The Effect of Police Enforcement on Road Traffic Accidents

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Abstract

The primary goal of this thesis is to investigate the effectiveness of police enforcement on Road Traffic Accidents; specifically, *'Does police enforcement activity have any real effect on levels of Killed and Seriously Injured road traffic accidents?'*

Data relating to forty one Police Force Areas in England and Wales was analysed by means of Zero Truncated Poisson regression, Cluster Analysis and Multilevel Modelling. Enforcement measures available to the police, for which data is available in this report, range from Prosecutions and Fixed Penalty Notices to Written Warnings and Vehicle Defect Rectification Notices.

Results from the Zero Truncated Poisson regression models have significant effects ($P < .05$), in relation to both contemporary and lagged Annual data and contemporary Quarterly data, for all proxy variables except Prosecutions. Significant effects ($P < .05$) are also found for Fixed Penalty Notices lagged by two quarters, Vehicle Defect Rectification Notices and speeding related Fixed Penalty Notices lagged by one quarter.

Results from Cluster Analysis verify the trend linking increased police enforcement with decreasing KSI rates. Clusters derived from population based KSI rates are more clearly defined than those using Vehicle kilometres travelled based KSI rates.

Multilevel modelling found significant fixed effects ($P < .05$) for Fixed Penalty Notices and speeding related Fixed Penalty Notices in relation to both derived and regional clusters, linking an increase in enforcement to a decrease in the overall KSI rate.

There would seem to be little doubt, based on the findings of this report, that higher levels of police enforcement, as measured here, lead to decreasing numbers of KSI accidents.

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Special thanks to my partner Hayley, always there, always supportive. Thank you, it meant so much. Also, to my daughter Amy, the sunshine in my life, just for being Amy.

Author's Declaration

I declare that no material contained in this thesis has been used in any other submission for an academic award and that the work presented is my own.

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Contents

Acronyms and Abbreviations

DV	Dependent Variable
FCM	Fuzzy C-means Clustering
FPN	Fixed Penalty Notices
FPN G16	Speeding Related Fixed Penalty Notices
GA	Geographical Area
IMD	Index of Mean Deprivation
KSI	Killed and Serious Injury/Killed and Seriously Injured
NB	Negative Binomial
PFA	Police Force Area
Pop	Population
Pros	Prosecutions
QTR	Quarter
RTA	Road Traffic Accident
Std	Standard
VDRN	Vehicle Defect Rectification Notices
Vkm	Vehicle Kilometres travelled
WW	Written Warnings
ZTP	Zero Truncated Poisson

Variable Descriptors

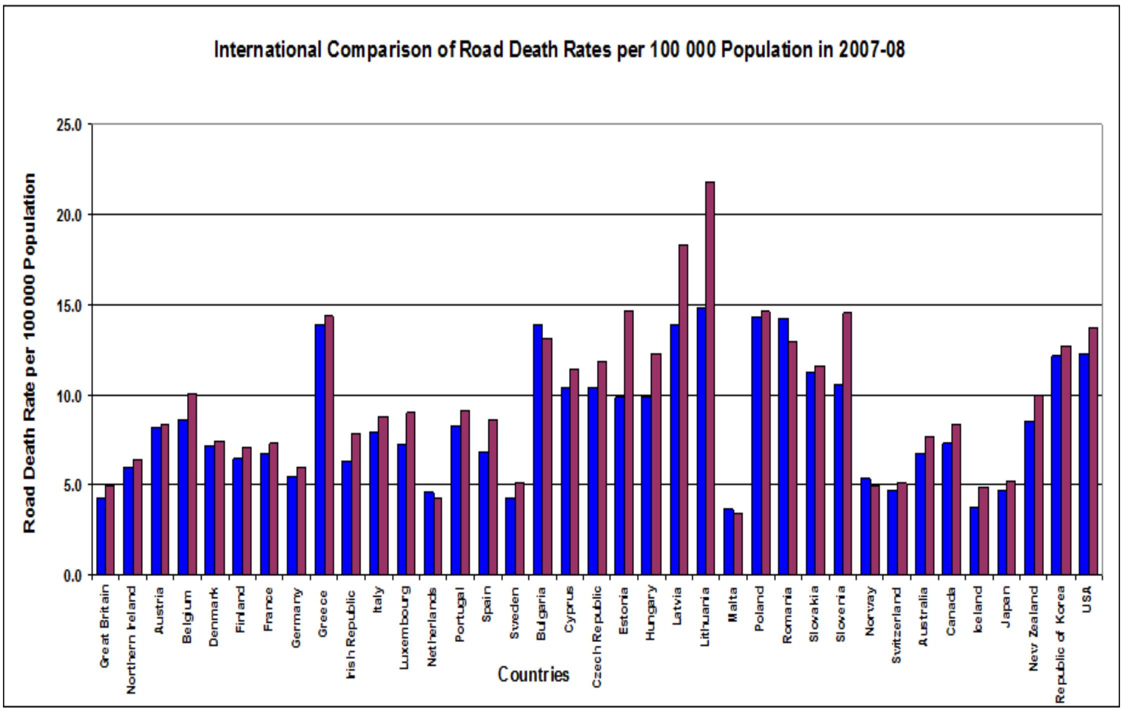
IMD	Index of Multiple Deprivation
Geographical Area sqkm	Geographical area of each PFA
Percent Motorway	Percentage of total motorway in each PFA
lnpop	Log of Population
lnvkm	Log of Vehicle kilometres
All Penalties	Sum of all Penalties
Lag1 All Penalties	Annual one Year Lag
FPN	Fixed Penalty Notices
Lag FPN	Annual one Year Lag
Lag 1 FPN	One quarter, 3 months, Lag

Lag 2 FPN	Two quarter, 6 months, Lag
FPN_G16	Speeding related FPN's
Lag FPN 16	Annual one Year Lag
Lag 1 FPN G16	One quarter, 3 months, Lag
Lag 2 FPN G16	Two quarter, 6 months, Lag
PROSECUTIONS	Successful Prosecutions
Lag Prosecutions	Annual one Year Lag
Lag 1 Prosecutions	One quarter, 3 months, Lag
Lag 2 Prosecutions	Two quarter, 6 months, Lag
VDRN	Vehicle Defect Rectification Notices
Lag VDRN	Annual one Year Lag
Lag 1 VDRN	One quarter, 3 months, Lag
Lag 2 VDRN	Two quarter, 6 months, Lag
WW	Written Warnings
Lag WW	Annual one Year Lag
Lag 1 WW	One quarter, 3 months, Lag
Lag 2 WW	Two quarter, 6 months, Lag

1. Introduction

The primary goal of this thesis is to investigate the effectiveness of police enforcement on Road Traffic Accidents (RTA's), specifically those classed as Killed and Seriously Injured (KSI) accidents. In other words, *'Does police enforcement activity have any real effect on levels of KSI road traffic accidents?'*

Accidents reported as having caused only slight injuries are not used due to problems associated with under-reporting. The role of police enforcement in the reduction of RTA's is of major concern in many countries worldwide as the number of accidents, although generally experiencing a continuing downward trend, is still viewed as too high, see Figure 1.1.



Adapted from, Transport Statistics Great Britain (2009). Chapter 10, International Comparisons

Figure 1.1 International Comparison of Fatality Rates per 100,000 Population 2007-08

Figure 1.1 and Table 1.1 compare the Fatality Rate per 100,000 Population in 2007-08 for 38 developed countries. In Table 1.1 only five of the thirty eight countries have experienced a rise in fatality rates, with the greatest rise in fatality rates occurring in less well developed countries. Great Britain is ranked third with a fatality rate of 4.3 per 100,000 population in 2008, down from a rate of 5.0 per 100,000 population in 2007.

Table 1.1 International Comparisons of Fatality Rates per 100,000 Population 2007-08 in Ascending Order

Country	Death Rate per 100 000 Population		Country	Death Rate per 100 000 Population	
	2007	2008		2007	2008
Malta	3.4	3.7	Austria	8.3	8.1
Iceland	4.9	3.8	Portugal	9.2	8.3
Great Britain	5.0	4.3	New Zealand	10.0	8.6
Sweden	5.2	4.3	Belgium	10.1	8.6
Netherlands	4.3	4.6	Estonia	14.6	9.8
Switzerland	5.1	4.7	Hungary	12.2	9.9
Japan	5.2	4.7	Czech Republic	11.9	10.4
Norway	5.0	5.4	Cyprus	11.4	10.4
Germany	6.0	5.4	Slovenia	14.6	10.6
Northern Ireland	6.4	6.0	Slovakia	11.6	11.2
Irish Republic	7.8	6.3	Republic of Korea	12.7	12.1
Finland	7.1	6.5	USA	13.7	12.3
Australia	7.7	6.7	Bulgaria	13.1	13.9
France	7.3	6.7	Greece	14.4	13.9
Spain	8.6	6.9	Latvia	18.4	13.9
Denmark	7.5	7.2	Romania	12.9	14.2
Luxembourg	9.0	7.2	Poland	14.6	14.3
Canada	8.4	7.3	Lithuania	21.8	14.8
Italy	8.8	7.9			

Adapted from, Transport Statistics Great Britain (2009). Chapter 10, International Comparisons

Zaidel (2002) stated that '*50% of traffic accidents in Europe could have been prevented if road users had committed no driving violations*'. Although this is a theoretical estimation it highlights the fact that there is still scope for improvement in reducing the number of RTA's.

The actual costs of accidents and resultant casualties are high in terms of both the human cost and direct economic cost. The average cost per casualty, calculated for Great Britain, in 2008, is £1,683,800 per fatality, £189,200 for a seriously injured casualty and £14,600 for a slightly injured casualty (Reported

Road Casualties Great Britain, 2008). With over 230,000 accidents in Great Britain during 2008, the costs, both in human and direct economic terms, are huge.

1.2 Aims

In the context of Section 1, this report aims to

- Investigate any associations between police enforcement activity and the level of KSI accidents across 41 Police Force Areas (PFA's) in England and Wales
- Develop proxies for enforcement from available data and investigate their effect on levels of KSI accidents
- Investigate effects of socio-demographic factors on level of KSI accidents
- Develop statistical methods to evaluate the effect of enforcement
- Produce recommendations to which road safety practitioners, policy makers and researchers can refer

1.3 Research Approach

The research for this study was informed by the aims presented in Section 1.2, above.

In order to investigate the effects of enforcement on KSI accidents a measurable proxy, or proxies, had to be identified with which the efficacy of current enforcement strategies could be evaluated. Assistance in this matter was provided by the UK Home Office who provided penalty data relating to RTA's. The penalty data consisted of successful Prosecutions, Fixed Penalty Notices (FPN's), Written Warnings (WW's) and Vehicle Defect Rectification Notices (VDRN's), and these were used as the proxies for enforcement. Prosecutions can be defined as the number of successful prosecutions for driving offences in England and Wales. FPN's can be defined as the number of fixed penalty notices issued for minor driving offences and FPN_G16 are fixed penalty notices issued for speeding. VDRN's are the number of vehicle defect rectification notices issued. These are issued if a vehicle is defective, for example, one of its brake lights is broken. In this case the fault must be rectified and proof provided to the police. WW's represent the number of written warnings issued by police in relation to traffic offences

Socio-demographic variables were also identified to further evaluate the effect of enforcement under different conditions. These data are freely available and their choice was informed by a review of the literature in the field of accident analysis and road safety, see Table 1.3.1, below.

Table 1.3.1: Socio-demographic Variables

Population
Vehicle km travelled
Geographical Area
Index of Mean Deprivation - Wales
Index of Mean Deprivation - England
Length of All Roads
Length of Trunk Motorway
Percentage of Trunk Motorway

The development of statistical methods was based on an in depth review of the literature covering this topic. No research could be found which had used the proxies for enforcement used in this report, but similar pieces of research did prove informative in the process of choosing, or not, to use a particular technique.

1.4 Data

The data under analysis related to forty one individual PFA's in England and Wales and has been analysed using a range of statistical analysis methods. Scotland was not included in the analysis due the unavailability of data relating to police enforcement,

The initial analysis phase involved the interrogation of a database created by merging Road Traffic Accident (RTA) information and police enforcement data relating to 43 Police Force Areas (PFA's) in England and Wales. The original dataset contained data on all forty three PFA's in England and Wales but two of these, the City of London and the Metropolitan Police PFA's, were omitted as a result of their geographical area size and population size. A fuller explanation as to why this was necessary is given in Chapter 3.

The enforcement measures available to the police, for which data is available in this report, range from Prosecutions and Fixed Penalty Notices (FPN's) to Written Warnings (WW's) and Vehicle Defect Rectification Notices (VDRN's). These data were used as proxies for police enforcement activity. The investigation was structured to identify any associations between the enforcement actions and the level of RTA's and the rate of KSI accidents. Data was derived from the UK RTA dataset (STATS19) and enforcement data, obtained from the UK Home Office. The STATS19 returns detail every road accident involving personal injury, reported to police, and the Home Office data supplies information on the number of prosecutions and FPN's issued. Annual time series data was available from 1997 to 2004 and quarterly data from 1999 to 2003. The database also included variables relating to population size, road, traffic and socio-demographic characteristics.

1.5 Analysis Plan

The main statistical analysis of the data covers three chapters of this report, Chapters 4, 5 and 6. Chapter 4 concentrates on Poisson Regression Analysis, Chapter 5 covers Cluster Analysis and Chapter 6 covers Multilevel Modelling.

In Chapter 4 Poisson Regression was chosen to model the data as it is considered the benchmark tool when modelling count data. Exploratory analysis, using Poisson Regression, revealed that the data violated distributional assumptions of the Poisson distribution was therefore not suitable for analysis under ordinary Poisson regression. As there are no zero counts in the data, the data is truncated at zero, an adapted form of Poisson Regression known as Zero Truncated Poisson (ZTP) regression is used. This allows models to be fitted without violating any distributional assumptions as the ZTP method takes into account the lack of zero counts and adjusts the properties of the Poisson distribution accordingly.

