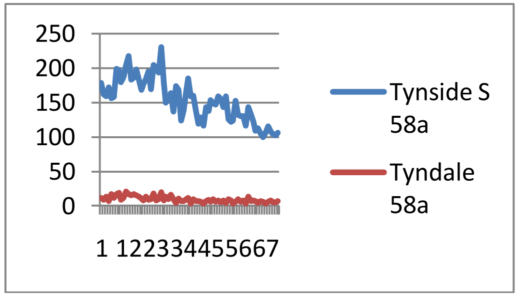
Crime Sub-Group Category 58A

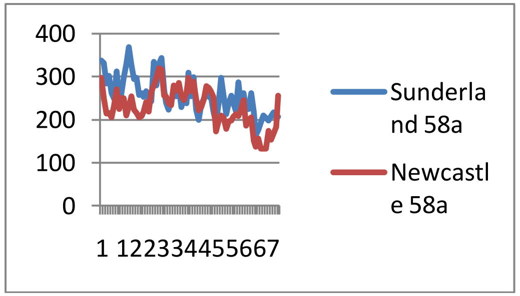


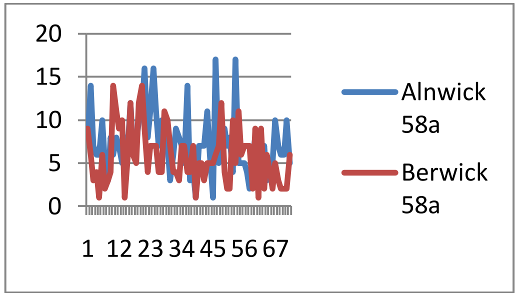


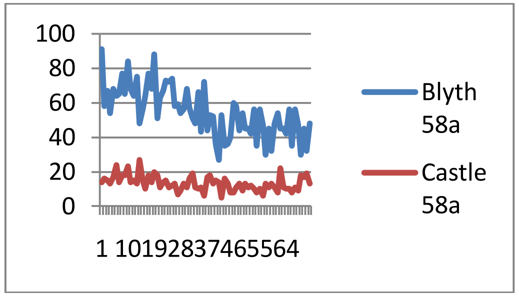


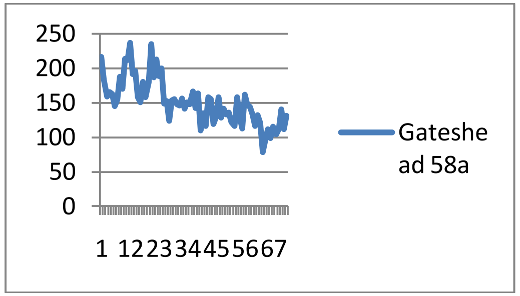




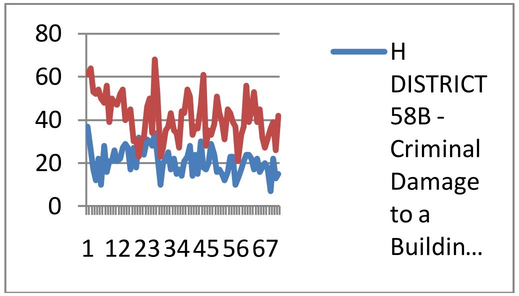


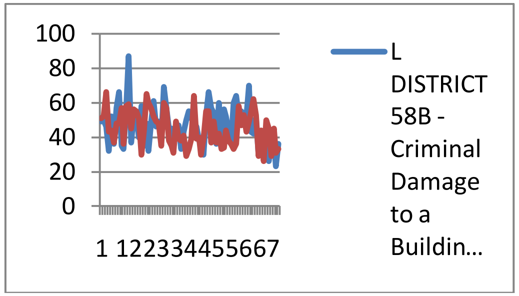


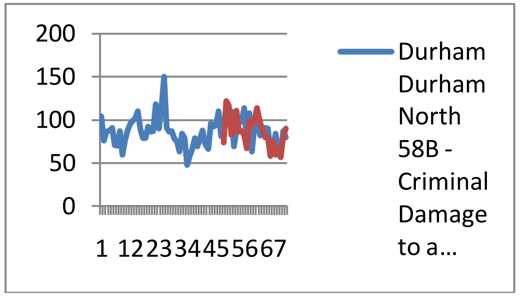


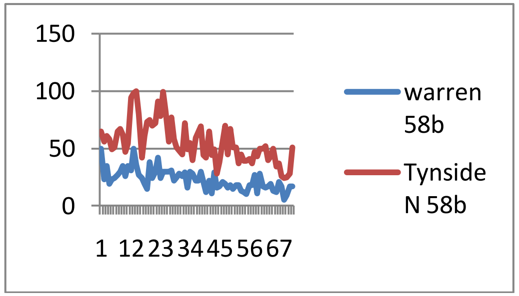


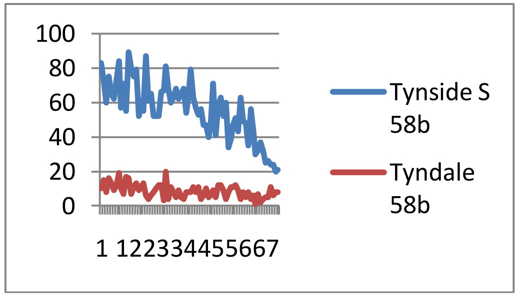
Crime Sub-Group Category 58B

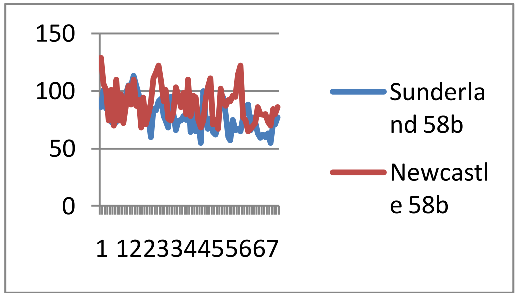


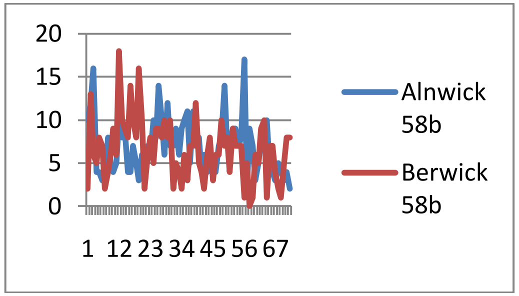


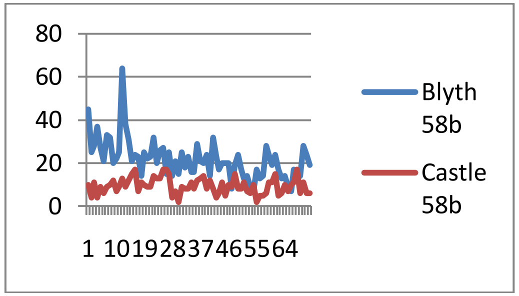


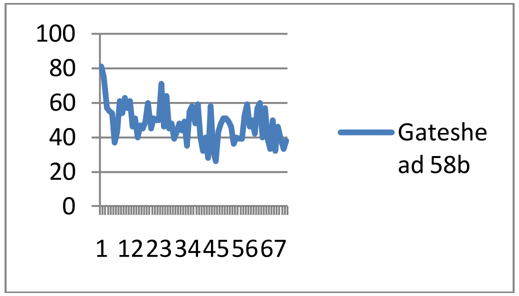




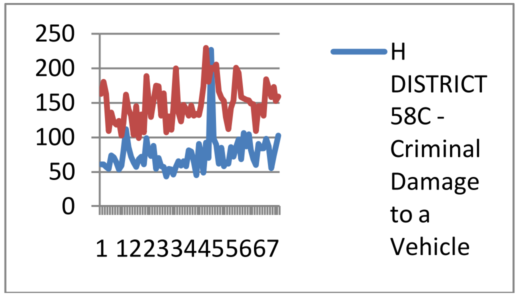


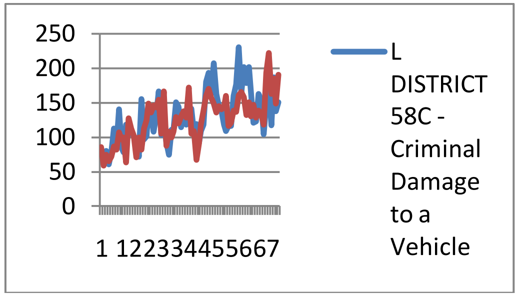


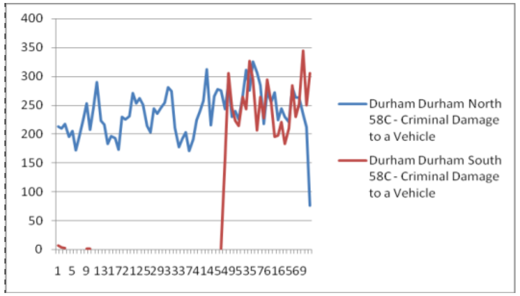


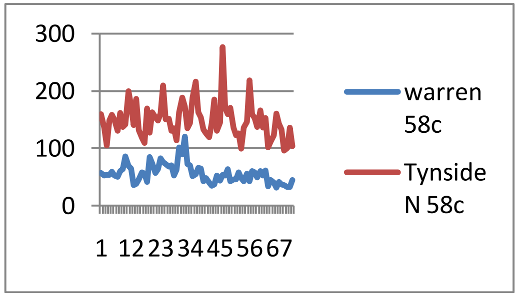


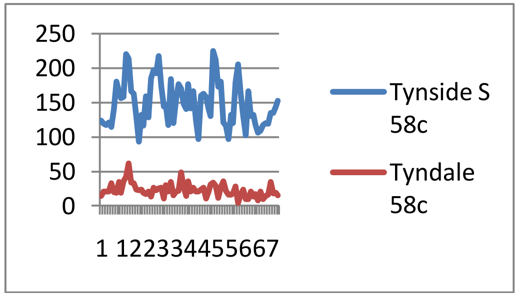
Crime Sub-Group Category 58C

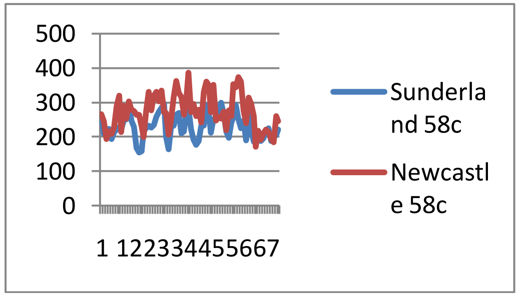


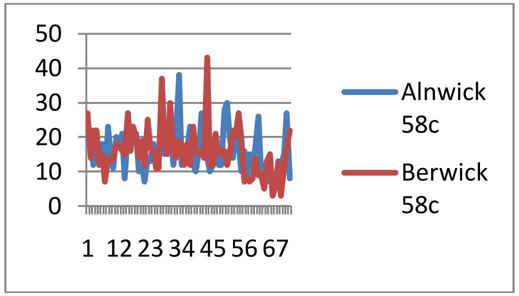


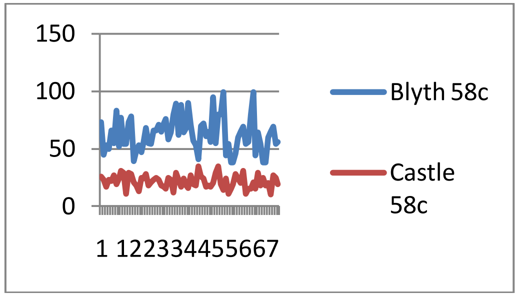


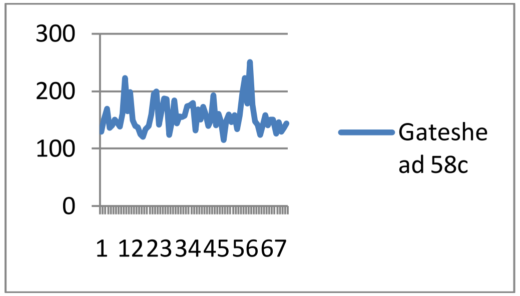




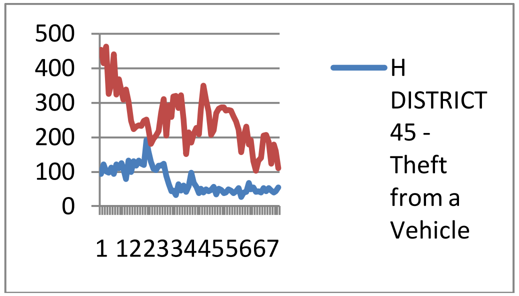


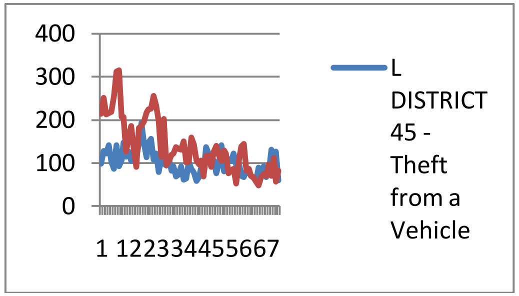


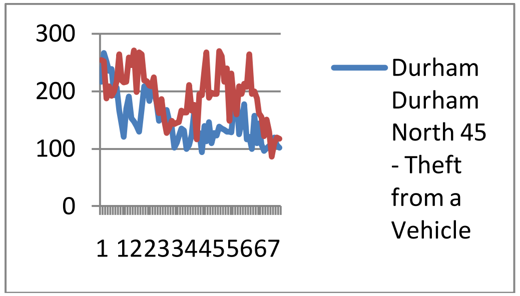


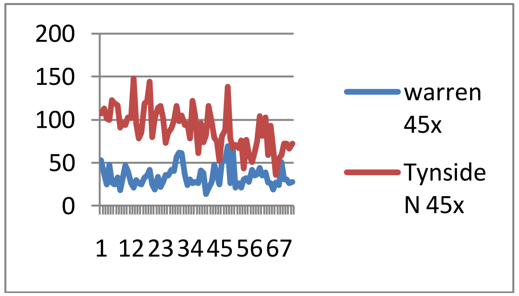


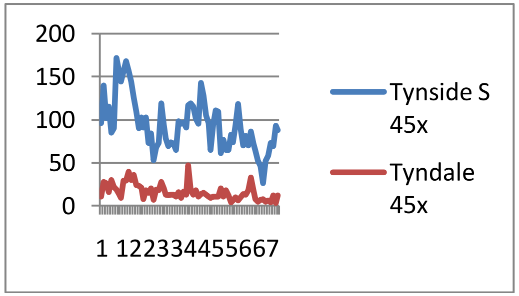
Crime Sub-Group Category 45

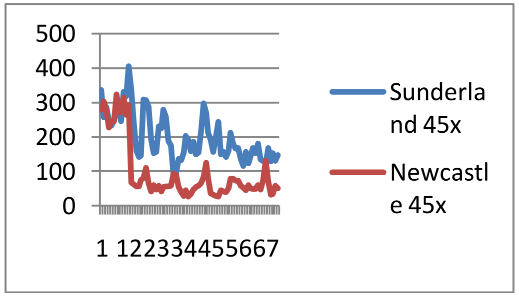


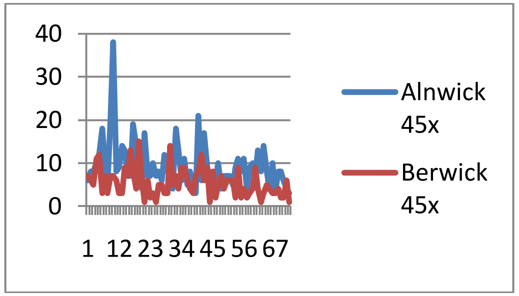


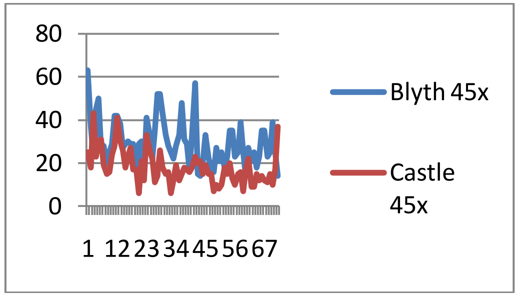


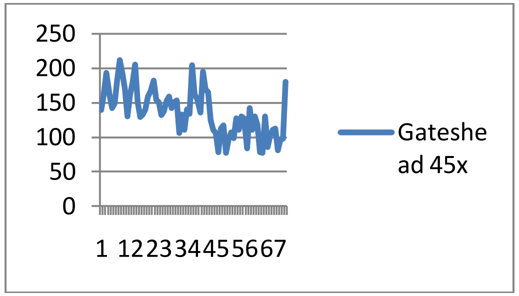




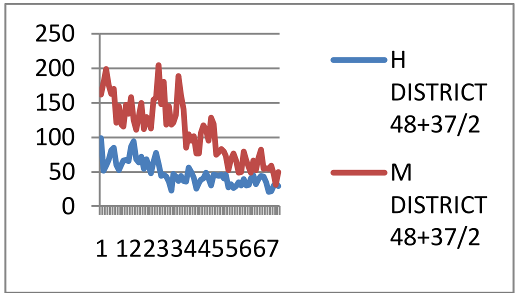


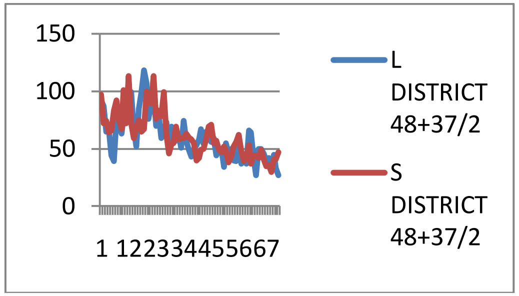