Following on from the ZTP regression Cluster Analysis, Chapter 5, is used to identify natural groupings, clusters, which may not be readily apparent within data. The aim of cluster analysis is to minimise variation within clusters and maximise variation between clusters. There are various methods available to define clusters and here Hierarchical Clustering is used as its use in the analysis of accidents is well documented (Wong et al., 2004, Yannis et al., 2007). Initially, data covering all KSI accidents for 2004 were used to develop the cluster analysis. The data are aggregated into forty one Police Force Areas (PFA's) which were entered into the cluster analysis in order to produce distinct clusters of similar PFA's. Further cluster analysis was carried out using another, more flexible, method of clustering – Fuzzy C-means clustering (FCM). The main difference between the clustering methods is that FCM allows for the possibility that data may be allocated to more than one cluster which can help to identify any ambiguous data, in the context of clustering, and is therefore a useful aid in producing well defined clusters.

The aggregation of data, as a result of the clustering process, leads to some loss of information and Multilevel Modelling can be used to investigate the variation between successive levels of aggregation, in this case PFA's and clusters. The main advantage of multilevel models are that they can provide more accurate results, when applied to data of a hierarchical nature, thereby allowing better understanding of where explanatory variables actually exert influence. In Chapter 6 multilevel models were developed to investigate the hierarchical nature of the data. The use of multilevel modelling to analyse road traffic accident data is increasing, although literature on the subject is sparse. This may be due to a lack of awareness of the benefits of the technique (Kim et al., 2007) or a lack of knowledge, or ignorance, of the hierarchical structure of road traffic accident data (Jones and Jorgensen, 2003).

1.6 Structure of Thesis

The construction and flow of this thesis is presented in Figure 1.6 followed by a brief description of how the thesis is formatted

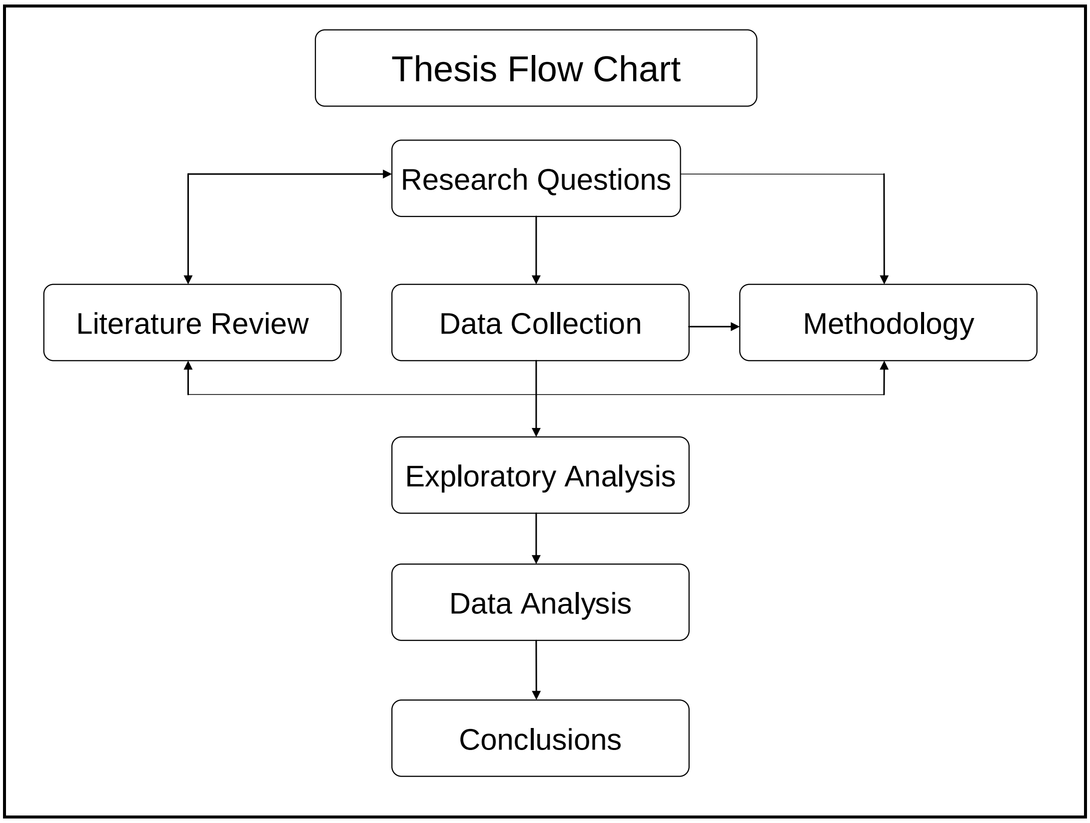


Figure 1.6: Thesis Flow Chart

Presented in chapter 2 is a literature review of relevant thinking and research on the issues of road safety and enforcement techniques and strategies. Research methods are presented in Chapter 3 and followed in Chapter 4 by regression analysis using Zero Truncated Poisson Regression. In Chapter 5 Cluster Analysis methods are used to identify similar groups within the data while Chapter 6 covers multilevel modelling. Finally, in Chapter 7 a discussion of the results and conclusions will be given along with recommendations for future research.

2. Literature Review

2.1 Introduction

The effect of road policing on road traffic accidents is currently the subject of much debate and investigation. The general belief resulting from recent studies is that increasing the level of police enforcement, both manual and automated, leads to a reduction in both road traffic accidents and traffic violations.

There are many methods available to enforcement agencies in trying to reduce rates of road traffic accidents and violations. The main aim of enforcement is to target irresponsible, dangerous and unlawful behaviour, and if necessary apply the proper enforcement strategy and related sanctions. According to Zaidel (2002), Traffic Law Enforcement (TLE) operates under two mechanisms which can help to prevent accidents and reduce their severity. The first of these is system management. By maintaining a safe road system, through system management, there are fewer hazards presented to the road user, which results in less risk and fewer accidents. The second mechanism is based on the assumption that a large proportion of accidents are caused by road users failing to comply with traffic laws and regulations. While it is clear that TLE can lead to changes in both driver and traffic behaviour it is also very clear that non-compliance is still a major problem. Zaidel also states that theoretical estimates for reducing accidents can be as high as 50%. This is based on achieving full compliance, through police enforcement, with existing laws. It also takes into account the roll of non-compliance by road users. However reduction estimates based on empirical evidence tend to present much lower figures. Elliott and Broughton (2005) list four methods of enforcement – methods used to enforce speed limits, drink driving, red light violations and seat belt enforcement.

The effective application of enforcement in relation to road traffic rules and regulations is dependent not only on the actions of the relevant enforcement agencies, but also on the attitudes of road users themselves. Changing the long term attitudes of drivers is extremely difficult to achieve, (Elliott et al., 2004). In this report the authors investigate the use of the ‘Theory of Planned Behaviour’ in determining the link between drivers’ attitudes and behaviour. They state that most attempts at changing driver attitudes fail due to a lack of long term exposure to the message of change and suggest that repeated exposure to persuasive arguments enhances the persuasive effect. It may be that attitudinal change in current drivers is beneficial in terms of road safety improvements but prevention of risk taking attitudes would probably result in more safety gains. Elliott states that the targeting of young, prospective and newly qualified drivers, before they develop unsafe attitudes and behaviours, should be made a priority if a lasting change to attitudes and behaviour is to be achieved.

2.2 Enforcement

Zaal (1994) in his review of the literature on traffic law enforcement states that for enforcement to be successful it must present a meaningful deterrent threat to road users. This can be achieved by increasing surveillance levels to ensure that the perceived risk of apprehension is high. Zaal also states that the most effective way of increasing the perceived risk of apprehension is to significantly increase the level of enforcement. Utilising the ‘blitz’ technique, short-term intensive enforcement activity, is more cost effective but may only have short-term effects on the road user. Another cost effective measure proposed by Zaal is to identify and specifically target accident black-spots and high risk behaviours.

Senserrick (2000) carried out a survey, in Victoria, Australia, exploring perceptions of overt and covert aspects of speed enforcement, risk of detection and speed related skills, attitudes and behaviours. From this four different driver profiles were identified using cluster analysis techniques. Cluster 1 was classed as having a positive profile with members of this group believing speed camera enforcement to be overt, with a high personal risk of detection. This group was least likely to speed and was predominantly female in its make up. Cluster 2, perceived speed camera enforcement as covert, and considered the risk of personal detection to be low. This group was also less likely to speed and was classed as having a very positive profile with males and females equally represented. All age groups were represented except for 20 – 29 year olds.

Cluster 3 was most representative of the 20 – 29 year old age group and was classed as having a negative profile. Members of this group were reported as perceiving all enforcement as overt with the risk of personal detection being low, although they believed the general risk of detection was high. Male and female drivers were equally represented in this group. The final cluster had equal numbers of males and females and was classed as having a very negative profile. Both levels of enforcement and general risk of detection were perceived as low by this group. Members reported positive speed related attitudes but negative speed related behaviour and this may explain why they see the personal risk of detection as high. The under 20 year old and 20 -29 year old age group were highly represented in this group.

Clusters 1, 2 and 4 believed that more overt measures would be effective in reducing speed, with cluster 3 disagreeing. In relation to more covert measures leading to greater detection of offenders, clusters 1, 3 and 4 were in agreement with this while cluster 2 did not agree.

From these results it is apparent that overt enforcement methods possess a general deterrent effect while covert methods need to ensure high detection rates in order to be effective. The members of Cluster 3 perceive their personal risk of detection as low and it would benefit all concerned if this perception could be changed while members of Cluster 4 need to be targeted, not just by enforcement, but in an effort to change their driving behaviour

De Waard and Rooijers, (1994), carried out two experiments investigating the effects of the visibility of police enforcement. The first experiment studied the effect of three variables on driving speed; intensity of enforcement, method of enforcement and time delay in informing the offender of their offence, by mailing fines to offenders rather than stopping them at the time of detection.

This was carried out over a period of four weeks. In the second experiment the intensity of the level of enforcement was related to the proportion of speeding vehicles and enforcement was carried out over a period of twelve consecutive weeks. The authors found that on-view stopping of offenders had a marked preventative effect on other drivers and was a more effective method of reducing driving speed than informing offenders by mail. De Waard and Rooijers showed that the deterrent effect on speeding behaviour continues even when the level of enforcement is reduced. If, however, all enforcement is completely discontinued the rates of violation were found to quickly return to previous levels. This is supported by research from Israel, Beenstock et al (2001), who also found that the withdrawal of enforcement leads to a rapid rise of accidents and violations to pre-enforcement levels.

Further evidence to support these findings is to be found in Summala et al, (1980). In February 1976 the Finnish police held a two week long strike which led to an almost complete cessation of the enforcement of speed limits. This lack of enforcement was widely known to the general public. Summala et al, (1980) report that during the strike the mean driving speed increased only slightly, yet the number of gross speed violations, where the speed limit was exceeded by more than 10km/ph, increased by 50-100%. This translates into a 20% increase in the standard deviation of travelling speeds. This increase in the standard deviation of travelling speed has the potential to lead to more severe accidents due to the relationship between increased speed and increasing severity.

Davis et al. (2006) report on the results of an aggressive approach to traffic law enforcement in Fresno, California. The study was initiated in an attempt to find out if an aggressive approach to police enforcement was effective in reducing the incidence of total road traffic accidents as well as producing reductions in the number of serious injury accidents, fatal accidents and fatal accidents related to speed. The authors found that during the study period the increase in enforcement and the pro-active approach adopted by police did produce significant reductions in accident numbers. Significant reductions were found in all accident categories under investigation throughout the treatment area.

These were not reproduced out with the study area lending weight to current evidence that increased police enforcement of traffic laws does lead to reductions in accident levels. Like many other studies (see Vaa 1997) the authors report that the reductions in accident levels were subject to time halo effects. In this case the time halo effect was approximately eight weeks. In order to combat the halo effect of enforcement strategies the method of enforcement has to remain constant and the perceived risk of apprehension, for violators, high.

Newstead, Cameron and Leggett (2001) found that a program of policing, Random Road Watch (RRW), in Queensland, Australia, which involved randomly scheduling low levels of policing with the intent of providing long-term, widespread coverage of a road network, was effective in achieving a reduction in road traffic accidents. The biggest reduction was seen in relation to accidents involving fatalities. This is further supported by Leggett (1988) who details the use of a long-term, low-intensity speed enforcement strategy in Tasmania, Australia. A reduction in speeding behaviour and a statistically significant reduction in overall average speed were reported, along with a significant reduction in serious casualty crashes of 58%. Leggett estimated that the two year enforcement program had resulted in a benefit-cost ratio of 4:1.

Blais and Dupont (2005) carried out a systematic review of thirty three studies covering a range of police enforcement initiatives. In all six methods of police enforcement were covered

1. Random Breath Testing (RBT)
2. Sobriety Checkpoints, where the BAC of suspected drink drivers was tested
3. Speed cameras and driver and number plate photography
4. Red light cameras
5. Random road watch. A selective traffic enforcement programme (STEP) approach where police patrols operate as usual but never in the same place at the same time on consecutive days

6. Varied programmes of activity including enforcement and educational publicity

In all but three of the studies investigated significant accident reductions were found. The three studies which did not produce significant reductions were all concerned with automated enforcement strategies; either speed cameras or red light cameras. According to the authors differing methods of enforcement all produce similar results with reductions ranging from 23% to 31% for severe injury accidents. On comparing the results between enforcement methods the authors report that no significant difference was found between enforcement methods. No real reason is given for the similarity in accident reductions achieved by each method of enforcement, but Blais and Dupont suggest that other indicators associated with enforcement should be taken into account. In relation to the three studies which found no significant reductions the authors emphasise the need to place cameras, be they automated speed cameras or red light cameras, at appropriate sites; sites where accident counts or violations are high compared to the norm. Also, in the case of red light cameras, other factors such as amber light interval may have an effect on the results. Increasing the length of the amber interval will obviously have an effect on the number of drivers who are running a red light.

It can be seen from the literature that there are many different methods of enforcement available to the relevant agencies operating in this field, however the most cost effective method, according to Zaal, is the use of automated enforcement devices.

2.3 Speed Cameras

The introduction of speed and red-light cameras in the early 1990's has led to a reduction in average speed and the number of accidents and casualties, ROSPA (2004), with casualty savings of 35% being reported as a result of the national camera safety scheme. Elvik et al (1997) conducted a meta-analysis of nine studies relating to the effect of speed cameras on road traffic accidents. This showed speed cameras were, on average, producing a reduction in all accidents of 19%, with accidents involving injury reduced by 17%. There was less of an effect in rural areas, mean accident reduction of 4%, than in urban areas, mean accident reduction of 28%. Zaidel (2002) conducted a meta-analysis of seventeen studies on manual speed enforcement and found an overall reduction in all accident rates of only 2%, with a reduction in injury accidents of 6%. He also reported a reduction in fatalities of 14%. Comparing the results from Elvik and Zaidel, with regard to all accidents and those involving injury, the reduction in accident rates achieved by speed cameras is much greater than can be achieved by manual speed enforcement.

Elliott and Broughton (2005) cite a study which responds to the criticism that reductions in violations, accidents and casualties at speed camera sites are actually representative of a regression to the mean effect (Hess, 2004). Hess studied the effects of speed cameras over a twelve year period in Cambridgeshire, England, thereby allowing regression to the mean effects to be discounted. The study reported a reduction in accidents involving injury can be reduced by approximately 45% by the use of speed cameras. Hess also reported significant reductions in accidents within a 2km radius of the camera site. Elliott and Broughton (2005) also cite research by Makinen and Oei (1992) and Makinen and Rathmayer (1994) in Finland, that further support the findings of Hess, with reported distance halo effects of between 4km and 10km. Other studies have found distance halo effects to be much smaller, Nilsson (1992) and Keenan (2002) both reported distance halo effects due to cameras of only 500m.

The subject of speed cameras has created a great deal of controversy, not least since the creation of partnerships of local authorities, the police and other enforcement agencies which use a percentage of fines levied to cover the costs of camera operations . This is viewed by many drivers and sections of the media as a ‘stealth’ tax, whose only purpose is to generate extra revenue, at the expense of unsuspecting drivers who feel they have done nothing wrong. This is untrue; if drivers are compliant with the current speed limit they will not be penalised. Ward (2004), discusses the use of Safety cameras in Great Britain, and notes that there has always been an acceptance of the validity of having safety cameras at traffic lights as most drivers perceive red light violations as dangerous. The negative attitude towards speed cameras can be directly related to the prevailing attitude that speeding is acceptable; the belief, here, being that it is wholly unnecessary, and unfair, to punish people who are doing nothing wrong and who pose no risk to safety. It would seem that this belief is more strongly, or perhaps exclusively, held by a small proportion of drivers who like to speed. Corbett (1995) describes four groups of drivers and their attitude towards speed cameras. These were termed as 'Conformers, the Deterred, Manipulators or Defiers'. Conformers normally complied with speed limits and therefore cameras made no difference to them, while the Deterred reduced their speed on roads known to be monitored.

The Manipulators slow down on approach to a camera site then speed up on passing the camera, while the Defiers carried on regardless, continuing to violate the speed limit even in the presence of cameras. The aim of speed camera enforcement, in this context, is to reduce the proportion of drivers classed as manipulators and defiers thereby increasing the proportion of conformers and deterred.

In order to reduce violations by those with a disregard for speed limits and no fear of overt cameras it may be necessary to increase the use of more covert methods in the case of those regarded as manipulators. Depriving them of their knowledge of camera sites will allow for less manipulative driving and may lead to a more safety oriented style of driving. Those drivers classed as defiers will be more difficult to dissuade from speeding. Their attitude and behaviour is that of the 'hard-core' violator and whose perception that they won't be prosecuted, even if caught, must be challenged. They must be made aware that their behaviour is not tolerable and that any violation will be met with the appropriate penalty.

In a study on the attitudes of European drivers, Cauzard and Quimby, (2000), state those drivers who are opposed to increased enforcement and increased severity of penalties are those drivers who consistently break the speed limit and would prefer an increase in the speed limit. They also report that it is the same drivers who have received more speeding penalties indicating that the current level of enforcement and penalties has had little or no effect on their attitudes and behaviour. This corresponds to the ‘manipulator and defier’ profiles defined by Corbett (1995).

It may be necessary, in the case of persistent speed violators, to take the decision, as to whether to speed or not, away from the driver by utilising more in car technology. This could include the use of engine mounted speed limiters or the use of in car active accelerator pedals (AAP). The latter approach was studied by Hjalmdahl and Varhelyi (2004), with the AAP producing a counterforce whenever the speed limit was approached, but the driver could over-ride this by pressing harder on the pedal. Over a period of six months twenty eight drivers had the system fitted to their cars and the reported results were very encouraging with regards to safety and improved driver behaviour. Drivers showed improved behaviour towards other road users and pedestrians and improved yielding behaviour at intersections. There was also an improvement in time gaps to the vehicle in front. The authors also report non-significant, negative driving behaviour modifications when the driver was not using the AAP. These include forgetting to adapt their speed to the speed limit or the prevailing traffic situation.

2.4 Traffic Light Cameras

The reported negative behavioural modifications would not represent a problem if all cars were fitted with an AAP and in any case the benefits to be gained by using an AAP seem to far outweigh the slight negatives reported.

The use of traffic lights, especially at intersections, can result in an increased safety factor due to the management and organisation of traffic flow. However, inherent in the use of traffic lights is the creation of a certain level of expectation regarding the behaviour of other road users where compliance to the traffic signal is the crucial factor.

In recent years enforcement agencies have increased the use of red light cameras at signalised intersections in an attempt to reduce red light violations and accidents. Retting et al (2003) carried out a review of the international literature on the effects of red light cameras on violations and accidents. During the six year period from 1992-1998 there were just under 6000 people killed, in the USA alone, in accidents resulting from red light violations. The authors found that enforcement due to red light cameras was extremely effective in reducing the rate of violations and injury accidents, with a best estimate of reduction at 25%-30%. The study also reports an increase in rear-end crashes but this was accompanied by a reduction in rear-end injury crashes. A meta-analysis by Zaidel (2002) on the effect of red light cameras on accidents reported a best estimate for reduction of all accidents at signalised junctions of 11% and a reduction of all injury accidents of 12%. Both of these results were statistically significant. In contrast to Retting, Zaidel reported a reduction of 15% in rear end collisions, although this was not statistically significant. Zaidel also cites a study (Kent et al., 1995) which looked at the effect of red light cameras in Melbourne, Australia. Here the authors found no significant relationship between the number of crashes at red light camera sites and non-camera sites.

2.5 Seat Belt Use

Seat belt use is now mandatory in most European countries but although violations of seat belt laws are liable to primary enforcement actual non-compliance is generally seen as a minor violation (Zaidel, 2002). It is generally considered that the use of seat belts by vehicle occupants reduces the severity of injuries suffered as a result of involvement in road traffic accidents (Elliott and Broughton, 2005, and ETSC. 1999). Bendak (2005) reports on the effect of the introduction of legislation in Saudi Arabia in 2000, requiring drivers and front seat passengers to wear seat belts. Although the study period was limited to the first few months immediately after the introduction of mandatory seat belt laws the author reports large increases in the number of drivers wearing seat belts. Previous to the introduction of the new legislation only 2.9% of drivers were reported as wearing seat belts while during the study period this had risen to 60%. This represents a highly significant increase and replicates the results found in other studies (Williams and Wells, 2004, Elliott and Broughton, 2005). Alongside the increase in seat belt use it was also reported that the number of serious injuries resulting from road traffic accidents had decreased as recorded by hospital admissions.

Non-compliance, in relation to drivers and front seat passengers, with seat belt laws on EU roads has been estimated to range from 8% to 30% (Makinen and Zaidel, 2003). The authors also report that police in almost all European countries consider the level of compliance with seat belt laws to be at a satisfactory level and, due to this attitude, see enforcement of these laws as being of minimal importance. This attitude is not to be encouraged as the goal of these laws is to achieve maximum compliance which leads to further reductions in fatalities and serious injuries due to road traffic accidents.

Elliot and Broughton, (2004), state that countries where the level of compliance with seat belt laws is high have experienced corresponding large reductions in casualties incurred due to involvement in road traffic accidents. This suggests that although police forces in many European countries see their role in enforcing compliance with seat belt laws as minimal at best, due to the belief that current levels of compliance are already at satisfactory levels, they would likely see the benefit of stronger enforcement, allied to other strategies, in the form of major reductions in the number of road traffic accident casualties.

In the USA the first mandatory seat belt laws were introduced in New York in 1984. Previous to this, national levels of seat belt usage were reported to be 17% (National Highway Traffic Safety Administration, 1997). By 2002, by which time all but one state had seat belt laws in force, this had risen to 75% (Grassbrenner, 2004), with national variation in usage ranging from a high of 93% to a low of 51%.

Seat belt laws, both primary and secondary, result in increased usage rates and a resulting reduction in serious injuries sustained in road traffic accidents. Increased police enforcement allied to well designed and wide reaching media campaigns are also important strategies in raising the levels of seat belt use (Houston and Richardson, 2005). Only one state in the USA has no mandatory seat belt law, with less than half of the remaining states having primary enforcement laws. Primary enforcement laws allow police to stop and cite vehicle occupants for not wearing a seat belt while in those states with secondary enforcement laws officers can only cite for seat belt violations if they have stopped the vehicle for another offence. Houston and Richardson, (2005), report that in states with primary enforcement usage rates are 9.1% higher than those with secondary enforcement and 21.6% higher than states with no mandatory law. Additionally the authors' report that increases in statutory fines levied for seat belt violations also increases the level of seat belt usage.

Further evidence to support the benefit of primary enforcement over secondary enforcement is provided by Farmer and Williams, (2005), who looked at the effect on fatality rates in road traffic accidents, in relation to states changing from secondary to primary seat belt enforcement. Ten states which moved from secondary to primary enforcement are compared with fourteen states with secondary enforcement. The authors report a reduction of 7% in fatalities as a result of changing to primary enforcement.

The main effect of the introduction of mandatory seat belt laws seems to be an immediate increase in seat belt usage. Typically the highest usage rates are achieved immediately after the introduction of new legislation followed by a steady decline in usage after the first few months, although not down to pre-legislation levels (Williams and Wells, 2004). This effect is generally seen when the new legislation is not complemented by increased police enforcement and mass media publicity campaigns. In Canada seat belt use was measures at 75% immediately after the introduction of mandatory seat belt laws, dropping to 50% six months later (Robertson, 1978). The use of increased police enforcement and mass media campaigns led to heightened public awareness of the seat belt law so that by 1994 seat belt usage was at 90% and has remained there ever since. Both the USA and Canada experienced difficulty in raising seat belt usage above 80%. Jonah and Grant

(1985), suggest that 80% is the maximum achievable usage rate due to enforcement alone, with sustained use of high profile media campaigns, allied to enforcement strategies, needed to breach the ‘80% barrier’.

It follows that if an increase in seat belt usage by car occupants leads to a reduction in fatalities and serious injuries then there must be a corresponding decrease in the risk of death for those drivers who wear a seat belt. Data from Sweden (Nilsson, 2004) puts the risk of death for those not wearing a seat belt at six times greater than for those wearing a seat belt. Nilsson reports that data from fatal accidents in Sweden show that 40% of fatalities in road traffic accidents were not wearing seat belts, with seat belt use, on average, being at 90%. From this it follows that, on average, 10% do not wear seat belts and the difference in risk between seat bet wearers and non seat belt wearers can be calculated as 40% / 10% for those not using a seat belt against 60% / 90% for those wearing a seat belt. For motorists in Sweden this means that unbelted motorists have a risk of death of 4 versus 0.67 which is approximately six times higher.

Many studies have shown that enforcement of seat belt laws, especially when run in tandem with other strategies, results in an increase in compliance with seat belt laws and a resulting reduction in fatal and serious injuries. The key to reaching maximum achievable compliance levels would appear to be the use of highly visible and well publicised, by means of sustained mass media campaigns, police enforcement. However there seems to be a hardcore of violators, approximately 10% in most Western countries, who are immune to current enforcement strategies. In order to bring this hardcore element into line it may be necessary to take the decision of compliance or non-compliance out of their hands. This can be done by introducing automatic in-car safety devices such as intelligent warning systems or compulsory interlock devices in every car.

2.6 Drink Driving

In terms of road safety drink driving is recognised as a major problem in most countries. Elliott and Broughton (2005) analysed the results from eleven studies on drink driving and report that all show the effect of enforcement on drink driving results in large reductions on the incidence of drink driving violations. Each study showed an overall decrease in the accident rates due to enforcement campaigns. Zaidel (2002) details the results of a meta-analysis conducted by Elvik (1997). This involved twenty-six studies that looked at the effect of enforcement on drink driving. The enforcement of drink driving sanctions resulted in an overall reduction of all accidents of 3.7%, with fatal accidents being reduced by 9%. Accidents involving injury were reduced by 7.1%. It is also reported that revoking the driving licence of offenders resulted in an 18% reduction in all accidents and this appears to be the most effective measure in reducing alcohol related accidents. There have been calls for treatment and rehabilitation programmes to replace license revocation as a sanctioning tool, but, the author states, where this has taken place the overall rate of accidents has risen by 28%.

The main thrust of many drink driving policies, in Western society, has been deterrence. Deterrence theory views people as rational actors or decision makers and states that there are two types of deterrence, restrictive and absolute. Punishing offenders can result in either absolute deterrence, which results in a complete cessation of offending or restrictive deterrence which reduces the level of offending in an attempt to avoid detection. The perception of the speed, certainty, and severity of punishment related to breaking the law is influential with respect to the deterrent effect for offenders. If offenders believe that the chance of detection is high and the punishment severe then the deterrent effect is high and offenders will be less likely to break the law.

In order to increase the perceived effect of deterrence for offenders many strategies have been applied, including, but not restricted to, increased police enforcement, random breath testing (RBT), lowering of the legal blood alcohol concentration (BAC) limits and mass media publicity campaigns. Such methods are all designed to produce decreases in the number of drink driving related accidents and injuries. In general one or more of these methods are used together in an attempt to reduce the number of reported incidents and are known to achieve the desired effect.

Homel (1994) in an analysis of daily fatal crashes in New South Wales, Australia, during the period July 1975 to December 1986, reports a significant reduction, 13%, in the number of fatal crashes occurring. This coincided with the introduction of new legal limits relating to Blood Alcohol Concentration (BAC), which reduced the BAC limit from 0.8mg/ml to 0.5mg/ml. The effect of reducing the BAC level was found to be significant, but only on Saturday nights throughout the study period. The author was surprised by this result as there had been little publicity or public debate on the issue, nor had there been any marked increase in police enforcement activity in relation to new BAC level. It is well established in literature (Elliot 1993, Elder et al 2004) that enforcement strategies are more effective when coupled with effective media campaigns which inform the public in relation to the enforcement strategy. However, this is not to say that media campaigns and increased police enforcement are necessary for a particular enforcement strategy to be effective as shown by Homel (1994). Only that the combination of enforcement and publicity tend to produce better results (Mathijssen, 2005).