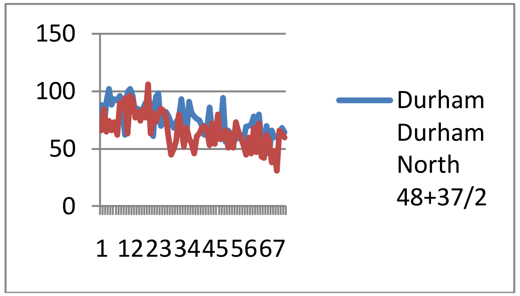


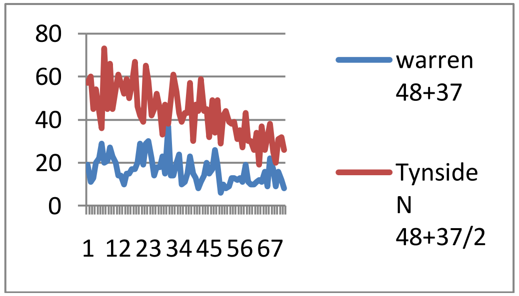


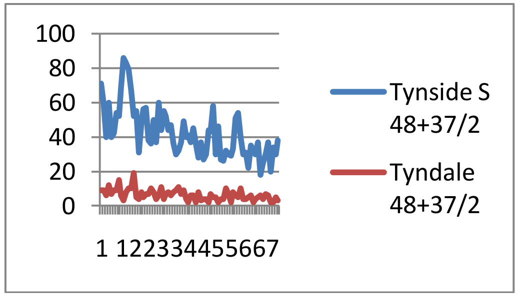
Crime Sub-Group Category 48 + 37/2

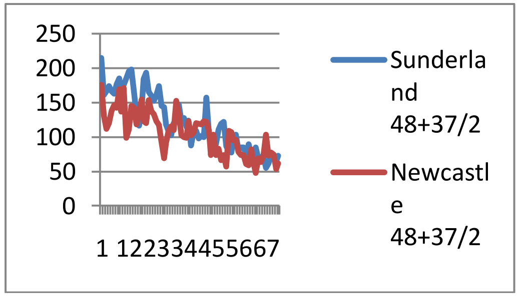


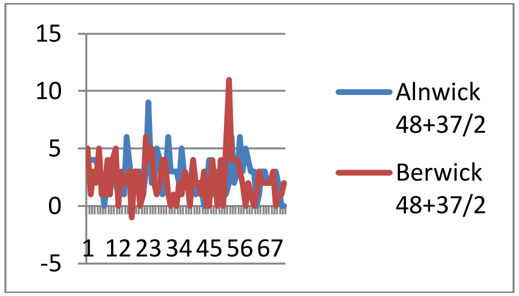


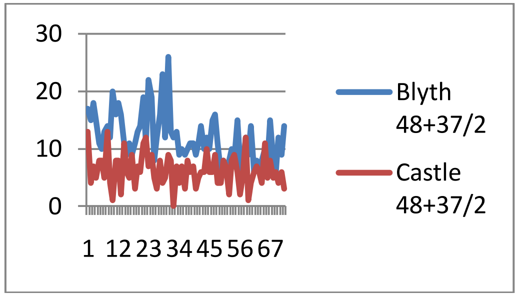


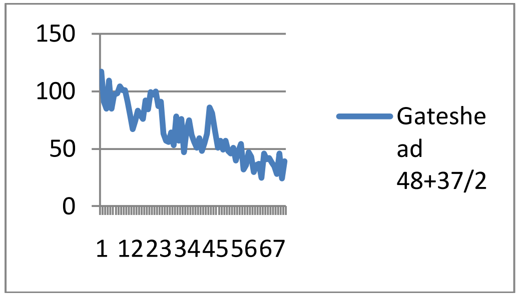




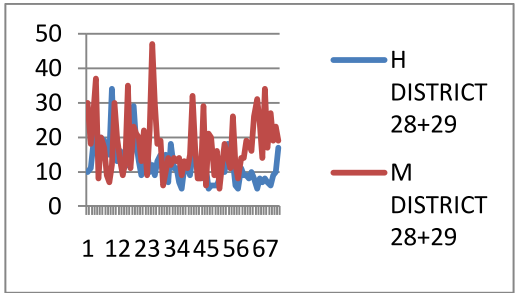


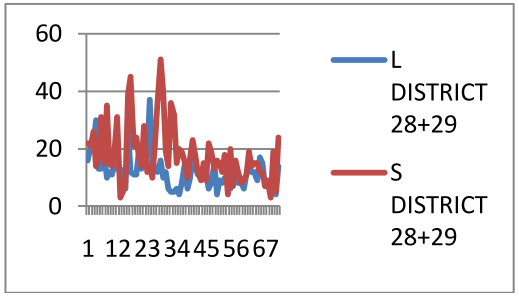


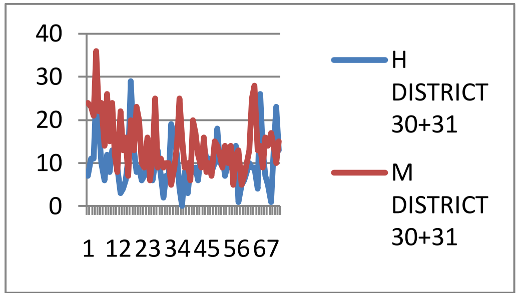


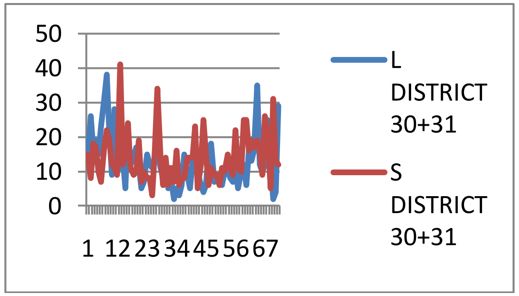


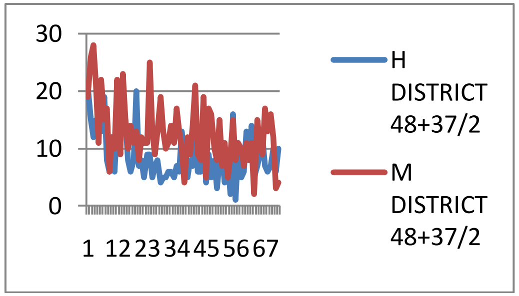
Detection Rates – Cleveland

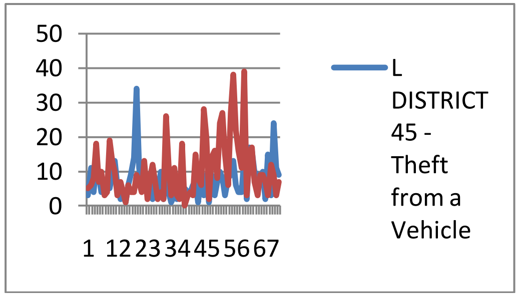


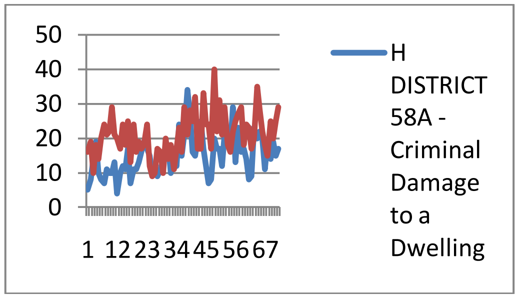


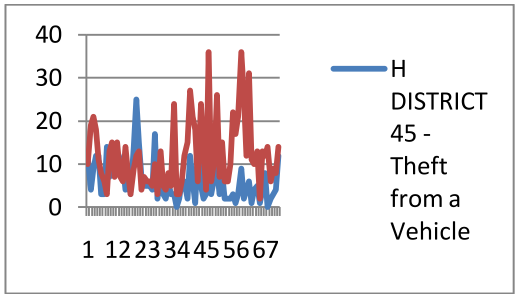


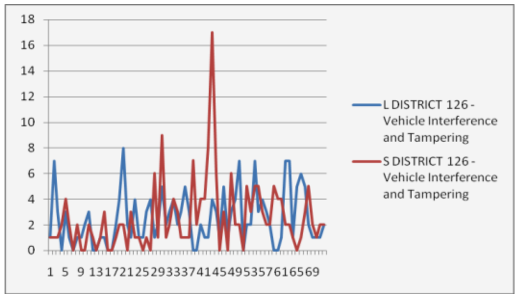


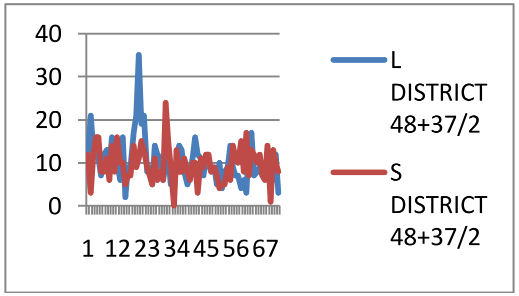




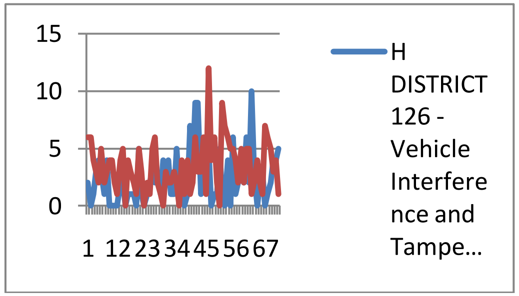




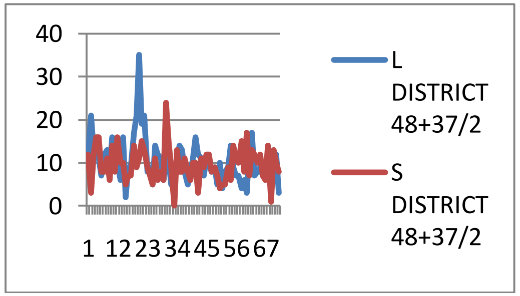




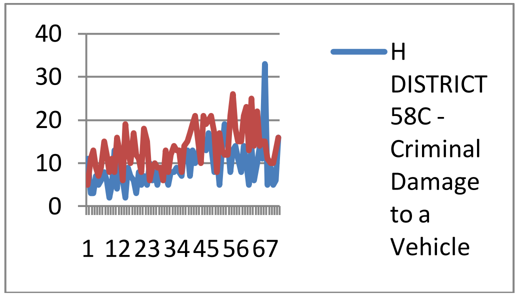
40
30
20
10
0
1 12 23 34 45 56 67
L DISTRICT 48+37/2
S DISTRICT 48+37/2



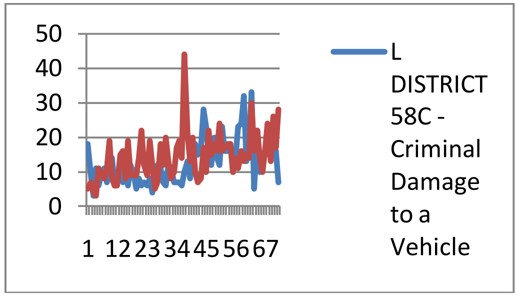
15
10
5
0
1 12 23 34 45 56 67
H DISTRICT 126 - Vehicle Interference and Tampe...



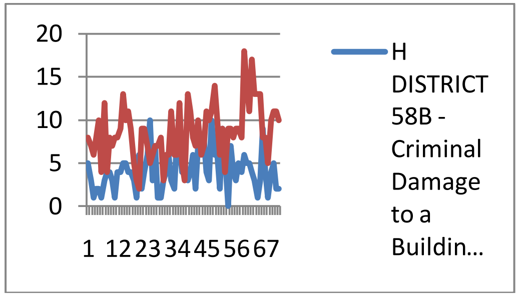
40
30
20
10
0
1 12 23 34 45 56 67
L DISTRICT 48+37/2
S DISTRICT 48+37/2



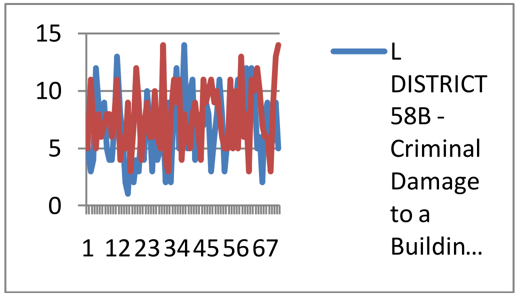
40
30
20
10
0
1 12 23 34 45 56 67
H DISTRICT 58C - Criminal Damage to a Vehicle

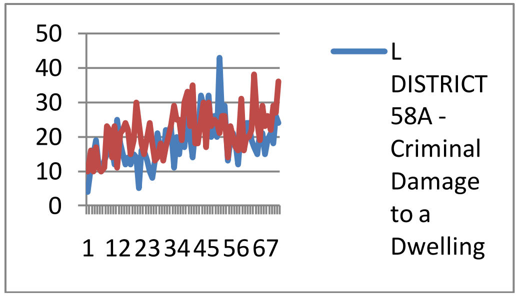


50
40
30
20
10
0
1 12 23 34 45 56 67
L DISTRICT 58C - Criminal Damage to a Vehicle

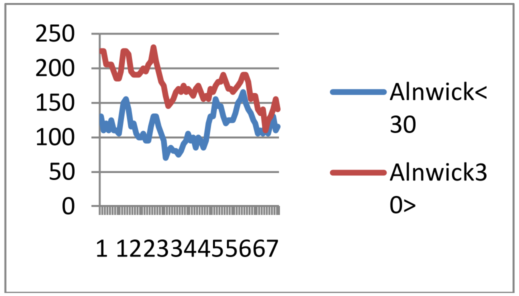