Homel also reports that the introduction of Random Breath Testing (RBT) had an immediate effect by reducing the level of fatal crashes by 19.5% overall and by 30% over holiday periods. The reduction in accidents is much greater when RBT is introduced in tandem with the lower BAC limit than reductions achieved solely by lowering the BAC limit. It is to be expected that a combination of enforcement strategies would lead to further reductions in accident levels but Briscoe, (2003), reports that a doubling of the penalties for drink driving offences in New South Wales, Australia, allied to the already high level of RBT enforcement, was expected to produce further reductions in the number of drink driving offences but in fact showed that there was, instead, an increase in the number of offences. Specifically there were significant increases in three non fatal accident categories, namely, overall injury accident rates, multiple vehicle day time accident rates and single vehicle night time accident rates. The increase in single vehicle night time accident rates was most unexpected as this is the category with the highest expectation of alcohol involvement, and the increase in reported offences in the face of more severe punishment is contrary to established evidence from literature on the subject (Elliott and

Broughton, 2005, Elvik, 1997). The author reports that there may be many reasons for this increase in accidents over the study period. These include a drop in the level of police enforcement at the time of the initiative, lack of publicity for the increased level of punishment and an increase in road usage. Any or all these could be responsible for the increase in accident rates. In any event not taking these possible confounders into account when designing the study leaves the results open to debate. The decrease in enforcement levels and the lack of publicity for the increased penalties would, together, be the most probable reason for the reported increase in accident rates. For offenders the perceived risk of detection would have gone down, thereby leading to an increase in illegal behaviour and the resulting increase in accidents.

Another method widely used to reduce the incidence of drink driving is the lowering of the legal blood alcohol concentration (BAC) in conjunction with high level of enforcement. Many countries have passed legislation which details the maximum permissible BAC level and this acts as the cornerstone for efforts to reduce and prevent drink driving related accidents, although the threshold set by each country varies considerably, from 1.0mg/ml to the zero tolerance level 0.0mg/ml. As of January 2005 the countries with the highest level are Albania and Algeria and those with zero tolerance include Armenia, Azerbaijan, Croatia, Czech Republic, Ethiopia, Hungary, Nepal, Romania and the Slovak Republic (ICAP 2005). BAC levels were available for 74 countries and within the range mentioned previously nine countries have zero tolerance, five have a BAC of 0.2mg/ml, , three have a BAC of 0.3mg/ml, one has a BAC of 0.4mg/ml, 28 had set a BAC of 0.5mg/ml, one has a BAC of 0.6mg/ml and 3 have a BAC of 0.7mg/ml,. Only one country has a variable level, Russia, ranging between 0.2-0.5mg/ml. This is an improvement on the level set in 2002 which stated only ‘drunkenness’ as the limiting factor.

The setting of BAC levels is not an arbitrary process, as may be suggested by the variation in levels throughout the world, but is determined by the results of clinical research into the impairment of driving skills at certain BAC levels. Moskowitz and Fiorentino, (2000), have shown that the overwhelming majority of driving skills suffer from impairment at a BAC level of 0.7mg/ml in more than

50% of behavioural tests. These tests include Cognitive Tasks, Psychomotor Skills, Choice Reaction Time, Tracking, Perception, Visual Functions, Vigilance, Drowsiness, Driving, Flying and Divided Attention. The authors also state that all subjects had shown impairment on at least one of the tests at a BAC level of 0.8mg/ml. Drowsiness, Psychomotor Skills, Cognitive Tasks, Tracking, Driving, Flying and Divided Attention all showed a level of impairment at a BAC level of ≤0.2mg/ml in at least one subject. These figures suggest that the BAC level set by most countries is too high and serious consideration should be given to establishing an international agreement on BAC levels. A zero tolerance approach is to be desired but is probably not possible due to confounding factors i.e. alcohol in food and some medicines or health products such as mouthwash.

Deshapriya and Iwase (1996), discuss the effects of lowering the legal blood alcohol limits, in Japan, on the rate of accidents involving drink driving. In Japan the Road Traffic Act states that drinking and driving is prohibited but for legal reasons the BAC limit has been set to 0.5mg/ml. The lowering of the BAC level and extensive enforcement of the legislation has led to a steady decrease in all accidents involving drink driving. Bernat et al, (2004), studied the effects of lowering the BAC level to 0.8mg/ml in 19 jurisdictions in the US. They report a best estimate, of changing the BAC level from 1.0mg/ml to 0.8mg/ml, as a reduction in alcohol involved fatal accidents of 5.2%.The authors also report that the implementation of Administrative License Revocation, where the authorities have the power to immediately suspend the driving license of anyone with too high a BAC level, led to a decrease in alcohol related accidents of 10.8%. The introduction of a BAC limit 0.5mg/ml, in Holland in 1974, led to an immediate drop in the number of drivers exceeding the legal limit from 15% to 1% (Mathijssen, 2005). However by the following year this had risen to 11% and remained relatively steady at this level until 1983. The introduction of RBT allied to stronger enforcement policies has led to further reductions so that in 1991 only 3.9% of those drivers tested had an illegal BAC level. By 2004 a national survey reported the proportion of those tested who had an illegal BAC level was 4.6%. This increase is probably due to a reorganisation of the police forces in Holland and a redirection of police of resources to concentrate on the enforcement of speed levels.

The counter effect of increasing the legal BAC level was studied by Vollrath et al, (2005), who looked at the increase in the BAC level in East Germany following the German reunification in 1990. As a result of reunification the BAC in the former East Germany was raised from 0 mg/ml to 0.8mg/ml in 1993. This was done to match the then legal level in West Germany. The authors compare results from a town in the former East Germany, where the BAC had been raised, to one in the West. The authors found that the increase in the legal BAC levels did not lead to an increase in the number of people driving under the influence of alcohol, but did result in a shift towards driving with higher BAC levels, below 0.8mg/ml, but higher than the previous level. It seems that drivers from East Germany although increasing their intake of alcohol were still aware of the legal limit and continued to limit the amount of alcohol consumed before driving. The incidence of alcohol related accidents had been in steady decline in West and East Germany since 1982 but after the collapse of communism in 1989 there was a dramatic increase in all accidents in the former East Germany. Alcohol related accidents rose from under 10% in 1989 to over 16% in 1993 before the trend was reversed. As of 1997 the incidence of alcohol related accidents was down to 11%.

This decrease in the number of alcohol related accidents, as reported by Vollrath et al., 2004, coincides with the increasing of the legal BAC level and is somewhat surprising. It may be that the strict moral code enforced under communism was still an influence on most drivers in the former East Germany, with the exception of young drivers who drove more under the influence of alcohol than their Western counterparts. The relaxing of laws and influence of the less rigid Western lifestyle was probably felt more profoundly by young people, who took the opportunity to live life to the full whereas older drivers still continued to obey the law, as was there habit under the previous regime. Thus any changes in behaviour were more than likely a result of changing attitudes rather than any legal factors.

2.7 Attitudes and Behaviour

The deterrent effect of enforcement depends very much on the type of offence and the severity of penalties associated with a particular offence. In 1997 a report was commissioned by the Scottish Office, The Deterrent Effect of Enforcement on Road Safety, System Three, 1997, to investigate driver knowledge and awareness of existing penalties relating to road traffic violations, the influence of risk factors relating to violations of road traffic laws and whether or not there were differing effects across the range of possible driving offences. The main offences considered being speeding, drink driving and careless/dangerous driving.

The findings from the report indicate that there are many influences responsible for the levels of compliance adhered to, in relation to traffic laws, by drivers. This varies depending on how each driver views each category of driving offence, with offences regarded as having severe penalties and a high level of social stigma attached being more likely to have high levels of compliance with the law. Speeding in particular is not associated with severe penalties or any form of social stigma by the large majority of drivers and is also viewed as having a low risk of detection and accident involvement. Drivers are therefore quite happy to violate speed limits as the perceived risk of both accident involvement and detection are low (DETR, 2000). At the time of the report drivers seemed to be unaware of the association between speeding and involvement in serious accidents.

The attitudes of drivers towards violating speed limits are in marked contrast to the prevailing attitude with regards to drink driving. Here the perception is of severe penalties, including imprisonment and loss of driving licence, and the social stigma, and possible social isolation, associated with convictions for drink driving. The public is well aware, due to hard-hitting media campaigns and increased police enforcement, of the severe punitive measures in place for those who choose to violate drink driving laws. Previous offenders have the added, if unwanted, benefit of having experienced these sanctions first hand and this increases the deterrent effect. Both previous and non-offenders, although strongly motivated to avoid drink driving by the current legislation, believe that even more punitive measures would be beneficial in reducing violations and this is a crucial factor in changing driver behaviour and attitudes. If the public view the sanctions as necessary and fair and accept that their behaviour is wrong then the deterrent effect of sanctions is more readily accepted and therefore more effective in reducing violations (Blais and Dupont, 2005).

Enforcement strategies are well known to have positive effects in terms of reducing the number of accidents, fatalities and injuries. However, even full compliance with existing traffic laws can only achieve a finite reduction in accident numbers. Theoretical estimates, based on full compliance, are thought to reduce accidents by up to 50% (Zaidel 2002). In reality, empirical studies generally produce results with much lower reductions than this; with 10% considered to be on the high side. In order to achieve further reductions enforcement needs to be combined with strategies that are designed to have a positive effect on driver behaviour.

This is probably the most challenging aspect, in relation to road safety, facing enforcement agencies at this time. The obvious starting point is to educate young and prospective drivers before they develop unsafe road behaviour. It may be much more difficult to eradicate unsafe driving behaviour amongst current drivers but the benefits to road safety make these drivers prime targets for enforcement agencies.

Ward and Lancaster (2004) carried out an international review of literature with the aim of identifying individual differences amongst drivers which are associated with driving behaviour and road traffic accidents. They note that drivers who possess high levels of confidence in their driving ability tend to commit driving violations while drivers with low confidence levels are more likely to be involved in crashes. They also state that above a certain level of minimum competence, in relation to vehicle and road reading skills, attitude is a better predictor of crash involvement than poor skills. Driving experience is associated with a reduction in risk of ‘at fault’ accidents but this effect is seen to level out after eight years. It may be that in the early stages drivers are more at risk due to lack of exposure in real situations and the relative risk reduces as experience is gained. The levelling out of the benefits of experience after eight years may be a result of drivers becoming over confident in their abilities and developing bad driving habits. This could be countered by introducing periodic evaluation and/or re-training for every driver in order to identify and rectify unwanted driving behaviour.

By studying how cars are driven Parker and Stradling (2001) have identified three distinct phases in the process of learning to drive,

1. Technical Mastery
2. Reading the road
3. Expressive phase

The expressive phase identifies psychological characteristics of the driver and three related driving behaviours have been identified from large scale studies in England and Wales,

1. Lapses
2. Errors
3. Violations

These types of behaviour have also been identified in Australia, Sweden and China.

Lapses are not generally considered life threatening while errors are defined as the failure of planned actions to achieve the intended objective and can be observational or judgemental in aspect. Violations are deliberate actions contrary to those requires to ensure safe operation of a potentially hazardous system-the road system. Speeding and drink driving are both classed as behavioural violations.

The fundamental difference between the three types of behaviour is that violations, not lapses or errors, are highly linked to crash involvement, including both active and passive accidents. High violators are just as likely to run into other vehicles as to cause other vehicles to run into them. As lapses and errors are generally caused by inexperience and lack of skill they can be countered and improved upon by further training. Violations however are a result of driver attitude and, as such, are much harder to deal with. As violators make conscious choices as to how they drive much of their behaviour is avoidable and it is this type of driver who is generally targeted by enforcement agencies. High violators have a high level of confidence in their driving ability, considering themselves to be better drivers than others and do not believe that their behaviour presents problems for other drivers. They also tend to over estimate the number of other drivers who are violators. This may be due to a distorted perception of driver behaviour derived from peer group knowledge.

Pennay (2005) in his report on community attitudes to road safety, in 2004, found strong support for the regulation and enforcement of road traffic laws. Support for random breath testing (RBT) was recorded at 98%, continuing a ten year trend where support had never been below 96%. In relation to speeding support for the 50kph (approximately 30mph) speed limit in residential areas was very strong with support increasing from 65% in 1999 to 91% in 2003. The 2004 survey asked a slightly different question than previous surveys, in relation to the 50kph speed limit. Rather than asking if people supported the 50kph speed limit they were asked if they thought the speed limit was too low. The results showed that 77% of respondents thought the speed limit was just right with a further 3% believing it was too high. The remaining 20% thought that 50kph was too low. Although this represents a reduction from the previous year it still shows that a large part of the community supports the legislation. These figures are similar to the New Zealand experience where 87% of respondents supported a 50kph speed limit in urban areas (Ministry of Transport, 2005). The New Zealand survey also reported strong public support for police enforcement in general. A slight reduction was noticed in the number who supported an increase in enforcement but this may be due to people who previously supported increasing enforcement now believing that enforcement had reached a level with which they were satisfied.

2.8 Road Safety Media Campaigns

Road safety media campaigns are generally used as part of a set of activities designed to improve road safety. The use of mass media gives a public face to the overall campaign but is not used in isolation if maximum effect is to be achieved. Maximum effectiveness is achieved by a combination of measures of which the media campaign is just one. Other measures such as increased police enforcement and/or changes in legislation are used in tandem with the publicity. The main role of such campaigns is to raise awareness and affect changes in attitude and behaviour of the target demographic. Linking the campaign with police enforcement is essential in order to increase the perceived risk of apprehension amongst the target demographic

Mass media campaigns have been implemented in many countries in the last few decades. Literature suggests (Elliot 1993, Mathijssen, 2005) that mass media campaigns are more effective if they are reinforced by other measures such as increased law enforcement. In their paper on the effect of mass media campaigns, Elder et al (2004), state that there is strong evidence to suggest that mass media campaigns that are well thought out and reach a large target audience and are carried out alongside other preventative measures are successful in achieving a reduction in drink driving related accidents. The authors also investigated the message content of mass media campaigns and show that message content is generally based on the opinion of experts or focus groups as opposed to using the available evidence on the effectiveness of changing behaviour. It is probably fair to say that the message content would be better designed and more effective if it was based upon existing theory and empirical evidence rather than the opinion of experts and focus groups.

Pre-testing of campaign themes before they are viewed by the general public is an important part of the overall process. This allows for an assessment as to how relevant the campaign is to the target audience. It also permits an assessment to be made regarding audience comprehension of the specific message carried by the campaign. Elder et al. (2004), cite an example which illustrates the importance of pre-testing media campaigns. The campaign in question was designed to prevent alcohol related problems by promoting drinking in moderation. No pre-testing was carried out and a survey mid-way through the campaign found that over a third of respondents thought the campaign was promoting alcohol consumption, with many respondents mistaking the campaign for beer advertisements!

The' Foolsspeed' media campaign (scotland.gov, 2002) was a five year campaign, starting in November 1998, in Scotland aimed at reducing speeding in urban areas. The campaign was targeted at male drivers 25 to 44 years of age. The campaign was built on foundations established by the Theory of Planned behaviour (TPB), which explains and predicts behaviour in relation to known psychological determinants. The campaign was subject to extensive pre-release testing to ensure that the intended message was being delivered and that the desired outcome was achieved. The pre-testing was in line with recommendations from literature on the subject (Elder et al., 2004). Results from an evaluation of the campaign show that attitudes towards speeding became significantly more negative towards speeding over the duration of the campaign,

The general consensus of those operating in the road safety arena is that advertising campaigns produce better results when carried out in tandem with enforcement strategies, and advertising that does not have the benefit of allied enforcement strategies is less effective, is challenged somewhat in a paper by Tay (2005a), using evidence from Australia and New Zealand. In his paper Tay states that even though both the media campaign and police enforcement, in this case targeting drink drivers, appeared to produce the desired result independently of each other, he found no evidence to suggest that the effectiveness of either measure was dependant on the other. Further evidence to support this view is given in Tay (2005b). In this paper the author believes that the lack of an interaction effect between the two measures is due to the message content of the media campaign. In this case the message is using a ‘fear factor’ to encourage compliance rather than concentrating on the deterrent effect of enforcement. Relating Tay’s findings to those of Elder et al (2004), it would seem that the effectiveness of mass media campaigns is based upon their ability to reach the target audience, and put across the desired message in a manner that the audience can understand. If it is assumed, as suggested by the literature, that both enforcement and media campaigns are effective in producing a decrease in accident rates, then it is perhaps surprising that Tay found no evidence of an increased effect when both were run in tandem.

3. Research Methods

3.1 Introduction to Research Methods

The intention of this study was to investigate the effects of police enforcement activity on the level of Road Traffic Accidents (RTA’s), specifically those classed as Killed and Seriously Injured (KSI) accidents. Accidents reported as having caused only slight injuries are not used as a separate category, but are included in total accidents, due to problems relating to the under-reporting of slight injury accidents. Many studies have focused on problems with under-reporting of accidents and casualties by the public and under-recording of those reported by the police; see, for example Alsop and Langley (2001). The effects of police enforcement activity were investigated by attempting to identify any differences between forty-three Police Force Areas (PFA’s) in England and Wales, with respect to the number of accidents occurring over time, and if differences or similarities were found, what were the reasons for these. It should be noted that although there are actually forty-three PFA’s in England and Wales only forty-one are being used in this study. Two PFA’s, the Metropolitan Police and City of London Police are treated as special cases due to certain anomalies. The City of London covers approximately 2.6 km^2 and has a resident population of fewer than 10,000 people, with a daytime population of more than 300,000. The increase in daytime population is mainly due to the fact that City of London is home to the financial district and all it's associated workers. This leads to a large increase in the level of through traffic and therefore exposure to road traffic accidents increases. Any accident or KSI rates calculated for this PFA tend to be an order of magnitude greater than the same rate for any other PFA; therefore it is excluded from any analysis. Data relating to the Metropolitan Police are also excluded from any analysis. The overall size of the Metropolitan PFA, with a population almost three times larger than the next most populous PFA, and approximately five times as many KSI accidents as the next largest PFA means that it exerts too much influence in any analysis. Regression models which include the Metropolitan PFA are discussed in chapter 4.

In order to determine if police effort has any value as a determinant in the reduction of KSI accidents, the following measures are used as proxies for police effort; numbers prosecuted and found guilty (Prosecutions), Fixed Penalty Notices (FPN), Written Warnings (WW) and Vehicle Defect Rectification Notices issued (VDRN). Through 1997 to 2004 the numbers of FPN's and Prosecutions far outstrip the number of VDRN's and WW's, Table 3.1.1 and Figure 3.1.1. During this period FPN's and Prosecutions account for, on average, over 95% of the total number of proxy measures. The percentage has increased from approximately 92% in 1997 to 97% in 2004 with a corresponding decrease in the number of VDRN's and WW's issued.

Table 3.1.1 Total Number of Enforcement Proxies

YEAR	FPN	PROSECUTIONS	VDRN	WW
1997	3,414,289	2,240,167	268,208	195,200
1998	3,425,176	2,196,183	245,854	151,527
1999	3,110,515	2,124,290	217,507	120,110
2000	2,975,538	2,059,452	169,483	96,422
2001	2,939,131	2,619,067	142,105	79,756
2002	2,979,610	2,124,220	127,463	50,303
2003	3,463,436	2,326,671	121,983	51,500
2004	3,420,463	2,291,538	125,485	58,930

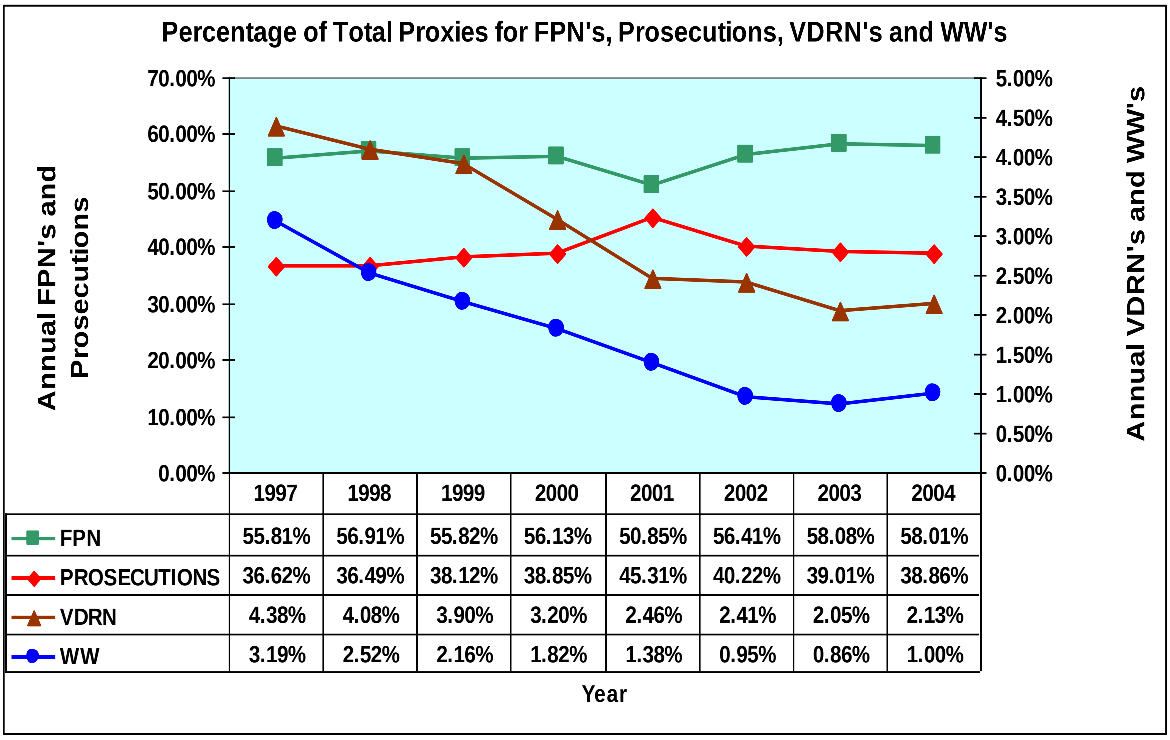


Figure 3.1.1 Percentage of Total Enforcement Proxies

3.2 Data Collection

In relation to data collection and assimilation two distinct datasets were used to construct a single Access database from which relevant data could be extracted. The first dataset contained details of all RTA's in England and

Wales during the period 1991 to 2004. Accident data was derived from the UK RTA dataset (STATS19). The Stats19 returns include details of all RTA's in Great Britain involving injury to one or more persons. Accidents included in the returns are those which take place on the public road system and which are reported to the police within 30 days. Details taken from the Stats19 returns are shown in Table 3.2.1. It should be noted that these data were first combined into a single database, with the exception of 2004 data, in 2005 as part of Andrew Scott's MSc dissertation. However only one year of data was used, 2003, and the methods of analysis used in this thesis are wholly new.

Table 3.2.1 Variables used in Database Construction

Variable Name	Data Source	Nature of Variability
Police Enforcement Proxies		
Fixed Penalty Notices	Home Office	Temporal and Spatial
Prosecutions	Home Office	Temporal and Spatial
Vehicle Defect Rectification Notices	Home Office	Temporal and Spatial
Written Warnings	Home Office	Temporal and Spatial
Socio-Demographic Variables		
Population	Office of National Statistics	Temporal and Spatial
Vehicle km (billion miles)	Office of National Statistics	Temporal and Spatial
Geographical Area	www.policecouldyou.co.uk	Spatial
Index of Mean Deprivation - Wales	Welsh Government	Temporal and Spatial
Index of Mean Deprivation - England	Office of the Deputy Prime Minister	Temporal and Spatial
Length of All Roads	Department for Transport	Spatial
Length of Trunk Motorway	Department for Transport	Spatial
Percentage of Trunk Motorway	Derived from Department for Transport figures	Spatial
Accident Data		
Driver Age	STATS19	Temporal
Driver Gender	STATS19	Temporal
Junction Detail	STATS19	Temporal
Killed and Serious Injury Accidents	STATS19	Temporal and Spatial
Lighting Conditions	STATS19	Spatial
Road Class	STATS19	Spatial
Road Surface	STATS19	Spatial
Road Type	STATS19	Spatial
Speed Limit	STATS19	Spatial
Time,(Hour, Day, Month)	STATS19	Temporal
Total Accidents	STATS19	Temporal and Spatial
Vehicle Type	STATS19	Temporal and Spatial

The second dataset contained the proxies for enforcement variables and these are also shown in Table 3.2.1. Enforcement data was obtained from the UK Home Office and details information on actual numbers issued, relating to each of the available proxy variables. Annual time series data was available from 1997 to 2004 for all four measures while quarterly data was available from 1999 to 2004 for Prosecutions and from 1999 to 2003 for FPN's, WW's and VDRN's. As a result of changes to data collection methods quarterly data is no longer available after 2004 and this limits this investigation, time wise. Although these variables do not cover the full spectrum of police enforcement activities, data on variables such as amount of road patrolling and safety campaigns were not readily available. It is hoped that Prosecution variables will cover these effects but it is realised that this is a limitation. With the database now containing matched information for road traffic accidents and enforcement proxies further information in the form of socio-demographic variables were added. These are listed in Table 3.2.1. The nature of variation, spatial, temporal or both, for all variables is also given in Table 3.2.1.

Measuring the effect of police enforcement is not an easy task. There are many forms of enforcement strategy utilised by enforcement agencies, with different levels of importance given to different strategies depending on the priorities of the relevant agency, or in this case, police force. Each Police Force Area (PFA) will have its own priorities, dependant on many factors, and measuring the effectiveness of these varying strategies is a complex task. Enforcement strategies include, but are not limited to, speed cameras, traffic light cameras, seat belt enforcement and mass media advertising campaigns.

Enforcement strategies are employed to target irresponsible, dangerous and unlawful behaviour. According to Zaidel (2002), Traffic Law Enforcement operates under two mechanisms which can help not only to prevent accidents but also to reduce the severity of accidents. The first of these is system management. Through system management enforcement agencies can manage and maintain a safe road system, creating an environment where fewer hazards are presented to road users resulting in less risk and fewer accidents. The second mechanism is based on the assumption that a large proportion of accidents are caused by the non-compliance of road users, in relation to traffic laws and regulations. While it is clear that Traffic Law Enforcement can lead to changes in driver and traffic behaviour it is also very clear that non-compliance still presents a major problem for enforcement agencies. The effective application of enforcement in relation to road traffic rules and regulations is dependent not only on the actions of the relevant enforcement agencies, but also on the attitudes and behaviour of road users.

3.3 Data Preparation

The first step in preparing the data was to extract, from the STATS19 dataset, accident records relating to KSI accidents, as these were to be the main focus of the study. The total number of accidents was also recorded to enable a calculation of accident severity rates. In order to simplify the data and reduce it to a state ready for analysis it was entered into an Access database from where it would be easier to extract the required data. As the main aim of any analysis was to investigate differences or similarities between individual PFA's, throughout England and Wales, data from the Stats19 returns, relating to the forty-one PFA's of interest, were extracted. The enforcement data on Prosecutions, FPN's, WW's and VDRN's were supplied already categorised by PFA and were also added to the new database. This allowed the incidence of accidents and associated accident, KSI and severity rates to be directly linked to the associated level of police enforcement measures for individual PFA's. Other variables, relating to each PFA, were selected in order to further broaden the scope of the analysis and these are detailed in Table 3.2.1. The data for all independent variables were also entered into the database allowing all data to be aggregated up into PFA groupings. Details and sources for all variables are given in Appendix 3, Table.1.

In order to simplify interrogation of the database, predefined queries were set up covering all aspects of the combined dataset. All queries used PFA's as a grouping variable which allowed for the selection of any combination of dependent and independent variables relating to any number, or combination, of PFA's. Once the desired information had been generated it could undergo visual exploration in Access and then exported to the SPSS software package for more complex analysis. Example screenshots from the database are shown Figures 3.3.1 and 3.3.2. On opening the database the user is presented with a selection of pre-defined queries from which to choose, see Figure 3.3.1. On selection of a query the user can then select any combination of data, relating to the specific query, see Figure 3.3.2. This will initially produce a table of data which can be used as the basis for further analysis.