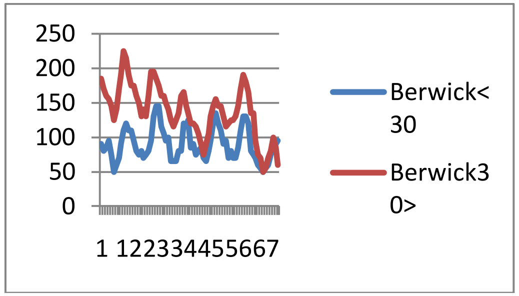
20
15
10
5
0
1 12 23 34 45 56 67
H DISTRICT 58B - Criminal Damage to a Buildin...

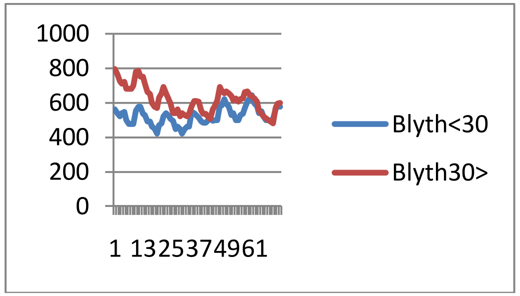

15
10
5
0
1 12 23 34 45 56 67
L DISTRICT 58B - Criminal Damage to a Buildin...

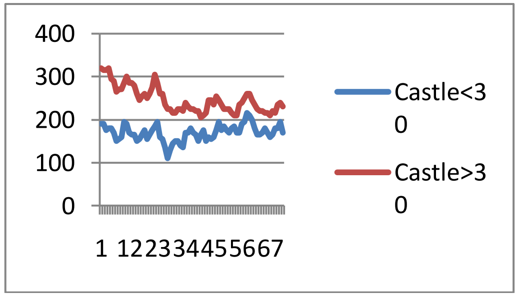

50
40
30
20
10
0
1 12 23 34 45 56 67
L DISTRICT 58A - Criminal Damage to a Dwelling

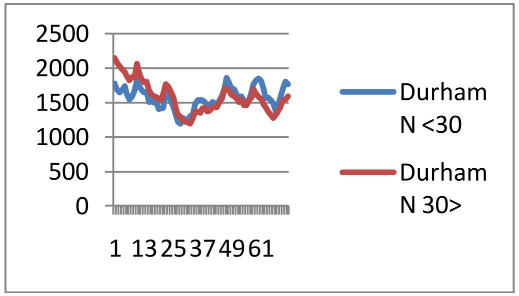
Claimant Counts

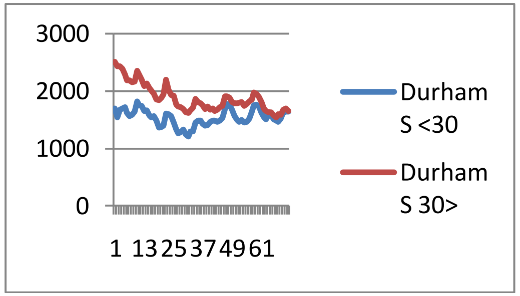


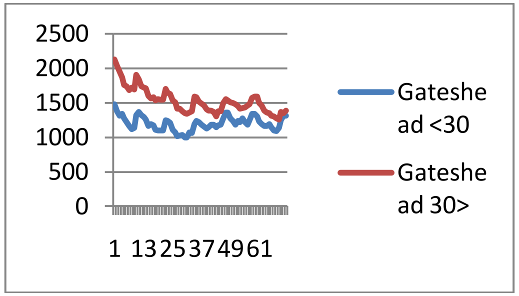


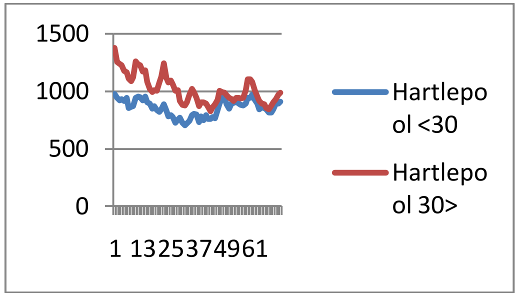


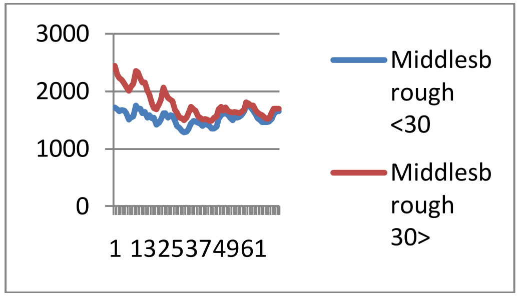


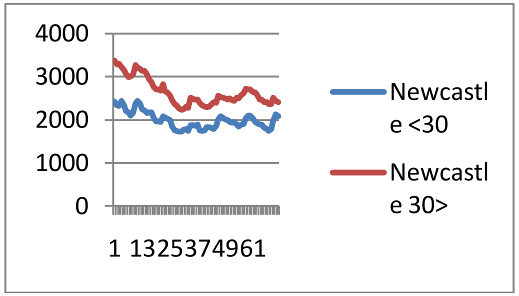


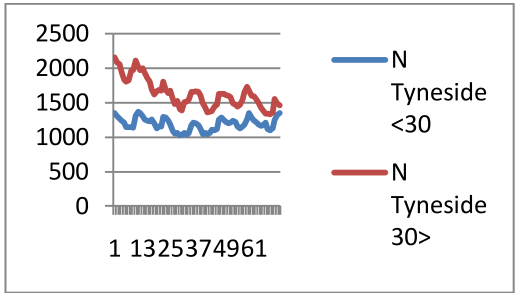


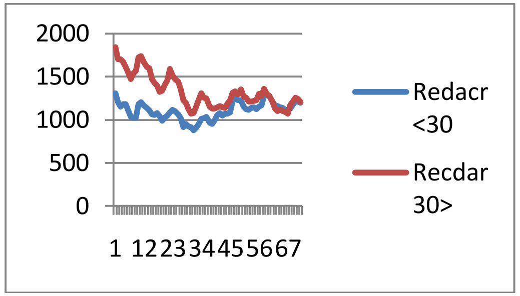


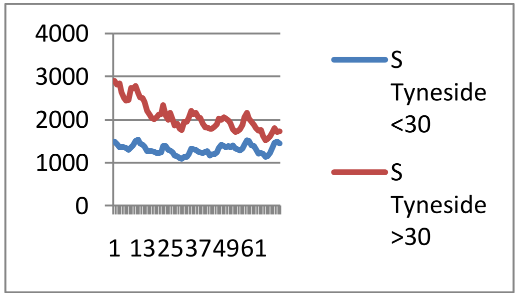


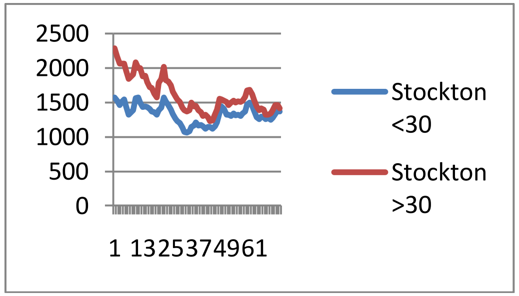


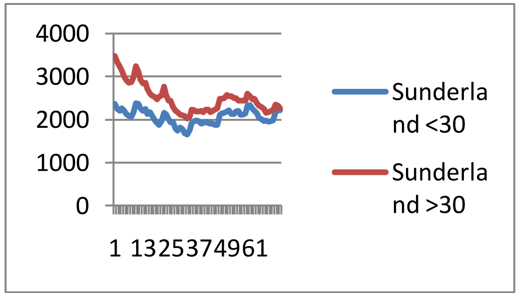

4000
3000
2000
1000
0
1 1325374961
Newcastle <30
Newcastle 30>

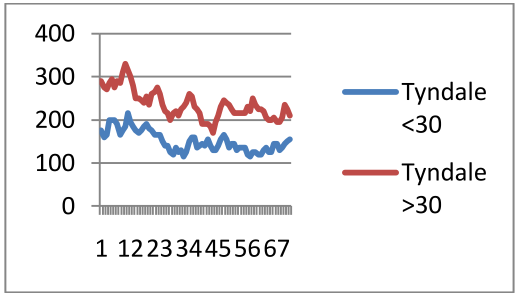

2500
2000
1500
1000
500
0
1 1325374961
N Tyneside <30
N Tyneside 30>

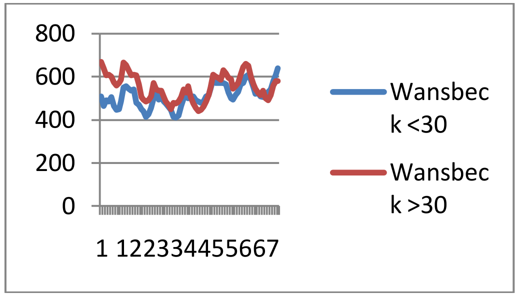

2000
1500
1000
500
0
1 122334455667
Redacr <30
Recdar 30>


4000
3000
2000
1000
0
1 1325374961
S Tyneside <30
S Tyneside >30


2500
2000
1500
1000
500
0
1 1325374961
Stockton <30
Stockton >30


4000
3000
2000
1000
0
1 1325374961
Sunderland <30
Sunderland >30


400
300
200
100
0
1 122334455667
Tyndale <30
Tyndale >30


800
600
400
200
0
1 122334455667
Wansbeck <30
Wansbeck >30

Appendix 4

Unit Root Results

Augmented Dickey Fuller Unit Root Test Results
All data, (Apr 2002 to Mar 2008)

Area Log (Crime Category)	Intercept	Trend & Intercept	None	1^{st} Difference
warren 28+29				**
warren 30+31	**	**		**
warren 45	**	**		**
warren 48+37/2	**	**		**
warren 58a		**		**
warren 58b		**		**
warren 58c		**		**
warren 126	**	**		**
Tynside N 28+29		**		**
Tynside N 30+31	**	**		**
Tynside N 45	**	**		**
Tynside N 48+37/2		**		**
Tynside N 58a		**		**
Tynside N 58b	*	**		**
Tynside N 58c	**			**
Tynside N 126	**	**		**
Tynside S 28+29		**		**
Tynside S 30+31		**		**
Tynside S 45	*	*		**
Tynside S 48+37/2	*	**		**
Tynside S 58a		**		**
Tynside S 58b				**
Tynside S 58c	**	**		**
Tynside S 126				**
Tyndale 28+29				**
Tyndale 30+31	**	**		**
Tyndale 45		**		**
Tyndale 48+37/2		**		**
Tyndale 58a		**		**
Tyndale 58b	**	**		**
Tyndale 58c		**		**
Tyndale 126		**		**
Sunderland 28+29		**		**
Sunderland 30+31		**		**
Sunderland 45				**
Sunderland 48+37/2		**		**
Sunderland 58a	**	**		**
Sunderland 58b	**	**		**
Sunderland 58c	**	**		**
Sunderland 126		**		**
Newcastle 28+29		**		**
Newcastle 30+31		*		**
Newcastle 45	**	**		**
Newcastle 48+37/2		**		**
Newcastle 58a				**
Newcastle 58b	**	**		**
Newcastle 58c	**	**		**
Newcastle 126	*	**		**
Alnwick 28+29	*	**		**
Alnwick 30+31	**	**		**
Alnwick 45				**
Alnwick 48+37/2				**
Alnwick 58a	**	**		**
Alnwick 58b	*	*		**
Alnwick 58c	**	**		**
Alnwick 126	**	**	*	**
Berwick 28+29	**	**		**
Berwick 30+31	**	**		**
Berwick 45	**	**		**
Berwick 48+37/2	**	**		**
Berwick 58a	**	**		**
Berwick 58b	**	**		**
Berwick 58c		**		**
Berwick 126	**	**	*	**
Blyth 28+29	**	**		**
Blyth 30+31		**		**
Blyth 45	**	**		**
Blyth 48+37/2	**	*		**
Blyth 58a		**		**
Blyth 58b	*	**		**

Blyth 58c	**	**		**
Blyth 126	**	**		**
Castle 28+29	**	**		**
Castle 30+31	**	**		**
Castle 45	**	**		**
Castle 48+37/2	**	**		**
Castle 58a	**	**		**
Castle 58b	**	**		**
Castle 58c	**	**		**
Castle 126	**	**		**
Gateshead 28+29		*		**
Gateshead 30+31				**
Gateshead 45	*	*		**
Gateshead 48+37/2		**		**
Gateshead 58a				**
Gateshead 58b		**		**
Gateshead 58c	**	**		**
Gateshead 126		*		**
Durham North 28+29		**		**
Durham South 28+29				**
Durham North 30+31	*	**		**
Durham South 30+31				**
Durham North 45		**		**
Durham South 45				**
Durham North 48+37/2		**		**
Durham South 48+37/2		**		**
Durham North 126	*	*		**
Durham South 126				**
Durham North 58a	**	*		**
Durham North 58b		**		**
Durham North 58c				**
H DISTRICT 28+29	*	**		**
M DISTRICT 28+29	**	**		**
L DISTRICT 28+29	*	**		**
S DISTRICT 28+29		**		**
H DISTRICT 30+31		**		**
M DISTRICT 30+31				**
L DISTRICT 30+31		**		**
S DISTRICT 30+31				**
H DISTRICT 45				**

M DISTRICT 45				**
L DISTRICT 45				**
S DISTRICT 45		**		**
H DISTRICT 48+37/2		**		**
M DISTRICT 48+37/2		**		**
L DISTRICT 48+37/2		**		**
S DISTRICT 48+37/2		**		**
H DISTRICT 126	**	**		**
M DISTRICT 126		**		**
L DISTRICT 126		**		**
S DISTRICT 126			**	**
H DISTRICT 58a	**	*		**
M DISTRICT 58a	**	**		**
L DISTRICT 58a	*	*		**
S DISTRICT 58a	**	**		**
H DISTRICT 58b	**	**		**
M DISTRICT 58b	**	**		**
L DISTRICT 58b	**	**		**
S DISTRICT 58b	**	**		**
H DISTRICT 58c	**	**		**
M DISTRICT 58c	**	**		**
L DISTRICT 58c		**		**
S DISTRICT 58c		**		**
Wansbeck <30		**		**
Wansbeck >30	*	*		**
Tyndale <30				**
Tyndale >30	*	**		**
Sunderland <30	*			**
Sunderland >30	*			**
Stockton <30	*			**
Stockton >30				**
S Tyneside <30	**	*		**
S Tyneside >30		**		**
Redacr <30				**
Recdar 30>				**
N Tyneside <30	**	*		**
N Tyneside 30>				**
Newcastle <30				**
Newcastle 30>	*			**
Middlesbrough <30				**

Middlesbrough 30>	**			**
Hartlepool <30				**
Hartlepool 30>				**
Gateshead <30				**
Gateshead 30>	**	*		**
Durham S <30	**	*		**
Durham S 30>				**
Durham N <30	*	*		**
Durham N 30>	**			**
Castle<30	*	*		**
Castle>30				**
Blyth<30				**
Blyth30>	*	*		**
Berwick<30	**			**
Berwick30>				**
Alnwick<30				**
Alnwick30>				**
H DISTRICT det 28+29		**		**
M DISTRICT det 28+29	**	**		**
L DISTRICT det 28+29		**		**
S DISTRICT det 28+29	**	**		**
H DISTRICT det 30+31	**	*		**
M DISTRICT det 30+31	**	**		**
L DISTRICT det 30+31	**	**		**
S DISTRICT det 30+31	**	**		**
H DISTRICT det 45	*	**		**
M DISTRICT det 45	**	**		**
L DISTRICT det 45	**	**		**
S DISTRICT det 45				**
H DISTRICT det 48+37/2		**		**
M DISTRICT det 48+37/2	**	**		**
L DISTRICT det 48+37/2	**	**		**
S DISTRICT det 48+37/2	**	**		**
H DISTRICT det 126	**	**		**
M DISTRICT det 1 126	**	**		**
L DISTRICT det 126	**	**		**
S DISTRICT det 126	*	**		**
H DISTRICT det 58a		**		**
M DISTRICT det 58a				**
L DISTRICT det 58a		**		**
S DISTRICT det 58a	**	**		**
H DISTRICT det 58b	**	**		**
M DISTRICT det 58b	**	**		**
L DISTRICT det 58b	**	**		**
S DISTRICT det 58b	**	**		**
H DISTRICT det 58c	*	**		**
M DISTRICT det 58c		**		**
L DISTRICT det 58c				**
S DISTRICT det 58c	**	**		**

Notes
* Significance against the 5% critical value
** Significance against the 1% critical value
ADF Unit root tests conducted using PCGive 12.1 software

Appendix 5

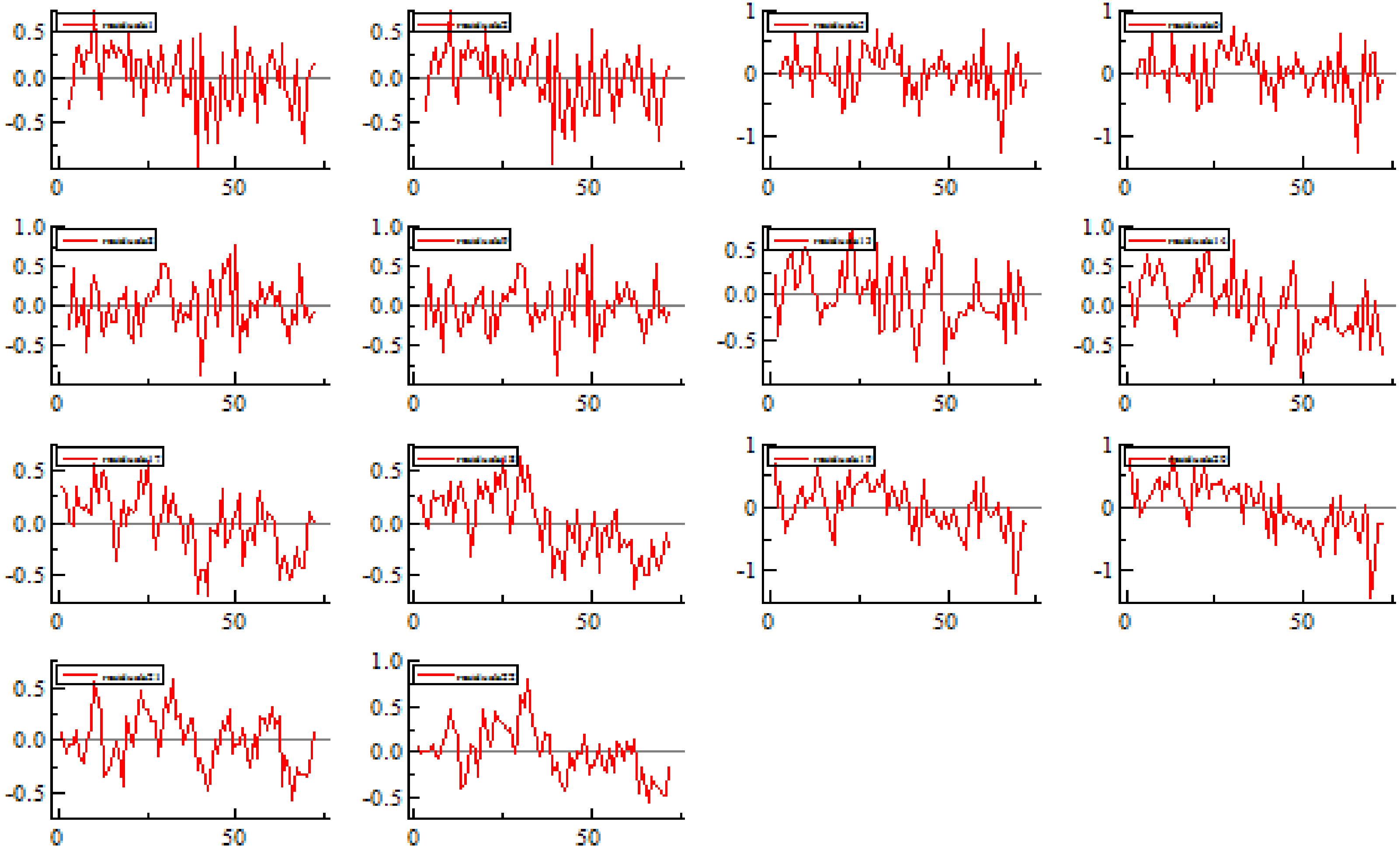
Co-integration regression test matrix – Individual relationships