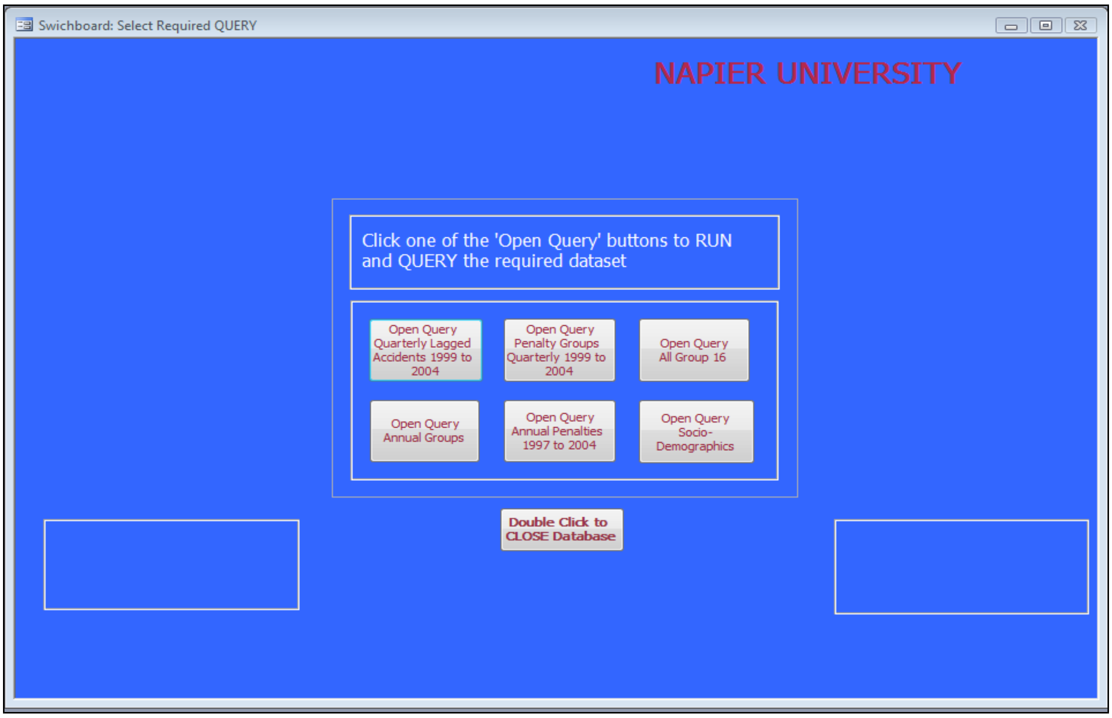


Figure 3.3.1: Database Query Select Switchboard

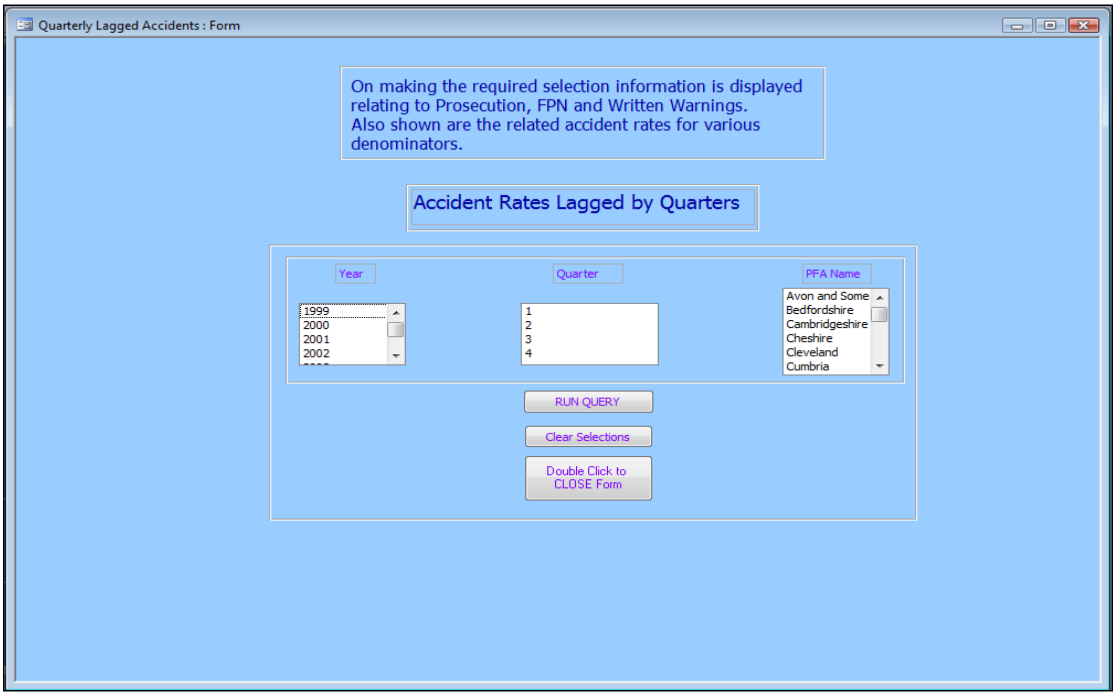
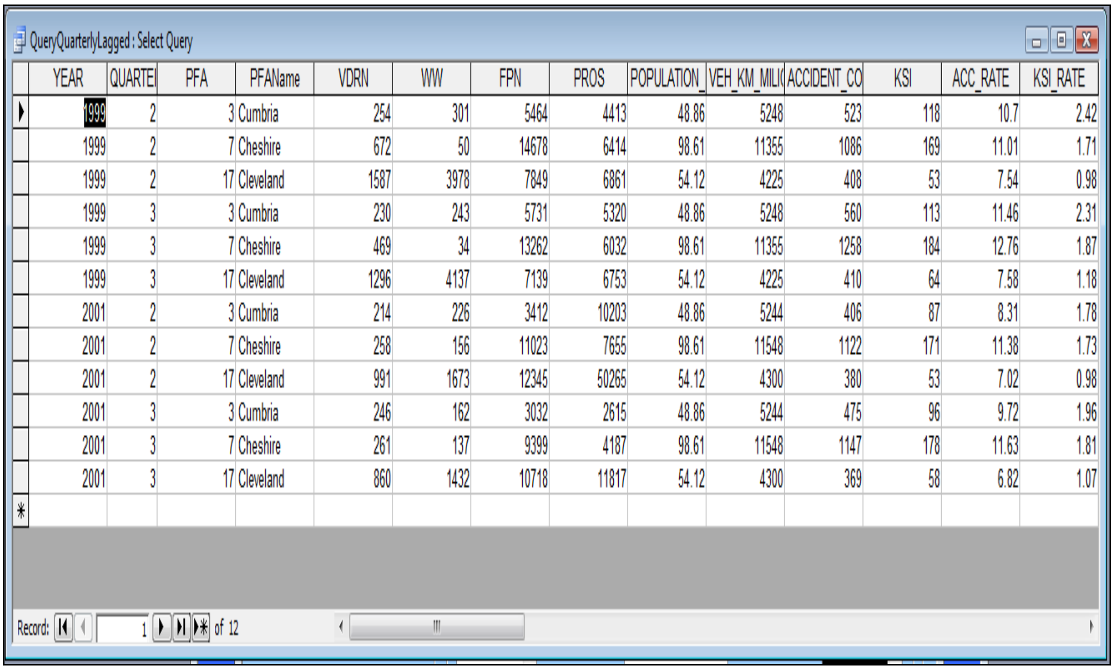


Figure 3.3.2: Screenshot of Database Query Switchboard

The pre-defined query, shown in Figure 3.2.2, produced the table shown in Figure 3.3.3. Here the selected criteria were Quarterly Lagged accidents for 1999 and 2001 covering quarters 2 and 3 for Police Force Ares Cumbria, Cheshire and Cleveland.


QueryQuarterlyLagged : Select Query

YEAR	QUARTE	PFA	PFAName	VDRN	WW	FPN	PROS	POPULATION_	VEH_KM_MILI	ACCIDENT_CO	KSI	ACC_RATE	KSI_RATE
1999	2	3	Cumbria	254	301	5464	4413	48.86	5248	523	118	10.7	2.42
1999	2	7	Cheshire	672	50	14678	6414	98.61	11355	1086	169	11.01	1.71
1999	2	17	Cleveland	1587	3978	7849	6861	54.12	4225	408	53	7.54	0.98
1999	3	3	Cumbria	230	243	5731	5320	48.86	5248	560	113	11.46	2.31
1999	3	7	Cheshire	469	34	13262	6032	98.61	11355	1258	184	12.76	1.87
1999	3	17	Cleveland	1296	4137	7139	6753	54.12	4225	410	64	7.58	1.18
2001	2	3	Cumbria	214	226	3412	10203	48.86	5244	406	87	8.31	1.78
2001	2	7	Cheshire	258	156	11023	7655	98.61	11548	1122	171	11.38	1.73
2001	2	17	Cleveland	991	1673	12345	50265	54.12	4300	380	53	7.02	0.98
2001	3	3	Cumbria	246	162	3032	2615	48.86	5244	475	96	9.72	1.96
2001	3	7	Cheshire	261	137	9399	4187	98.61	11548	1147	178	11.63	1.81
2001	3	17	Cleveland	860	1432	10718	11817	54.12	4300	369	58	6.82	1.07

Record: 1 of 12

Figure 3.3.3: Screenshot of Query Results

The data table produced from the query can now be used as it is or can be exported to a more advanced software package for further analysis. All work on the database was done by the author of this thesis.

3.4 Exploratory Data Analysis

3.4.1 Introduction

Analysis of the data, now contained in the Access database, was done in progressive steps. Before using the data for any analysis the data was checked for missing values, outliers and any other extraneous values. These are necessary steps to ensure the reliability and validity of the data. Descriptive statistics for the enforcement proxies and socio-demographic variables are given in Tables 3.4.1.1 and 3.4.1.2.

Table 3.4.1.1 Descriptive Statistics of Annual Data 1997 to 2000

Descriptive Statistics of Annual Data 1997 to 2000						
YEAR = 1997	Number of Police Force Areas	Minimum	Maximum	Sum	Mean	Std. Deviation
GEOGRAPHIC AREA sqkm	41	566.70	10240.86	141859.05	3459.98	2341.75
MEAN IMD SCORE	41	7.49	33.82	782.93	19.10	6.62
PERCENT MOTORWAY	41	0.00	3.18	41.73	1.02	0.75
PROSECUTIONS 1000s	41	16.98	182.75	1975.32	48.18	37.27
FPN's 1000s	41	19.94	251.76	3126.03	76.24	51.99
FPN's G16 1000s	41	1.86	54.69	666.75	16.26	13.82
VDRN's 1000s	41	0.59	18.67	251.67	6.14	3.87
WW's 1000s	41	0.27	26.54	181.43	4.43	6.18
YEAR = 1998	Number of Police Force Areas	Minimum	Maximum	Sum	Mean	Std. Deviation
GEOGRAPHIC AREA sqkm	41	566.70	10240.86	141859.05	3459.98	2341.75
MEAN IMD SCORE	41	7.49	33.82	782.93	19.10	6.62
PERCENT MOTORWAY	41	0.00	3.18	41.73	1.02	0.75
PROSECUTIONS 1000s	41	17.63	184.51	1979.01	48.27	36.84
FPN's 1000s	41	23.42	226.80	3108.96	75.83	49.18
FPN's G16 1000s	41	2.51	62.83	743.42	18.13	12.95
VDRN's 1000s	41	0.98	17.16	244.65	5.97	3.53
WW's 1000s	41	0.02	21.16	145.40	3.55	4.77
YEAR = 1999	Number of Police Force Areas	Minimum	Maximum	Sum	Mean	Std. Deviation
GEOGRAPHIC AREA sqkm	41	566.70	10240.86	141859.05	3459.98	2341.75
MEAN IMD SCORE	41	7.49	33.82	782.93	19.10	6.62
PERCENT MOTORWAY	41	0.00	3.18	41.73	1.02	0.75
PROSECUTIONS 1000s	41	17.19	188.73	1936.58	47.23	35.77
FPN's 1000s	41	21.60	173.24	2831.16	69.05	42.08
FPN's G16 1000s	41	2.05	64.32	761.80	18.58	13.38
VDRN's 1000s	41	0.58	17.30	216.33	5.28	3.63
WW's 1000s	41	0.04	16.46	116.13	2.83	3.81
YEAR = 2000	Number of Police Force Areas	Minimum	Maximum	Sum	Mean	Std. Deviation
GEOGRAPHIC AREA sqkm	41	566.70	10240.86	141859.05	3459.98	2341.75
MEAN IMD SCORE	41	7.49	33.82	782.93	19.10	6.62
PERCENT MOTORWAY	41	0.00	3.18	41.73	1.02	0.75
PROSECUTIONS 1000s	41	15.59	193.03	1889.81	46.09	34.87
FPN's 1000s	41	14.45	162.66	2665.11	65.00	40.07
FPN's G16 1000s	41	2.10	71.89	883.89	21.56	15.61
VDRN's 1000s	41	0.45	14.58	166.32	4.06	3.08
WW's 1000s	41	0.00	10.40	94.54	2.31	2.75