	Claimant Count <30	Claimant Count >30	Detection	30+31	48+37/2	58a	58b	58c	126
warren 28+29	*	*		*		*			
warren 30+31	*	*					*		
warren 45	*	*			*			*	*
warren 48+37/2	*	*						*	*
warren 58a	*	*							
warren 58b	*	*							
warren 58c	*	*							
warren 126	*	*							
Tynside N 28+29	*	*		*		*			
Tynside N 30+31	*	*					*		
Tynside N 45	*	*			*			*	*
Tynside N 48+37/2	*	*						*	*
Tynside N 58a	*	*							
Tynside N 58b	*	*							
Tynside N 58c	*	*							
Tynside N 126	*	*							
Tynside S 28+29	*	*		*		*			
Tynside S 30+31	*	*					*		
Tynside S 45	*	*			*			*	*
Tynside S 48+37/2	*	*						*	*
Tynside S 58a	*	*							
Tynside S 58b	*	*							
Tynside S 58c	*	*							
Tynside S 126	*	*							
Tyndale 28+29	*	*		*		*			
Tyndale 30+31	*	*					*		
Tyndale 45	*	*			*			*	*
Tyndale 48+37/2	*	*						*	*
Tyndale 58a	*	*							
Tyndale 58b	*	*							
Tyndale 58c	*	*							
Sunderland 28+29	*	*		*		*			
Sunderland 30+31	*	*					*		
Sunderland 45	*	*			*			*	*
Sunderland 48+37/2	*	*						*	*
Sunderland 58a	*	*							
Sunderland 58b	*	*							
Sunderland 58c	*	*							
Sunderland 126	*	*							
Newcastle 28+29	*	*		*		*			
Newcastle 30+31	*	*					*		
Newcastle 45	*	*			*			*	*
Newcastle 48+37/2	*	*						*	*
Newcastle 58a	*	*							
Newcastle 58b	*	*							
Newcastle 58c	*	*							
Newcastle 126	*	*							
Alnwick 30+31	*	*					*		
Alnwick 45	*	*			*			*	*
Alnwick 58a	*	*							
Alnwick 58b	*	*							
Alnwick 58c	*	*							
Berwick 30+31	*	*					*		
Berwick 58b	*	*							
Berwick 58c	*	*							
Blyth 28+29	*	*		*		*			
Blyth 30+31	*	*					*		
Blyth 45	*	*			*			*	*
Blyth 48+37/2	*	*						*	*
Blyth 58a	*	*							
Blyth 58b	*	*							
Blyth 58c	*	*							

Castle 28+29	*	*		*		*			
Castle 30+31	*	*					*		
Castle 45	*	*			*			*	*
Castle 48+37/2	*	*						*	*
Castle 58a	*	*							
Castle 58b	*	*							
Castle 58c	*	*							
Castle 126	*	*							
Gateshead 28+29	*	*		*		*			
Gateshead 30+31	*	*					*		
Gateshead 45	*	*			*			*	*
Gateshead 48+37/2	*	*						*	*
Gateshead 58a	*	*							
Gateshead 58b	*	*							
Gateshead 58c	*	*							
Gateshead 126	*	*							
Durham North 28+29	*	*		*		*			
Durham South 28+29	*	*		*		*			
Durham North 30+31	*	*					*		
Durham South 30+31	*	*					*		
Durham North 45	*	*			*			*	*
Durham South 45	*	*			*			*	*
Durham North 48+37/2	*	*						*	*
Durham South 48+37/2	*	*						*	*
Durham North 126	*	*							
Durham South 126	*	*							
Durham North 58a	*	*							
Durham North 58b	*	*							
Durham North 58c	*	*							
H DISTRICT 28+29	*	*	*	*		*			
M DISTRICT 28+29	*	*	*	*		*			
L DISTRICT 28+29	*	*	*	*		*			
S DISTRICT 28+29	*	*	*	*		*			
H DISTRICT 30+31	*	*	*				*		
M DISTRICT 30+31	*	*	*				*		
L DISTRICT 30+31	*	*	*				*		
S DISTRICT 30+31	*	*	*				*		
H DISTRICT 45	*	*	*		*			*	*
M DISTRICT 45	*	*	*		*			*	*
L DISTRICT 45	*	*	*		*			*	*
S DISTRICT 45	*	*	*		*			*	*
H DISTRICT 48+37/2	*	*	*					*	*
M DISTRICT 48+37/2	*	*	*					*	*
L DISTRICT 48+37/2	*	*	*					*	*
S DISTRICT 48+37/2	*	*	*					*	*
H DISTRICT 126	*	*							
M DISTRICT 126	*	*							
L DISTRICT 126	*	*							
S DISTRICT 126	*	*							
H DISTRICT 58a	*	*	*						
M DISTRICT 58a	*	*	*						
L DISTRICT 58a	*	*	*						
S DISTRICT 58a	*	*	*						
H DISTRICT 58b	*	*	*						
M DISTRICT 58b	*	*	*						
L DISTRICT 58b	*	*	*						
S DISTRICT 58b	*	*	*						
H DISTRICT 58c	*	*	*						
M DISTRICT 58c	*	*	*						
L DISTRICT 58c	*	*	*						
S DISTRICT 58c	*	*	*						

Appendix 6

Cointegrating Regression Residual plots(1-22 claimant counts only)



Appendix 7

csc_t	Claimant Count <30	Claimant Count >30	Detection	30+31	48+37/2	58a	58b	58c	126	ε_t	β_1	β_2	R_2	DW	t	t-prob	AR 1-2	Arch 1-1	Normality	Hetero	Hetero-x	RESET
Castle 48+37/2									*	-0.0104	0.193	-1.263	0.6385	2.1	2.73	0.008			**			
Castle 48+37/2								*		-0.0083	0.3454	-1.2599	0.6324	1.98	2.21	0.0303			**			
Castle 48+37/2	*									-0.0121	-1.147	-1.206	0.6196	2.04	-1.53	0.1302			**			
Castle 48+37/2		*								-0.0064	0.9141	-1.2232	0.6127	2.05	0.682	0.4973			**			
Tyndale 48+37/2									*	-0.0039	0.3707	-1.1519	0.6086	2.05	5.75	0						
Berwick 58b	*									0.0156	-1.3757	-1.0193	0.5657	1.96	-2.82	0.0064			**			
Berwick 58b		*								-0.0068	-1.0498	-1.0938	0.5564	2	-1.61	0.112			**			
Castle 58c		*								0.0023	1.2665	-1.0755	0.5543	2.04	1.84	0.0705						
Alnwick 45		*								0.011	1.3061	-1.0934	0.5493	1.99	1.51	0.136				*	**	
Tyndale 58b	*									-0.004	-0.614	-1.0315	0.5426	2.0	-	0.39			*			

														2	0.859	35			*			
Castle 58c	*									-0.0023	0.5415	-1.0686	0.5395	2.0 2	1.36	0.17 74						
Gateshead 58b		*								-0.0072	0.297	-1.029	0.5257	2.0 5	0.555	0.58 09						
Tyndale 58b		*								-0.0074	-0.381	-1.0055	0.5161	2.0 2	- 0.399	0.69 15			* *			
Alnwick 45	*									0.0063	0.9124	-1.026	0.5117	1.9 1	1.63	0.10 74						
Alnwick 45								*		0.0046	0.1246	-1.0339	0.5103	1.9 5	1.1	0.27 72						*
Tyndale 58a		*								-0.0058	0.4049	-1.0039	0.5099	2.0 8	0.496	0.62 17						
Alnwick 58a		*								-0.0106	-0.8236	-0.998	0.5078	1.9 6	-0.86	0.39 28			* *			
Alnwick 45									*	0.0043	0.1949	-1.0507	0.5055	1.9 4	1.98	0.05 21						*
Alnwick 58c	*									-0.0066	-1.3416	-0.9164	0.5018	1.8 7	-3.18	0.00 22						
Alnwick 45					*					0.0026	-0.1305	-1.0034	0.5013	1.9 4	-1.63	0.67 4						
Durham South 28+29		*								0.0069	1.5987	-0.8575	0.4987	1.9 5	3.69	0.00 05						
Tyndale 58c	*									0.0088	1.54	-0.9996	0.4935	1.9 5	2.38	0.02						
H DISTRICT 58b		*								-0.0121	-0.6089	-0.9309	0.4789	1.9 9	- 0.782	0.43 72			*			
H DISTRICT 58b			*							-0.0092	0.062	-0.9009	0.4775	2.0 3	1.44	0.15 48			*			
H DISTRICT 58b	*									-0.011	-1.931	-0.902	0.4774	1.9 9	-2.19	0.03 18			*			

Tyndale 58c		*								0.0071	0.6969	-0.9405	0.4751	2.0 2	0.835	0.40 66			* *			
Alnwick 58a	*									-0.0032	-0.067	-0.9491	0.4743	1.9 9	- 0.109	0.91 32			* *			
warren 28+29						*				-0.006	0.6036	-0.696	0.472	2.0 1	4.42	0						
Castle 58a		*								0.0018	0.8884	-0.9017	0.4671	2	1.17	0.24 68						
Alnwick 58c		*								-0.0047	0.1338	-0.9379	0.4658	1.9 6	0.19	0.85						
Castle 28+29		*								-0.00652	1.4086	-0.9535	0.4651	2.0 1	0.851	0.39 78			* *			
Tyndale 58a	*									-0.0037	0.4072	-0.9233	0.4633	2.1 2	0.615	0.54 08	*					
Tyndale 45		*								-0.0063	-1.372	-0.8448	0.4626	2.2	-1.27	0.20 97	*		* *			
Tyndale 48+37/2	*									-0.0101	-1.3192	-0.8278	0.4594	2.0 1	-1.76	0.08 22						
Alnwick 30+31		*								-0.0013	0.7798	-0.9193	0.4568	1.9 6	0.934	0.35 37						
Tyndale 48+37/2		*								-0.0103	-0.2344	-0.8961	0.4559	2.0 1	- 0.234	0.81 57						
Castle 58b		*								-0.0122	-2.0184	-0.9066	0.4541	2.0 1	-1.82	0.07 31			* *			
warren 30+31							*			-0.0014	0.3985	-0.7504	0.453	1.9 5	4.07	0.00 01						
Berwick 30+31	*									-0.0096	-0.9757	-0.8622	0.4522	1.8 8	-2.63	0.01 05						
Blyth 30+31							*			-0.0061	0.2612	-0.8695	0.4519	2.0 1	2.13	0.03 67			* *			* *
Castle 28+29						*				-0.0104	0.1259	-0.8969	0.4512	2.0	0.637	0.52			*			

														9		65			*			
Blyth 45									*	-0.0129	0.1838	-0.8617	0.4484	1.9 4	4.36	0						
Tyndale 45	*									0.0024	-0.3658	-0.8467	0.448	2.0 4	- 0.432	0.66 69			* *	*	* *	
Castle 30+31		*								-0.0061	1.2487	-0.8851	0.444	2.0 4	1.49	0.14 13						
Castle 126	*									0.0039	0.8427	-0.8699	0.4424	1.9 9	0.894	0.37 43						
Alnwick 30+31							*			-0.0032	0.1364	-0.8761	0.4422	1.9 8	1.37	0.17 63			*			
Castle 58b	*									-0.005	-1.3919	-0.8666	0.4422	1.9 9	-2.24	0.02 81			* *			
S DISTRICT 58b		*								0.0001	0.5173	-0.9124	0.4421	1.9 8	0.836	0.40 59						
L DISTRICT 58b		*								-0.0057	-0.637	-0.8688	0.4411	2.0 1	- 0.966	0.33 75						
Castle 126		*								-0.0013	-0.8084	-0.8644	0.4359	1.9 5	- 0.482	0.63 1						
L DISTRICT 58b			*							-0.0019	0.0836	-0.8185	0.4355	2.0 1	2	0.04 94						
H DISTRICT 58c	*									0.0065	2.4	-0.7589	0.4351	2.0 8	3.57	0.00 07			* *	*	*	
L DISTRICT 48+37/2									*	-0.0082	0.341	-0.4281	0.4334	1.9 8	6.45	0	*					* *
Blyth 30+31		*								-0.0066	0.7263	-0.8547	0.4328	2	0.707	0.48 22			* *			* *
Castle 28+29				*						-0.0089	0.1773	-0.8669	0.432	2.1 1	0.963	0.33 9	*		* *		*	
Durham South 48+37/2		*								0.0023	0.7511	-0.8312	0.431	2.1	1.22	0.22 59						

S DISTRICT 58b	*									-0.003	-0.2698	-0.8504	0.43	2.01	-0.426	0.6711						
Alnwick 30+31	*									-0.0032	0.2326	-0.8583	0.4284	2	0.438	0.6626						
Tyndale 45									*	0.0029	0.2313	-0.846	0.4241	2.04	2.6	0.0113			**	*		
Gateshead 58c		*								0.0102	1.3608	-0.6987	0.4233	1.97	3.42	0.0011						
warren 45								*		-0.0065	0.4901	-0.8068	0.4197	1.98	3.15	0.0024						
L DISTRICT 58b	*									-0.0027	-0.8454	-0.8371	0.4189	2.01	-1.19	0.2371						
Castle 30+31							*			-0.0117	-0.1416	-0.8001	0.4188	2.12	-1.98	0.0521						
Berwick 30+31		*								-0.0143	-0.162	-0.8245	0.4183	1.96	-0.336	0.7379			*			
Tyndale 48+37/2								*		-0.0093	0.1898	-0.8144	0.4156	2.02	1.79	0.0782						
Castle 28+29	*									-0.0098	0.0975	-0.827	0.4147	2.11	0.101	0.92	*		**			*
Tyndale 30+31		*								-0.0136	-1.144	-0.7123	0.4147	2.01	-1.8	0.0763						
Berwick 30+31							*			-0.0095	-0.0198	-0.811	0.4141	1.94	-0.323	0.7477						
S DISTRICT 58b			*							-0.0044	0.1004	-0.748	0.4111	1.99	2.11	0.0382		*				
warren 45									*	-0.0062	0.0975	-0.7848	0.4086	2	2.57	0.0125						
Tyndale 45								*		-0.0002	0.3669	-0.7597	0.4079	2.11	3.03	0.0035			**			
Blyth 28+29						*				-0.0007	0.666	-0.7729	0.407	2	4.09	0.00			*			

																01						
Blyth 58c		*								0.0005	0.8429	-0.7891	0.4065	1.97	1.55	0.1269						*
M DISTRICT 58a		*								0.0022	0.6796	-0.7951	0.4054	1.92	1.61	0.1124		**				*
Tynside N 45					*					-0.0022	0.3603	-0.6686	0.404	1.98	4.07	0.0001						
Castle 30+31	*									-0.0109	0.3079	-0.7683	0.4039	2.12	0.633	0.5289						
H DISTRICT 58c			*							0.004	0.1393	-0.7769	0.4036	2.06	3.13	0.0026			**			
Gateshead 58b	*									-0.0081	-0.2238	-0.7707	0.4033	2.17	-0.44	0.6616						
Gateshead 45									*	0.003	0.2441	-0.4459	0.4022	2.01	5.04	0						
warren 45		*								-0.005	1.5025	-0.752	0.4013	1.84	1.98	0.0517						
M DISTRICT 58b			*							-0.0061	0.0171	-0.7685	0.4012	2.01	0.325	0.7465						
M DISTRICT 58a			*							-0.0015	0.0793	-0.7506	0.3998	1.96	1.78	0.0798		*				
Castle 58a	*									-0.0006	0.4324	-0.7631	0.3992	2.06	0.935	0.3531						
Durham South 48+37/2								*		-0.0012	-0.0235	-0.8045	0.3978	2.11	-0.608	0.5449	*					
Durham North 48+37/2		*								-0.0052	-0.5657	-0.7533	0.3974	2.02	-1.25	0.2139						
H DISTRICT 126		*								-0.0771	1.364	-0.7625	0.3967	2.01	1.14	0.2595						
Tynside N 48+37/2									*	-0.0065	0.2351	-0.6528	0.3963	2.32	4.05	0.0001	**					

Blyth 58c	*									-0.0027	0.5396	-0.776	0.3953	1.98	1.11	0.273						*
H DISTRICT 58c		*								0.0106	1.495	-0.7305	0.394	2.18	2.39	0.0198			**			
warren 48+37/2								*		-0.0048	0.5556	-0.7047	0.3918	1.94	3.57	0.0007						
Blyth 30+31	*									-0.0099	0.2827	-0.7691	0.3916	2.06	0.297	0.7674			**			**
Blyth 45					*					-0.0123	0.1852	-0.7956	0.3874	1.85	1.8	0.0765						
Sunderland 58b		*								-0.0044	-0.3786	-0.7539	0.3873	2.08	-0.701	0.4855						
warren 30+31		*								-0.0042	1.2259	-0.7458	0.384	2.06	1.39	0.1701						
M DISTRICT 58a	*									-0.001	0.0988	-0.7688	0.3838	1.95	0.215	0.8305		**				*
Newcastle 58b	*									-0.0062	-0.3886	-0.718	0.3833	2.19	-0.756	0.4521	*					
warren 30+31	*									-0.0108	1.1977	-0.7638	0.383	2.04	1.31	0.1938						
Blyth 45	*									-0.0144	-0.1863	-0.7474	0.3825	1.85	-0.272	0.7864						
Blyth 48+37/2	*									-0.0058	0.9091	-0.6875	0.3822	2.19	1.42	0.1607						
Berwick 58c		*								-0.0057	0.3193	-0.7496	0.3801	2.01	0.788	0.4335			*	*	*	
M DISTRICT 58b	*									-0.0052	-0.5724	-0.7247	0.3797	2.02	-0.752	0.4546						
warren 45					*					-0.0067	0.1108	-0.7576	0.3785	1.95	1.13	0.2606						
Castle 45		*								-0.0043	0.0079	-0.7793	0.3779	1.9	0.008	0.99						

													5	68	31						
Durham South 30+31							*			-0.0071	0.0051	-0.7363	0.377	2.2	0.138	0.89 04	*					
H DISTRICT 28+29				*						-0.007	0.3476	-0.5828	0.3758	2.1 2	4.39	0						
Newcastle 58b		*								-0.0048	0.1878	-0.7276	0.3751	2.1 5	0.267	0.79 04	*					
Durham North 58a		*								0.0042	1.0779	-0.5828	0.3735	2.1 5	2.92	0.00 47						
warren 48+37/2	*									-0.0094	0.0339	-0.7159	0.3729	2.0 6	0.042 8	0.96 6						
warren 58b	*									-0.0144	0.5543	-0.671	0.3726	2.2	0.652	0.51 65			*			
Blyth 45		*								-0.0125	0.4253	-0.7247	0.3724	1.8 3	0.545	0.58 76		*				
Blyth 45								*		-0.014	0.0113	-0.7291	0.3709	1.8 5	0.085 2	0.93 23						
Gateshead 58c	*									0.0036	0.81	-0.6925	0.3709	1.9 5	2.29	0.02 52						
Berwick 58c	*									-0.0068	-0.0276	-0.7253	0.3702	2.0 7	- 0.087 8	0.93 03			* *			
warren 45	*									-0.0094	0.4083	-0.7668	0.3691	1.9 1	0.505	0.61 55						
Blyth 48+37/2									*	-0.006	0.0385	-0.7304	0.3681	2.1 1	0.93	0.35 58						
Tyndale 45					*					0.0035	0.249	-0.7286	0.3678	2.1 3	2.25	0.02 74			* *		* *	
Blyth 58a		*								-0.0069	0.3231	-0.6926	0.363	2.2 5	0.587	0.55 94	* *					
S DISTRICT 45					*					-0.0061	0.5995	-0.5018	0.3616	2.0	4.11	0.00			*			

														5		01						
Tynside N 30+31							*			-0.0061	0.3101	-0.5912	0.3603	2.06	3.72	0.0004						
Tynside N 48+37/2		*								-0.0045	0.5299	-0.7222	0.3595	2.2	0.804	0.4244	**					
Alnwick 58b		*								-0.0086	0.5648	-0.7331	0.3593	2.04	0.684	0.4963						
Tynside N 58c		*								0.0022	0.9262	-0.728	0.3561	1.99	1.78	0.0794				*		
Blyth 48+37/2		*								0.0009	1.461	-0.6618	0.3553	2.14	1.99	0.0508						
H DISTRICT 48+37/2									*	-0.0119	0.2127	-0.4512	0.3551	1.98	4.95	0				*		
S DISTRICT 58a		*								0.0073	0.3281	-0.6764	0.3549	1.95	0.721	0.4735						
Durham North 58b	*									-0.0028	-0.5035	-0.6857	0.3541	2.08	-1.18	0.244				**	**	
Durham North 58b		*								-0.003	0.0107	-0.6938	0.3533	2.05	0.0198	0.9842						
Blyth 58b		*								-0.007	1.2403	-0.6791	0.3523	2.06	1.54	0.1282						
Tyndale 28+29		*								-0.0119	-1.934	-0.585	0.351	2.27	-1.57	0.1206	*		*			**
Tynside N 58c	*									-0.0025	0.8667	-0.6446	0.35	1.97	1.72	0.09						
Tyndale 30+31	*									-0.0072	-0.2176	-0.6596	0.348	2.01	-0.413	0.6812						
Tynside N 30+31		*								-0.0038	0.8117	-0.5844	0.3452	2.04	1.58	0.1194						
Alnwick 58b	*									-0.0113	-0.2409	-0.7333	0.343	2.04	-0.454	0.6512		*		**	**	

S DISTRICT 48+37/2							*		**-0.0138**	**0.3519**	**-0.2117**	**0.343**	**2.19**	**4.02**	**0.0001**						
L DISTRICT 45				*					**-0.0009**	**0.2496**	**-0.6668**	**0.3426**	**2.08**	**2.42**	**0.0182**						
L DISTRICT 30+31		*							**-0.0082**	**-0.0495**	**-0.6293**	**0.3415**	**2.11**	**-0.101**	**0.9202**						
H DISTRICT 126	*								**-0.0129**	**1.3864**	**-0.6304**	**0.3398**	**2.06**	**0.969**	**0.3361**			**			
L DISTRICT 58a		*							**0.0088**	**0.7722**	**-0.5809**	**0.3392**	**2.17**	**1.88**	**0.0649**						
M DISTRICT 58c			*						**-0.002**	**0.0781**	**-0.6413**	**0.3383**	**2.12**	**1.65**	**0.1036**						
Durham South 30+31		*							**-0.0003**	**1.0986**	**-0.6026**	**0.338**	**2.16**	**2.09**	**0.0404**						
Tynside N 45		*							**-0.0054**	**-0.0894**	**-0.6537**	**0.3364**	**2.11**	**-0.142**	**0.8877**						
Durham North 30+31		*							-0.005	-0.4045	-0.6481	0.3363	2.1	**-1.09**	**0.2802**						
Gateshead 126		*							**0.0081**	**2.563**	**-0.6788**	**0.3362**	**2.11**	**2.34**	**0.0225**			**			
Newcastle 48+37/2								*	**-0.0107**	**0.4056**	**-0.3945**	**0.3348**	**2.34**	**5.38**	**0**	*					
Sunderland 58b	*								**-0.001**	**-0.1796**	**-0.6432**	**0.3347**	**2.15**	**0.369**	**0.7134**						
M DISTRICT 58c		*							**0.0006**	**0.3208**	**-0.6492**	**0.3345**	**2.17**	**0.626**	**0.5332**	*					
L DISTRICT 58c		*							**0.0142**	**1.071**	**-0.5675**	**0.3345**	**2.26**	**1.83**	**0.0723**						
Tynside N 28+29					*				**-0.0065**	**0.468**	**-0.4883**	**0.3325**	**2.15**	4.07	0.0001						
Durham North 48+37/2							*		**-0.0007**	**0.0674**	**-0.6481**	**0.3322**	**2.1**	**0.62**	**0.53**						

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Tynside S 48+37/2									*	-0.0073	0.0969	-0.6425	0.3322	2.1 1	2.88	0.00 54					*	
Durham North 30+31							*			-0.003	0.1479	-0.5951	0.331	2.0 9	2.13	0.03 65						
Castle 45					*					0.0013	0.1566	-0.5834	0.3289	2.0 4	2.91	0.00 49						
S DISTRICT 58c		*								0.0158	1.0706	-0.5515	0.3286	2.1 5	1.98	0.05 19						
Blyth 28+29		*								-0.0058	-0.062	-0.6476	0.3271	2.0 9	- 0.065 7	0.94 78						
Blyth 48+37/2								*		-0.0041	0.1464	-0.6326	0.327	2.1 6	1.13	0.26 1						
Tyndale 30+31							*			-0.0068	0.0665	-0.6228	0.3252	2.0 9	1.1	0.27 71						
Tynside N 28+29				*						-0.008	0.3399	-0.4565	0.3234	2.2	3.32	0.00 14						
Blyth 58a	*									-0.0085	-0.4189	-0.6296	0.3233	2.3	- 0.812	0.41 96	*		*			
H DISTRICT 58a			*							-0.0003	0.1072	-0.6102	0.323	2.1 1	2.7	0.00 88						
Gateshead 58a		*								0.0024	1.573	-0.5026	0.3191	2.1 8	3.7	0.00 04						
Tynside N 45									*	-0.004	0.163	-0.6219	0.3184	2.1 1	2.75	0.00 77			*			
warren 28+29		*								-0.0088	0.2543	-0.6821	0.317	2.1 1	0.3	0.76 54	*					
Durham North 30+31	*									-0.0035	-0.4466	-0.604	0.3168	2.1 2	-1.46	0.15 01						
S DISTRICT 45								*		-0.0185	0.4924	-0.204	0.315	2.3	3.57	0.00	*					

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S DISTRICT 58a			*							0.0035	0.1358	-0.6564	0.3142	1.9 9	2.24	0.02 87						
Tynside S 58c		*								0.0094	1.0097	-0.06	0.3128	2.1 1	2.2	0.03 15						*
Durham South 48+37/2	*									-0.0005	0.005	-0.62	0.3126	2.2 9	0.009 5	0.99 24	* *					
Blyth 58b	*									-0.0118	1.0377	-0.549	0.3117	2.1 9	1.4	0.16 58						
Durham North 28+29				*						-0.0041	0.073	-0.614	0.3117	2.0 8	0.522	0.60 33						
Durham North 48+37/2	*									-0.0032	-0.1599	-0.6232	0.3116	2.1 6	- 0.403	0.68 8						
Durham South 30+31	*									-0.006	0.745	-0.5249	0.3081	2.2 6	1.74	0.08 66						
Durham South 28+29	*									0.0008	0.9405	-0.54	0.307	2.1 1	2.35	0.02 15						
Durham North 28+29						*				-0.0041	-0.265	-0.5567	0.3067	2.0 6	-1.99	0.05 05						
Gateshead 45					*					0.0044	0.3175	-0.6086	0.3059	1.9 1	3.17	0.00 23						
warren 28+29	*									-0.01147	0.8245	-0.6352	0.305	2.1 2	0.939	0.35 1						
Blyth 28+29				*						-0.004	0.1529	-0.6201	0.3041	2.1 4	1.74	0.08 67			* *			
Durham North 28+29	*									-0.0041	0.4163	-0.555	0.3038	2.0 8	0.998	0.32 19						
Tynside S 48+37/2								*		-0.0093	0.3839	-0.4871	0.3027	2.3 5	2.82	0.00 64	*					
Castle 45									*	-0.0018	0.0892	-0.6279	0.3023	2.0 6	1.67	0.10 02						