Table 3.4.1.2 Descriptive Statistics of Annual Data 2001 to 2004

Descriptive Statistics of Annual Data 2001 to 2004						
YEAR = 2001	Number of Police Force Areas	Minimum	Maximum	Sum	Mean	Std. Deviation
GEOGRAPHIC AREA sqkm	41	566.70	10240.86	141859.05	3459.98	2341.75
MEAN IMD SCORE	41	7.49	33.82	782.93	19.10	6.62
PERCENT MOTORWAY	41	0.00	3.18	41.73	1.02	0.75
PROSECUTIONS 1000s	41	16.20	284.47	2403.85	58.63	49.58
FPN's 1000s	41	13.52	209.16	2678.76	65.34	43.23
FPN's G16 1000s	41	3.14	154.52	1104.73	26.94	28.15
VDRN's 1000s	41	0.48	10.39	138.88	3.39	2.34
WW's 1000s	41	0.00	10.94	77.75	1.90	2.52
YEAR = 2002	Number of Police Force Areas	Minimum	Maximum	Sum	Mean	Std. Deviation
GEOGRAPHIC AREA sqkm	41	566.70	10240.86	141859.05	3459.98	2341.75
MEAN IMD SCORE	41	7.49	33.82	782.93	19.10	6.62
PERCENT MOTORWAY	41	0.00	3.18	41.73	1.02	0.75
PROSECUTIONS 1000s	41	10.22	203.28	1946.76	47.48	38.65
FPN's 1000s	41	11.79	241.61	2731.86	66.63	45.45
FPN's G16 1000s	41	2.96	180.53	1366.33	33.33	34.37
VDRN's 1000s	41	0.61	9.98	125.65	3.06	2.24
WW's 1000s	41	0.00	5.58	48.84	1.19	1.49
YEAR = 2003	Number of Police Force Areas	Minimum	Maximum	Sum	Mean	Std. Deviation
GEOGRAPHIC AREA sqkm	41	566.70	10240.86	141859.05	3459.98	2341.75
MEAN IMD SCORE	41	7.49	33.82	782.93	19.10	6.62
PERCENT MOTORWAY	41	0.00	3.18	41.73	1.02	0.75
PROSECUTIONS 1000s	41	16.85	214.31	2122.23	51.76	40.91
FPN's 1000s	41	10.38	236.05	3096.04	75.51	47.83
FPN's G16 1000s	41	1.01	191.83	2016.68	49.19	37.61
VDRN's 1000s	41	0.52	8.69	120.35	2.94	1.92
WW's 1000s	41	0.00	7.14	50.09	1.22	1.58
YEAR = 2004	Number of Police Force Areas	Minimum	Maximum	Sum	Mean	Std. Deviation
GEOGRAPHIC AREA sqkm	41	566.70	10240.86	141859.05	3459.98	2341.75
MEAN IMD SCORE	41	7.49	33.82	782.93	19.10	6.62
PERCENT MOTORWAY	41	0.00	3.18	41.73	1.02	0.75
PROSECUTIONS 1000s	41	12.80	201.31	2071.39	50.52	42.67
FPN's 1000s	41	12.79	170.99	3065.35	74.76	40.73
FPN's G16 1000s	41	0.86	94.32	1813.11	44.22	25.50
VDRN's 1000s	41	0.52	8.42	125.17	3.05	1.96
WW's 1000s	41	0.04	7.09	58.14	1.42	1.70

Having ensured the data was suitable for analysis an initial investigation was carried out to identify any apparent or hidden trends in the data. This was important in the sense that it helped to further develop ideas for more complex analysis used to identify any relationships between accident rates and measures of police enforcement activity as well as the various socio-demographic variables. Analysis of the trends allows for specific regression models to be developed**.** Originally Poisson Regression was considered as the optimal method for the regression analysis of count data as it is considered to be the benchmark in the statistical analysis and modelling of count data and rare events such as the occurrence of Road Traffic Accidents (RTA's); see for example Maher and Summersgill (1996) and Lord, (2006). Further data exploration revealed that an extension of Poisson Regression, Zero Truncated Poisson Regression, was better able to model the accident data due to a lack of zero counts in the accident data: further explanation of this decision is given in Chapter 4 of this thesis. Following on from the regression analysis Chapter 5 is devoted to Cluster Analysis. The aim here is to identify natural groupings, or clusters, which are not initially apparent. Two methods of clustering are used; Hierarchical Clustering and Fuzzy C-means clustering. The final method of analysis is Multilevel Modelling. Multilevel modelling techniques (Jones and Jorgensen, 2003, Wong et al., 2004) are used to compensate for the multi-layered nature of the data which was not possible using standard regression methods. It is believed that this will produce a greater degree of accuracy. In depth analysis and discussions pertaining to these analyses is covered in later chapters.

3.4.2 Trends in Data

In this section the aim is to identify any relationship or association between the dependant and independent variables and also to identify any underlying trends in the data. This will provide a deeper understanding of the data and may better inform as how to progress with more complex analyses.

3.4.3 Annual Trends in Data

In general the overall trend in road traffic accidents presents an encouraging view. Between 1980 and 2007 the number of road casualties in Great Britain has decreased by 24%. During the same period the numbers of KSI casualties have dropped by 64% (Transport Trends, 2008).

This continuing downward trend is mirrored by both the accident and KSI rates, for the period 1991 to 2004, and can be observed in Figure 3.4.3.1. Accident rates have decreased by approximately 11%, while KSI rates for the same period have decreased by approximately 37%.

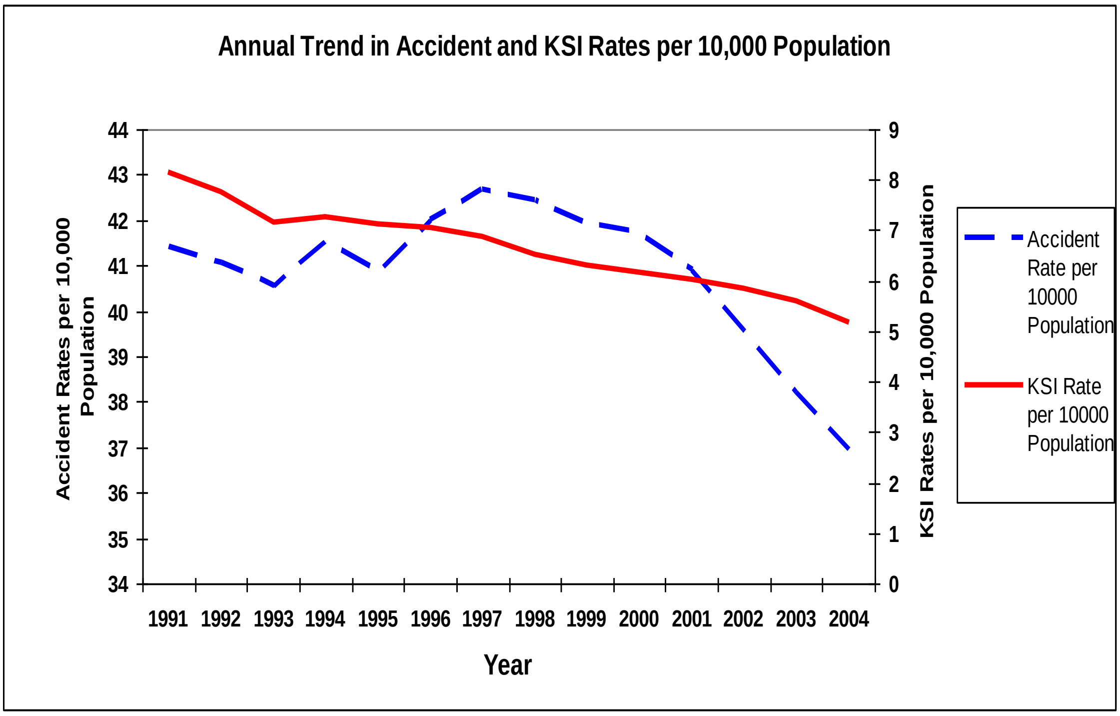


Figure 3.4.3.1 Annual Trend in Accident and KSI Rates per 10 000 Population 1991 to 2004 in England and Wales

There may be many reasons for these downward trends but many observers believe that the main reasons are increased levels of the four 'E's of road safety; Education, Engineering, Enforcement and Encouragement. The four 'E's of road safety are all integral parts of road safety strategy and are seen as vital in the continuing effort to reduce the number of road traffic accidents and casualties. For the purposes of this study Enforcement strategies employed by the police and other relevant authorities constitute the main area of investigation, although due consideration will be given to the others where necessary.

The annual trends, both spatial and temporal, in accident and KSI rates have shown there is a steady decline in the number of total accidents and KSI accidents in Great Britain. In Appendix 3, Figures 1 and 2, show comparisons of individual PFA's for accident rates and KSI rates respectively for the period 1991 to 2004. It is still apparent that the general trend follows that of Great Britain as a whole for both accident and KSI rates. There is a high amount of variation amongst PFA's and some of this is to be expected due to the different make up of each PFA. However, it may be that some of the variation between PFA's is a result of differing methods of policing. It is this variation between PFA's which represents the field of interest in this study. Can it be explained in relation to the previously stated proxies for police enforcement and the additional information supplied by including variables covering various socio-demographic factors?

The ten highest and lowest ranked PFA's, in relation to accident and KSI rates, are shown in Tables 3.4.3.1 and 3.4.3.2.

Table 3.4.3.1 Ten Highest and Lowest Accident Rates by PFA

Ten Highest Accident Rates per 10,000 Population 1991		**Ten Highest Accident Rates per 10,000 Population 1997**		**Ten Highest Accident Rates per 10,000 Population 2004**	
PFA_NAME	**1991**	**PFA_NAME**	**1997**	**PFA_NAME**	**2004**
Wiltshire	51.27	Wiltshire	57.07	Wiltshire	51.32
Merseyside	50.78	Merseyside	48.92	Cambridgeshire	48.16
Greater Manchester	49.13	Cambridgeshire	48.75	Surrey	46.72
Cambridgeshire	49.09	Cheshire	48.53	Cheshire	43.34
Staffordshire	47.33	Warwickshire	48.32	Warwickshire	42.37
Nottinghamshire	46.33	Greater Manchester	48.28	Lincolnshire	41.78
Humberside	43.13	Staffordshire	46.92	Staffordshire	41.35
Warwickshire	42.76	West Yorkshire	45.48	North Yorkshire	40.89
Norfolk	42.74	Lancashire	45.06	Hertfordshire	40.83
North Yorkshire	41.91	**North Yorkshire**	43.88	Greater Manchester	39.18
Average for all PFA's	**38.83**	**Average for all PFA's**	**40.29**	**Average for all PFA's**	**36.81**
Ten Lowest Accident Rates per 10,000 Population 1991		**Ten Lowest Accident Rates per 10,000 Population 1997**		**Ten Lowest Accident Rates per 10,000 Population 2004**	
PFA_NAME	**1991**	**PFA_NAME**	**1997**	**PFA_NAME**	**2004**
Avon and Somerset	30.51	Avon and Somerset	32.43	Cleveland	27.46
Gwent	30.60	Gloucestershire	32.77	Bedfordshire	29.06
Hertfordshire	30.72	Suffolk	33.10	North Wales	29.77
Durham	33.28	Norfolk	33.68	Durham	30.11
South Yorkshire	34.17	South Wales	34.09	Gwent	30.91
Dorset	34.33	Dyfed-Powys	34.16	Northamptonshire	30.95
Devon and Cornwall	34.63	Gwent	34.29	West Mercia	30.95
Gloucestershire	34.76	Northamptonshire	34.63	South Wales	32.67
Suffolk	35.13	Cleveland	34.74	Suffolk	33.04
Lincolnshire	35.19	Durham	34.82	Norfolk	33.73
Average for all PFA's	**38.83**	**Average for all PFA's**	**40.29**	**Average for all PFA's**	**36.81**

Table 3.4.3.2 Ten Highest and Lowest KSI Rates by PFA

Ten Highest KSI Rates per 10,000 Population 1991		Ten Highest KSI Rates per 10,000 Population 1997		Ten Highest KSI Rates per 10,000 Population 2004	
PFA_NAME	**1991**	**PFA_NAME**	**1997**	**PFA_NAME**	**2004**
North Yorkshire	13.91	North Yorkshire	12.18	North Yorkshire	9.03
Dyfed-Powys	13.07	Warwickshire	12.11	Warwickshire	8.47
Warwickshire	12.37	Cumbria	9.62	Dyfed-Powys	8.26
Wiltshire	12.35	Northamptonshire	9.54	Cambridgeshire	7.80
Cambridgeshire	11.91	Nottinghamshire	9.42	Wiltshire	7.75
Norfolk	11.39	West Mercia	9.31	Humberside	7.35
Nottinghamshire	10.41	Cheshire	9.20	Nottinghamshire	7.11
Northamptonshire	10.14	Cambridgeshire	9.05	Cumbria	6.90
Cumbria	9.66	Wiltshire	8.96	Essex	6.85
Lincolnshire	9.42	**Lancashire**	8.92	Northamptonshire	6.58
Average for all PFA's	**8.15**	**Average for all PFA's**	**6.82**	**Average for all PFA's**	**5.44**

Ten Lowest KSI Rates per 10,000 Population 1991		Ten Lowest KSI Rates per 10,000 Population 1997		Ten Lowest KSI Rates per 10,000 Population 2004	
PFA_NAME	**1991**	**PFA_NAME**	**1997**	**PFA_NAME**	**2004**
Derbyshire	5.07	South Wales	3.21	South Wales	3.29
Thames Valley	5.27	Cleveland	4.31	Devon and Cornwall	3.30
South Wales	5.41	Greater Manchester	4.32	Greater Manchester	3.77
Cleveland	5.91	Staffordshire	4.32	Staffordshire	3.80
Gwent	5.92	Thames Valley	4.51	Leicestershire	3.89
Cheshire	6.01	Durham	4.56	Bedfordshire	3.91
South Yorkshire	6.11	Avon and Somerset	4.57	Durham	4.00
Durham	6.18	Gloucestershire	4.67	North Wales	4.00
Essex	6.26	Leicestershire	4.74	West Midlands	4.05
Surrey	6.41	Northumbria	4.94	Gloucestershire	4.11
Average for all PFA's	**8.15**	**Average for all PFA's**	**6.82**	**Average for all PFA's**	**5.44**

From Table 3.4.3.1 it can be observed that at least five of the top ten PFA’s with the highest accident rates appear in all three tables covering 1991, 1997 and 2004. A similar pattern is seen in relation to the top ten for KSI rates with seven PFA’s appearing in all three tables, see Table 3.4.3.2. While it also seems that there may be a relation between high accident rates and high KSI rates. When figures for the lowest ranked PFA’s are looked at similar patterns emerge, but only for 1997 and 2004 where seven out of ten PFA’s have consistently low accident rates and the same number have consistently low KSI rates. There may also be some relationship between low accident and KSI rates although this may be a little weaker than for PFA’s with higher rates.

At this stage it is not possible to identify any cause which would explain why certain PFA's have consistently high or low accident and KSI rates, but this will be subject to further research.

Annual trends for all proxy measures of police enforcement are shown in Figure 3.4.3.2. Here it can be seen that there is a distinct pattern to the trend for Prosecutions and FPN's at the national level of aggregation. For both these proxy variables there is a decrease in levels from 1997 to 2000 and then levels start to increase from then on. At lower levels of aggregation, PFA level or local authority level, there may be some variation in the level of Prosecutions and FPN's linked with each area. It may also be possible to pick up on any identifiable trend to enforcement measures at these lower levels. For the VDRN's and WW's the trend is downward with the numbers issued steadily decreasing year on year.