Durham North 58a	*									0	0.2154	-0.6114	0.301	2.21	0.673	0.5035	*					
warren 58b		*								-0.0132	-0.027	-0.5715	0.3	2.22	-0.0312	0.9752			*			
Castle 45	*									-0.0005	0.4114	-0.5895	0.2992	2.06	0.732	0.4669						
M DISTRICT 58c	*									-0.0012	-0.1411	-0.5859	0.2992	2.14	-0.247	0.8054						*
Sunderland 30+31							*			-0.0074	0.2987	-0.4863	0.2987	2.19	3.22	0.002						
Castle 45								*		-0.0007	0.1848	-0.6108	0.2985	2.04	1.6	0.1135						
Blyth 28+29	*									-0.0057	-0.1682	-0.5887	0.2968	2.17	-0.193	0.8471			* *			
S DISTRICT 30+31		*								-0.0061	0.6497	-0.5664	0.2958	2.22	1.32	0.1902	* *					
Tynside N 48+37/2								*		-0.0066	0.2835	-0.5638	0.2955	2.38	2.13	0.0365	* *					
L DISTRICT 45								*		-0.0021	-0.1661	-0.5587	0.295	2.09	-1.55	0.1252				*		
Durham North 28+29		*								-0.0038	0.0286	-0.5749	0.2936	2.04	0.0556	0.9559						
warren 48+37/2		*								-0.0059	0.5701	-0.5839	0.293	2.01	0.705	0.4833						
Tynside S 30+31		*								0.0005	0.5079	-0.583	0.2917	2.18	0.933	0.3243						
Gateshead 30+31		*								-0.001	0.9923	-0.5289	0.2894	2.15	1.9	0.0618						
S DISTRICT 28+29				*						-0.0168	0.161	-0.4315	0.2877	2.27	1.48	0.1425						

M DISTRICT 48+37/2									*	-0.0081	0.4016	-0.3656	0.2869	2.12	4.89	0	*					
Tynside S 30+31							*			0.0001	0.2687	-0.5958	0.2862	2.12	2.35	0.022						
Sunderland 48+37/2								*		-0.0134	0.5202	-0.0918	0.286	2.49	4.92	0	**					
Tyndale 28+29				*						0.0034	0.5544	-0.4828	0.2856	2.28	2.92	0.0048	*					**
S DISTRICT 58a	*									0.0038	-0.282	-0.5284	0.283	2.1	-0.57	0.5705						
warren 28+29				*						-0.0066	0.0856	-0.6574	0.283	2.28	0.937	0.3522	**					
M DISTRICT 30+31		*								-0.01	0.2393	-0.5055	0.2827	2.5	0.401	0.69	**					
H DISTRICT 58a		*								0.0037	0.4862	-0.5336	0.2822	2.1	1.31	0.1953						
Newcastle 126		*								0.0048	1.9044	-0.0509	0.2807	2.14	1.73	0.889						
Sunderland 30+31		*								-0.0117	-0.5219	-0.482	0.28	2.09	-1.04	0.3002						
L DISTRICT 45									*	-0.002	0.1139	-0.5286	0.2794	2.17	1.87	0.0656	*					
H DISTRICT 58a	*									0.0018	0.4624	-0.5126	0.2777	2.09	1.09	0.2806						
Tyndale 28+29						*				-0.0014	0.0268	-0.5294	0.2754	2.31	0.18	0.8574	**		**			*
Newcastle 48+37/2								*		-0.0127	0.5109	-0.2252	0.2738	2.2	4.23	0.0001						
Newcastle 28+29						*				-0.0044	0.5	-0.516	0.2731	2.18	3.21	0.002	**					
Durham South 28+29				*						0.0018	0.29	-0.3963	0.2726	2.1	2.95	0.00						

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L DISTRICT 126	*								-0.0143	-0.3088	-0.5759	0.2703	2.0 9	- 0.262	0.79 45						
Tynside S 58c	*								0.0029	0.3052	-0.5428	0.2695	2.0 6	0.59	0.55 71						
warren 58a	*								-0.0102	0.8071	-0.4457	0.2683	2.2 7	1.38	0.17 14						
Sunderland 48+37/2								*	-0.0101	0.2963	-0.2815	0.2671	2.2 4	4.92	0						
H DISTRICT 45					*				-0.0057	0.1998	-0.4338	0.267	2.4 8	1.7	0.09 3	* *					
Sunderland 58a		*							-0.0021	0.6393	-0.4653	0.267	2.0 5	1.48	0.14 27						
Sunderland 126		*							-0.0049	1.4621	-0.5341	0.2663	2.1	1.55	0.12 48						
Tynside N 48+37/2	*								-0.0073	0.3307	-0.531	0.2652	2.4 3	0.476	0.63 54	* *					
H DISTRICT 30+31			*						-0.0089	0.1757	-0.2286	0.2649	2.5	4.45	0	* *					
L DISTRICT 58c	*								0.0095	1.3035	-0.4722	0.2648	2.2 9	2	0.05	*				*	
Tynside S 45					*				0.0009	0.2664	-0.4561	0.2645	2.0 2	2.93	0.00 46			*			
L DISTRICT 58c			*						0.0075	0.0763	-0.5358	0.2636	2.2 8	1.51	0.13 69	*				*	
Tynside N 45	*								-0.004	-0.3192	-0.5212	0.2623	2.1 5	- 0.489	0.62 62						
Newcastle 28+29				*					-0.0037	0.3272	-0.5	0.2613	2.2 5	2.43	0.01 79	*					
Gateshead 126	*								-0.0028	1.012	-0.4983	0.2601	2.3 3	1.06	0.29 2	* *		* *			

Tynside N 58b		*								-0.0029	0.2211	-0.4854	0.26	2.0 8	0.35	0.72 72						
Sunderland 45					*					-0.0061	0.3753	-0.4571	0.2597	1.8 1	2.34	0.02 2			*			
Gateshead 45		*								0.0041	0.5478	-0.505	0.2595	2.0 5	0.939	0.35 11						
Newcastle 126	*									-0.0022	0.816	-0.5	0.2593	2.1 4	0.985	0.32 81						
H DISTRICT 48+37/2		*								-0.012	0.5675	-0.4656	0.2573	1.9 1	1.01	0.31 64						
L DISTRICT 30+31	*									-0.0065	0.6405	-0.4096	0.257	2.1 4	1.13	0.26 43						
Newcastle 58c		*								0.003	0.7286	-0.4994	0.256	2.1 2	1.04	0.30 13						
Tynside N 45								*		-0.0045	0.0169	-0.5127	0.2557	2.1 8	0.132	0.89 55						
Sunderland 58c	*									-0.0015	0.558	-0.4533	0.2554	1.7	1.4	0.16 68						
L DISTRICT 58a			*							0.00165	0.1014	-0.4586	0.2546	2.2 6	2.11	0.03 89						
Sunderland 58c		*								0.0016	0.6322	-0.4628	0.2537	1.7 2	1.33	0.18 69						
L DISTRICT 45	*									-0.0027	0.564	-0.5067	0.2532	2.1 1	0.821	0.41 47						
L DISTRICT 45			*							-0.0038	0.0347	-0.5226	0.2531	2.1 5	1.31	0.19 48	*					
L DISTRICT 126		*								-0.0047	1.5998	-0.4995	0.2503	2.0 5	1.45	0.15 27						
S DISTRICT 30+31							*			-0.009	0.3414	-0.2431	0.2494	2.4 4	4.33	0.00 01	* *			*	* *	
Tynside S 45								*		-0.0021	0.3875	-0.3092	0.2483	2.2	3.24	0.00			*			

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H DISTRICT 30+31		*								-0.0096	-0.4245	-0.4191	0.2462	2.25	-0.606	0.5466						
Sunderland 45									*	-0.0074	0.2734	-0.4314	0.2437	1.79	3.21	0.0021			**			
warren 58c	*									-0.004	0.0533	-0.465	0.242	2.19	0.1	0.9203						
Tynside S 58a		*								-0.0005	0.8184	-0.2858	0.2415	2.1	3.29	0.0016	*					
Tynside S 45									*	0.0007	0.0882	-0.4169	0.2413	1.98	2.92	0.0047						*
Durham North 45		*								-0.0086	-0.1128	-0.4662	0.2405	2.19	-0.237	0.8132						
H DISTRICT 28+29		*								-0.0136	-0.699	-0.3557	0.2398	2.27	-1.24	0.2208						
Newcastle 58c	*									-0.0008	-0.1041	-0.4777	0.2385	2.12	-0.202	0.8407						
M DISTRICT 45									*	-0.0127	0.2583	-0.2805	0.2373	2.11	3.67	0.0005				**	**	
L DISTRICT 58a	*									0.0043	0.3483	-0.4551	0.2357	2.3	0.7848	0.4568						
M DISTRICT 28+29				*						-0.0128	0.0622	-0.4744	0.2354	2.07	0.66	0.5116						
Durham South 45					*					-0.0083	0.2569	-0.36	0.2351	2.31	3.17	0.0023						
Tynside S 126		*								-0.0238	1.983	-0.5103	0.2319	2.25	0.785	0.4354	**	*	**			
Tynside S 45		*								0.0038	0.8783	-0.4728	0.2319	2.04	1.6	0.115						
M DISTRICT 30+31			*							-0.0106	0.158	-0.2891	0.2311	2.64	3.49	0.0008	**					

Tynside S 48+37/2	*									-0.0075	0.5207	-0.4367	0.2292	2.34	0.741	0.4609	*					
Sunderland 45								*		-0.0095	0.4999	-0.2699	0.2271	1.91	2.98	0.004			*			
Durham South 45		*								-0.005	0.5765	-0.4449	0.2255	2.29	1.07	0.2897						
Tynside S 30+31	*									-0.0014	0.4247	-0.4295	0.2243	2.33	0.715	0.4773	*					
L DISTRICT 48+37/2		*								-0.0061	1.194	-0.4385	0.224	2.03	1.85	0.0482				* *	*	*
warren 58a		*								-0.0044	0.8788	-0.4057	0.2221	2.31	1.53	0.1318	* *	*				
Sunderland 28+29				*						-0.0065	0.4301	-0.2526	0.2207	2.16	3.56	0.0007						
Gateshead 48+37/2									*	-0.0119	0.1686	-0.387	0.219	2.41	2.76	0.0073	*					
L DISTRICT 30+31							*			-0.0077	0.0684	-0.4151	0.2187	2.19	0.96	0.3404	*					
S DISTRICT 48+37/2									*	-0.008	0.1273	-0.3907	0.2156	2.18	2.17	0.0331						
S DISTRICT 45									*	-0.0102	0.1563	-0.3878	0.2151	2.26	1.8	0.077						
Durham South 28+29						*				-0.0013	-0.0095	-0.4252	0.2135	2.23	0.271	0.7871						
Gateshead 45								*		0.0023	0.3295	-0.3678	0.2127	2.11	2.3	0.0246						
Durham North 45					*					-0.008	0.2601	-0.3821	0.2124	2.27	2.49	0.0154					*	*
S DISTRICT 58c			*							0.0068	0.1194	-0.4318	0.2123	2.3	2.35	0.0217	*					
H DISTRICT 48+37/2			*							-0.0137	0.0843	-0.3707	0.2114	1.9	2.23	0.02						

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Sunderland 45		*							-0.0129	-0.3351	-0.3963	0.2104	1.73	-0.445	0.658	*					
Tynside N 30+31	*								-0.0073	0.5245	-0.3527	0.2099	2.18	0.93	0.3559						
Gateshead 58a	*								-0.0049	0.8388	-0.3007	0.2086	2.51	2.19	0.0316	**					
M DISTRICT 45					*					-0.0148	0.1647	-0.3538	0.2076	2.01	1.72	0.0905			*	**	**	
S DISTRICT 48+37/2			*							-0.009	0.0823	-0.2287	0.2075	2.28	3.07	0.0031						
Durham South 45								*		-0.0126	0.0651	-0.3114	0.2056	2.5	1.96	0.0542	**					
L DISTRICT 48+37/2								*		-0.0145	0.0976	-0.3765	0.2054	2.17	0.853	0.3966	*			*		
S DISTRICT 126		*								-0.0043	1.613	-0.3511	0.2054	2.43	1.72	0.0896	**					
Tynside N 28+29		*								-0.0098	0.213	-0.4105	0.2049	2.23	0.372	0.7109						
Sunderland 58a	*									-0.0053	0.3344	-0.372	0.203	2.17	0.871	0.3867						
L DISTRICT 30+31			*							-0.0075	0.0488	-0.4308	0.2002	2.14	1.39	0.1679	*					
Tynside N 58b	*									-0.0027	-0.0511	-0.3714	0.1986	2.12	-0.0773	0.9386						
S DISTRICT 45		*								-0.003	1.3842	-0.4158	0.1985	2.18	1.8	0.0766						
S DISTRICT 48+37/2		*								-0.0036	0.9133	-0.3815	0.1971	2.08	1.81	0.0743						
Tyndale 28+29	*									-0.0005	-0.2975	-0.444	0.197	2.5	-	0.77	*			*		*

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Newcastle 45								*		-0.0223	0.5489	-0.1706	0.1962	1.94	2.64	0.0103			**			
S DISTRICT 58c	*									0.0091	0.2814	-0.3872	0.1953	2.38	0.456	0.6495	**					
M DISTRICT 28+29						*				-0.0141	0.2708	-0.3	0.1952	2.1	2.24	0.0282						
Sunderland 30+31	*									-0.0079	-0.1296	-0.3338	0.1951	2.21	-0.28	0.7802						
Durham South 45	*									-0.0078	0.4952	-0.362	0.1943	2.39	1.14	0.2584	*					
Gateshead 45	*									0.001	-0.4782	-0.3949	0.194	2.14	-0.923	0.3591						
Tynside S 28+29						*				-0.0063	0.0766	-0.385	0.1939	2.09	0.336	0.7382						
warren 58c		*								-0.0016	0.4007	-0.369	0.1936	2.24	0.756	0.4523						
S DISTRICT 126	*									-0.0117	1.571	-0.31	0.1931	2.5	1.61	0.1123	**					
H DISTRICT 30+31							*			-0.0055	0.2157	-0.286	0.1922	2.33	2.61	0.0111	*					*
Tynside S 28+29		*								-0.0014	0.6437	-0.3947	0.1888	2.1	1.21	0.2292						
Gateshead 30+31							*			-0.0057	0.1209	-0.3719	0.1878	2.38	1.37	0.1754	**					
Tynside S 58b		*								-0.0083	1.044	-0.3494	0.1862	2.41	2.07	0.0418	**					
L DISTRICT 48+37/2	*									-0.0138	-0.1449	-0.3842	0.1856	2.19	-0.207	0.8365						*
Sunderland 126	*									-0.0132	0.5528	-0.3637	0.1845	2.26	0.652	0.5166						

Gateshead 28+29				*						-0.0114	0.4442	-0.1996	0.1841	2.21	3.53	0.0007						
Tynside N 58a		*								-0.0056	0.8952	-0.3469	0.1822	2.39	1.77	0.0804	*					
Gateshead 48+37/2		*								-0.0051	1.549	-0.2966	0.1805	2.44	2.41	0.0185	**					*
H DISTRICT 48+37/2	*									-0.0149	0.2068	-0.3049	0.176	2.01	0.307	0.7597						
Sunderland 45	*									-0.0107	-0.5651	-0.3085	0.1756	1.84	-0.856	0.3951						
Gateshead 30+31	*									-0.0066	-0.0445	-0.3485	0.1753	2.42	-0.0935	0.9258	**					
Newcastle 28+29		*								-0.005	0.4398	-0.3548	0.1744	2.39	0.591	0.5566	**					
M DISTRICT 28+29		*								-0.011	0.5331	-0.3908	0.1726	2.04	0.956	0.3424				*	*	
H DISTRICT 45		*								-0.0061	0.2199	-0.3142	0.1702	2.51	0.334	0.7392	*					*
H DISTRICT 28+29			*							-0.0097	0.1524	-0.3592	0.1663	2.29	2.05	0.0441	*					
M DISTRICT 30+31	*									-0.0112	0.6133	-0.2695	0.166	2.74	0.889	0.3773	**					
Tynside S 45	*									-0.0003	0.4532	-0.3152	0.1657	2.13	0.731	0.4674			*			
S DISTRICT 30+31	*									-0.0098	0.0298	-0.3091	0.1649	2.47	0.0543	0.9568	**					
Tynside N 28+29	*									-0.0105	-0.532	-0.294	0.1636	2.4	-0.937	0.3523	*					
Newcastle 28+29	*									-0.006	0.3093	-0.3325	0.1635	2.42	0.561	0.577	**					

Durham North 45	*									-0.009	-0.4001	-0.3027	0.1634	2.3 8	- 0.978	0.33 18	*					*
M DISTRICT 45			*							-0.0181	0.0643	-0.1827	0.1621	2.0 9	2.51	0.01 43						
M DISTRICT 45								*		-0.0176	0.2564	-0.1877	0.1613	2.1 5	2.32	0.02 33						
Tynside S 28+29				*						-0.0043	0.2	-0.3395	0.161	2.1 8	1.76	0.08 21						*
L DISTRICT 48+37/2			*							-0.0126	0.1166	-0.4124	0.1605	2.2 3	2.11	0.03 88						
H DISTRICT 48+37/2								*		-0.0162	0.0606	-0.2701	0.1588	2.0 1	0.657	0.51 33						
M DISTRICT 30+31							*			-0.0108	0.1769	-0.2834	0.1588	2.6 8	1.94	0.05 26	* *					
Durham North 45								*		-0.0075	0.0882	-0.2963	0.1564	2.3 7	0.767	0.44 56	*					
S DISTRICT 28+29		*								-0.0113	1.129	-0.2565	0.1556	2.2 3	2.08	0.04 17						
M DISTRICT 48+37/2								*		-0.0154	0.3245	-0.1119	0.1531	2.2 5	2.55	0.01 31	*					
H DISTRICT 28+29	*									-0.0117	-1.2026	-0.2123	0.1528	2.3 5	-1.82	0.07 34	*					
M DISTRICT 28+29			*							-0.014	0.0136	-0.3162	0.1519	2.1 5	0.395	0.69 42						
H DISTRICT 45			*							-0.006	0.0227	-0.2626	0.1503	2.5	0.705	0.48 31	*					*
Newcastle 30+31		*								-0.0091	0.4859	-0.3011	0.147	2.0 2	0.812	0.41 94						
H DISTRICT 45									*	-0.0062	0.0925	-0.2517	0.1466	2.5 5	1.71	0.09 16	* *					
Newcastle 30+31	*									-0.0104	0.1552	-0.2725	0.145	2.0	0.354	0.72						

														8		45						
M DISTRICT 28+29	*									-0.014	0.194	-0.3048	0.1443	2.15	0.325	0.7465						
M DISTRICT 126	*									-0.0192	-1.4703	-0.251	0.1434	2.33	-1.58	0.1182						
Tynside S 126	*									-0.0397	-0.1076	-0.3029	0.1358	2.49	-0.124	0.9017	**	**	**	*	*	
H DISTRICT 30+31	*									-0.0081	-0.4786	-0.2602	0.1354	2.38	-0.565	0.5736	*					
Newcastle 48+37/2		*								-0.0095	0.7651	-0.2764	0.1347	2.21	0.874	0.3851						
S DISTRICT 48+37/2	*									-0.0088	0.2148	-0.261	0.133	2.25	0.403	0.6883				*	**	
Gateshead 28+29		*								-0.0065	1.3665	-0.2116	0.1277	2.09	2.1	0.0394						
Tynside N 58a	*									-0.0105	0.6672	-0.2056	0.127	2.51	1.32	0.1925	**					
Newcastle 48+37/2	*									-0.0131	-0.1663	-0.2508	0.1237	2.33	-0.257	0.7979						
Gateshead 48+37/2	*									-0.0131	0.6802	-0.1882	0.1235	2.68	1.22	0.2271	**					*
H DISTRICT 45	*									-0.0081	-1.0095	-0.1912	0.1223	2.65	-1.34	0.1838	**					
Newcastle 45	*									-0.022	0.0881	-0.2164	0.1219	1.84	0.0831	0.934			**			
S DISTRICT 45			*							-0.012	-0.0111	-0.235	0.1216	2.42	-0.369	0.7134	*					
S DISTRICT 45	*									-0.0115	0.1028	-0.2512	0.1192	2.39	0.127	0.8994	*					
Sunderland 28+29						*				-0.0093	0.2442	-0.2097	0.1192	2.18	1.57	0.1201						

S DISTRICT 30+31			*							-0.0104	0.0341	-0.2113	0.1158	2.54	0.998	0.3216	**					
Newcastle 45		*								-0.0255	-0.3354	-0.2238	0.1129	1.84	-0.228	0.8204			**			
Tynside S 28+29	*									-0.0045	-0.2552	-0.2032	0.1073	2.26	-0.422	0.6741	*				*	
Sunderland 28+29		*								-0.0124	-0.2867	-0.1853	0.1068	2.27	-0.47	0.6402						
Newcastle 30+31							*			-0.0109	0.0894	-0.1807	0.1063	2.16	1.07	0.2876	*					*
Gateshead 48+37/2								*		-0.0143	0.0597	-0.2005	0.106	2.69	0.383	0.7029	**					*
M DISTRICT 126		*								-0.017	0.2556	-0.2229	0.1048	2.32	0.287	0.7752						
Newcastle 58a	*									-0.0027	-0.1456	-0.1939	0.104	1.95	-0.374	0.7097						
Newcastle 45					*					-0.0214	0.2035	-0.1882	0.1023	1.89	1.06	0.292			**			
Newcastle 58a		*								-0.0016	0.1722	-0.1934	0.0998	1.96	0.325	0.7464						
M DISTRICT 48+37/2			*							-0.0138	0.1017	-0.1563	0.0995	2.31	2.34	0.0223	*					
Gateshead 28+29						*				-0.01236	0.2812	-0.2463	0.0989	2.19	1.64	0.1051	*					
Newcastle 45									*	-0.0236	-0.0539	-0.1553	0.0966	1.87	-0.395	0.694			**			
M DISTRICT 45		*								-0.0166	0.1544	-0.2244	0.0965	2.09	0.263	0.7933						
M DISTRICT 45	*									-0.0177	-0.2515	-0.2031	0.0959	2.16	-0.402	0.689						
M DISTRICT 48+37/2		*								-0.0115	0.6824	-0.1697	0.0944	2.2	1.03	0.30						

														9		7						
Durham North 58c	*									-0.0087	0.0227	-0.3701	0.0936	1.53	0.0536	0.9574			**			
H DISTRICT 28+29						*				-0.0109	0.012	-0.1789	0.0926	2.38	0.0713	0.9434	**					
Durham North 58c		*								-0.0097	-0.2029	-0.3576	0.0917	1.54	-0.396	0.6932			**			
H DISTRICT 45								*		-0.0082	0.0974	-0.1491	0.0911	2.66	0.918	0.0122	**					
S DISTRICT 28+29			*							-0.0191	0.0725	-0.1139	0.0834	2.42	2.04	0.0453						
Tynside S 58b	*									-0.017	-0.3633	-0.1961	0.082	2.61	-0.606	0.5466	**					**
Sunderland 48+37/2		*								-0.0142	0.0528	-0.1563	0.0775	2.16	0.0991	0.9213						
S DISTRICT 28+29	*									-0.0188	0.019	-0.143	0.0732	2.4	0.0327	0.974						
Tynside S 58a	*									-0.0064	0.1431	-0.1443	0.07	2.29	0.464	0.6443	*					
M DISTRICT 48+37/2	*									-0.0155	-0.4765	-0.135	0.0663	2.38	-0.661	0.5106	*					
Sunderland 48+37/2	*									-0.0144	0.0347	-0.1153	0.0641	2.22	0.075	0.9405						
Gateshead 28+29	*									-0.0143	0.2854	-0.124	0.0637	2.25	0.51	0.6115	*					
Sunderland 28+29	*									-0.0111	-0.4388	-0.1039	0.0587	2.32	-0.818	0.4161						
L DISTRICT 28+29				*						-0.0019	0.257	0.0221	0.0546	2.65	1.88	0.0644	**	*	**			
S DISTRICT 28+29						*				-0.0188	-0.0898	-0.1302	0.053	2.4	-0.682	0.4973						

L DISTRICT 28+29			*							-0.0038	0.1023	-0.0112	0.0464	2.67	1.81	0.0747	**	*	*			
L DISTRICT 28+29						*				-0.0048	0.2245	-0.022	0.0337	2.64	1.38	0.1706	**	*	**			
warren 48+37/2									*	-0.0003	0.0717	-0.0217	0.02	2.69	1.05	0.2989	**					
Tynside N 126		*								0.0004	1.0727	0.0341	0.0138	2.77	0.785	0.4354	**	*				
L DISTRICT 28+29		*								-0.0006	0.5572	-0.0232	0.0111	2.67	0.844	0.4017	**		*			
L DISTRICT 28+29	*									-0.0033	0.5666	-0.0091	0.0109	2.66	0.792	0.4312	**		*			
Tynside N 126	*									-0.054	-0.1646	0.049	0.0053	2.79	-0.124	0.9017	**	*		*		
Durham North 126	*																					
Durham North 126		*																				
Durham North 45									*													
Durham North 48+37/2									*													
Durham South 126	*																					
Durham South 126		*																				
Durham South 45									*													
Durham South 48+37/2									*													
L DISTRICT 45		*																				
M DISTRICT 58b		*																				
Tynside S 48+37/2		*								error wrong cc variable used												