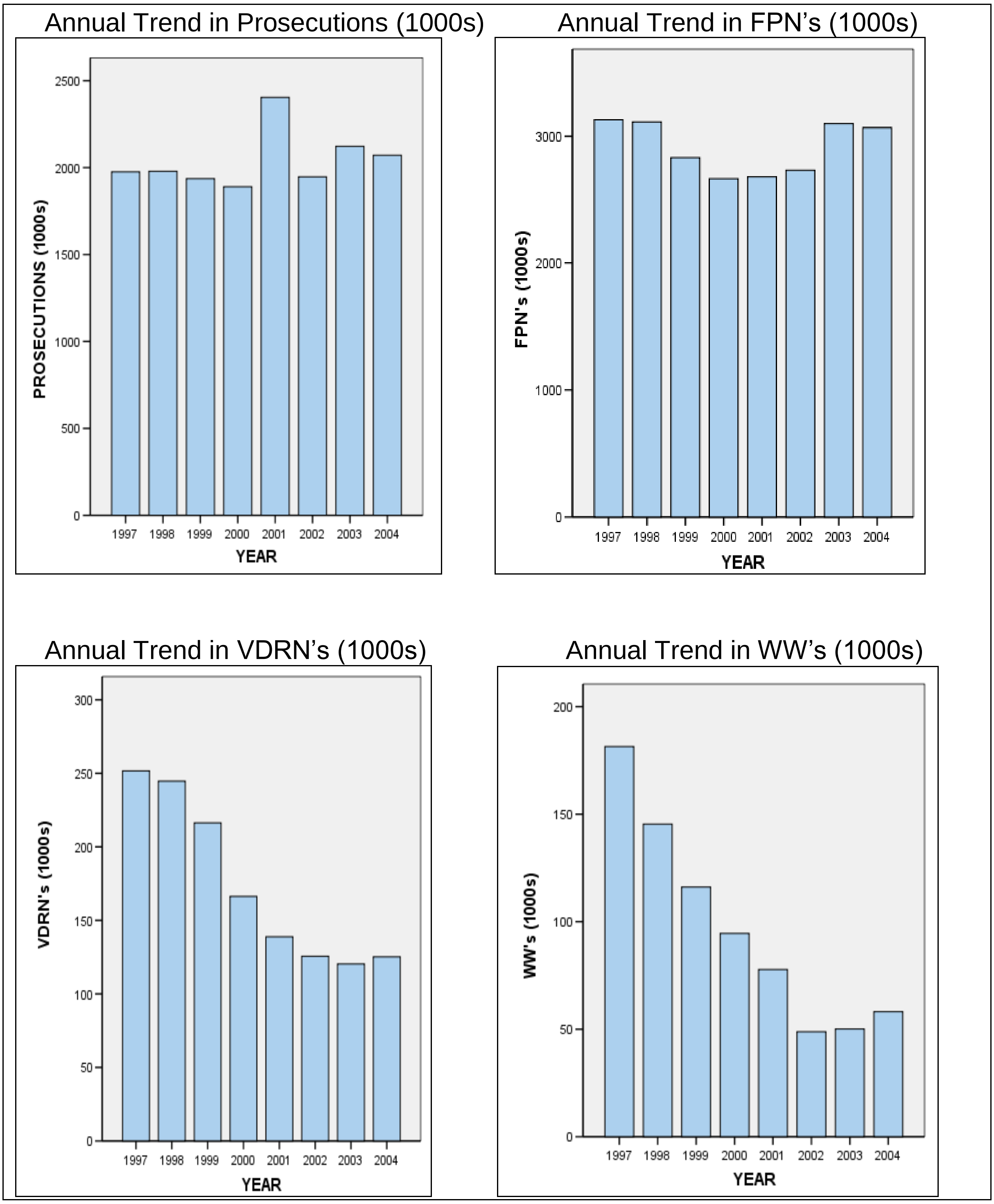


Figure 3.4.3.2: Overall Annual Trends in Proxy Measures for Police Enforcement

Figures 3 to 6, Appendix 3, show the trends in police enforcement proxies by PFA and it is clear that there is more variation in the data at this level than at the national level. In trying to determine the effect on accident and KSI rates by measures of police enforcement, by means of the proxy variables, this variation may play an important part by showing how different methods and levels of police enforcement impact on each individual PFA.

3.4.4 Quarterly Trends in Data

Quarterly trends in the data are analysed from 1999 to 2004. This period is chosen to match up with the availability of quarterly figures for proxies of police enforcement, namely FPN's, Prosecutions, VDRN's and WW's.

It is believed that analyses of the data on a quarterly basis will prove to be more informative than the annual analyses, as it should be possible to identify any seasonal effects in the accident data. Other researchers in Great Britain have identified a seasonal composition to the occurrence of road traffic accidents; see Harvey and Durbin (1986) and Raeside (2004). Each quarter represents a three month period, with Quarter 1 being representative of January to March and Quarters 2, 3, and 4 following on from this.

The quarterly trends in accident and KSI rates are shown in Figure 3.4.4.1 and, in terms of the general trend, it mirrors the annual data in that both accident and KSI rates are continuing to decrease year on year and quarter on quarter.

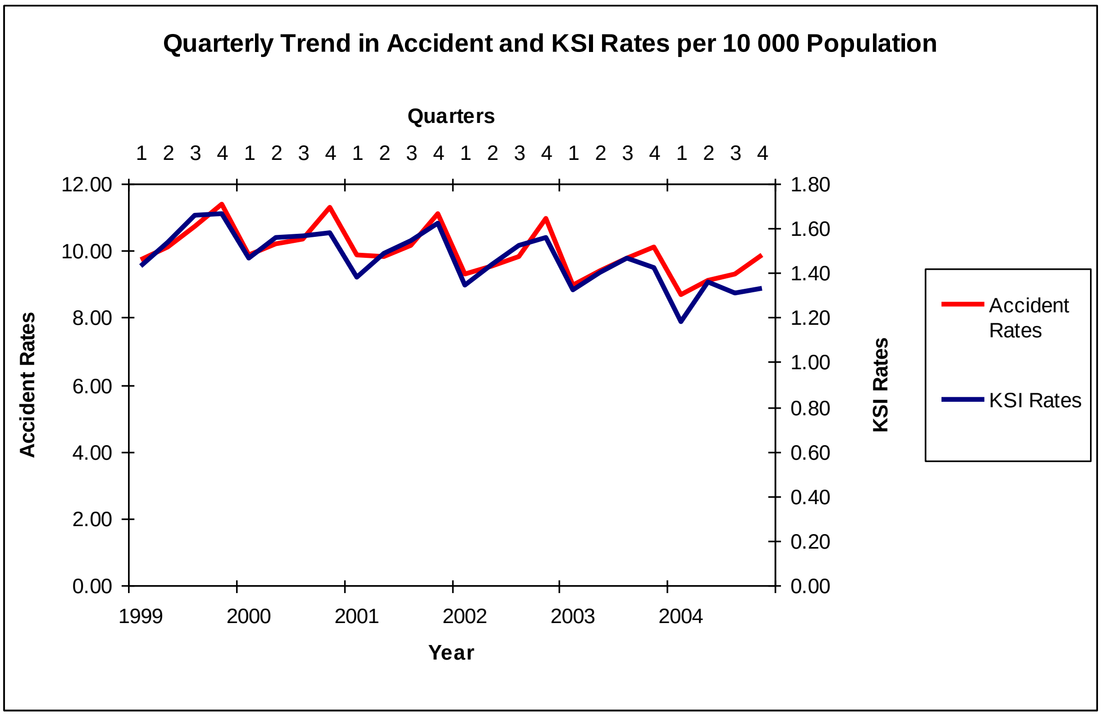


Figure 3.4.4.1 Quarterly Trend in Accident and KSI Rates per 10 000 Population 1991 to 2004 in England and Wales

It is clearly evident, from Figure 3.4.4.1, that the quarterly series are subject to seasonal effects, with accident and KSI rates both tending to increase throughout the year, from a minimum in Quarter 1 to a maximum in Quarter 4 for accident rates with the maximum for KSI rates occurring in either Quarter 3 or 4. There may be many reasons for this seasonal variation, with variations in weather conditions, the amount of daylight and variations in traffic volume being just a few.

Another advantage which may be gained from analysing this data on a quarterly basis is related to time lags. By analysing the data at different time lags, say one and two quarters, it may be possible to identify any real effect of police enforcement.

3.5. Proposed Methods of Analysis

As the main thrust of this study is to investigate any links between the effects of police enforcement activity and the level of Road Traffic Accidents (RTA's), in particular the level of Killed and Seriously Injured accidents (KSI's), it is proposed that regression models be developed to investigate any possible link between the decrease in KSI rates and levels of police enforcement.

As the accident data are classed as count data, ordinary regression methods are unlikely to properly model any effects that may be found. The generally accepted method is to use Poisson regression, (see Johansson, 1993, Lord, 2006 and Dossou-Gbété and Mizère, 2006). The Poisson distribution was derived by the French mathematician Simeon-Denis Poisson in 1837 and is considered to the benchmark for modelling count data. As the data are also truncated at zero, there are no zero counts in the dataset it is likely that Zero Truncated Poisson (ZTP) regression will actually be used as this is better suited to modelling a zero truncated dataset, (see Quddus, 2008).

Following on from the Zero Truncated Poisson Regression, Hierarchical Cluster Analysis is used to identify natural groupings, clusters, within the dataset. The use of hierarchical cluster analysis in the analysis of Road Traffic Accidents is well documented (see Karlaftis and Tarko, 1998 and Yannis et al., 2007). The initial clusters will be developed from data covering all Killed and Seriously Injured (KSI) accidents for 2004. Further clusters, based on regional groupings of Police Force Areas will then be developed and analysed.

The use of multilevel modelling to analyse road accident data is becoming more popular (Yannis et al., 2007) but the literature related to this is still somewhat sparse. It may be that researchers are unaware of the method (Kim et al., 2007) or it could be that the hierarchical nature of road accident data is commonly ignored by researchers (Jones and Jorgensen, 2003).
The main advantage of multilevel models over traditional regression methods are that they provide a higher level of understanding, in relation to the influence of variables, when applied to data of a hierarchical nature. The hierarchical nature of the accident data, with Police Force Areas nested within clusters should be ideal for this method of analysis. It is proposed that the use of multilevel modelling will improve the understanding of where explanatory variables actually exert influence.

With a method in place for the collection and analysis of the accident data the next step is to begin the analysis of the data. This begins with the Zero Truncated Poisson Regression, in Chapter 4, and is followed by Cluster Analysis and Multilevel Modelling in Chapters 5 and 6 respectively.

4. Poisson Regression Analysis.

4.1 Introduction to Poisson Regression Analysis.

The Poisson regression model is regarded as a yardstick in the statistical analysis and modelling of count data and is generally used to model the occurrence of rare events i.e. the occurrence of Road Traffic Accidents (RTA's), see Maher and Summersgill (1996) and Lord, (2006). Count models are developed from situations where the endogenous variables i.e. the number of RTA's, or dependent variables, can take only positive integer values. The Poisson distribution is characterised by the expected number of events to occur, λ. If Y is equal to the number of event occurrences, then the Poisson probability distribution can be written as

$$P(Y = y) = \frac{e^{-\mu}\mu^{y}}{y!} \quad y = 0,1,2... \qquad \text{Equation 4.1.1}$$

With mean and variance

E(Y) = μ,   VAR(Y) = μ

The introduction of covariates into the Poisson model is achieved as follows

$$\mu_i = \exp(\beta \mathrm{X}_i) \qquad \text{Equation 4.1.2}$$

From this it can be seen that the mean and variance, for a Poisson distributed variable, are equal. This highlights one of the main features, and problems, of the Poisson distribution in that, regardless of the value of *μ*, the variation to mean ratio is always one. This dependence of the Poisson distribution on a single parameter leads to a distinct lack of flexibility when attempting to model count data under a Poisson distribution.

The variation to mean ratio can be used as a measure of overdispersion or underdispersion in relation to the Poisson distribution. Overdispersion in a Poisson model is represented by extra Poisson variation; the true variance is greater than the mean. Underdispersion is the direct opposite to overdispersion, where the true variance is less than the mean. In Poisson regression models there may be many reasons for the occurrence of overdispersion or underdispersion including, the exclusion of important covariates, incorrectly specified models, correlation and the presence of influential outliers. Other possible reasons are given by Lord et al. (2005), including the clustering of data (neighbourhoods, regions, etc.) and unaccounted temporal correlation.

In the case of overdispersion in the Poisson model, where the true variance is greater than the mean, the standard errors are incorrectly specified, under-estimated, which can result in an invalid Chi-Square statistic. If, however, the model is correctly specified the regression parameters remain unaffected by any overdispersion. In the presence of underdispersion, where the true variance is smaller than the mean, the estimates of the standard errors will be conservative, that is to say they will be over-estimated, and this would seem to be less problematic than the under-estimation produced by overdispersion. The regression parameters are also unaffected by the presence of underdispersion.

The problem of overdispersion in Poisson models used to analyse accident data is well documented, (see Miaou, (1994) and Shankar et al., (1995)). In order to deal with overdispersion in the basic Poisson model, Maher and Summersgill (1996), suggest two methods. The first of these methods is the use of the 'Quasi-Poisson' model where the variance is given by

$VAR(Y) = k^2\lambda$ Equation 4.1.3

Where k^2 is derived from either Scaled Deviance / (N-p) or Pearson χ^2 / (N-p), with N= the number of subjects and p=the number of independent variables.

The model parameters are unaffected by the addition of the dispersion parameter $k^{2.}$ The only change in the model caused by the use of a dispersion parameter is in the size of the standard errors which are inflated by a factor of *k*. This may lead to an increase in the p-value of some variables resulting in them becoming non-significant in relation to the 'Quasi-Poisson' model.

The second suggested method is the use of the Negative Binomial (NB) model. The NB, or Poisson Gamma, distribution is the most widely used distribution for modelling count data that show extra Poisson variation i.e. overdispersion, and has been stated as such by many researchers, (see Shankar et al., (1997), Carson and Mannering (2001) and Noland and Quddus (2004)). In relation to overdispersed accident data the NB model is better suited to dealing with the extra variation due as it does not suffer from the same constraints as the Poisson model in relation to the mean/variance ratio being equal to one. The NB model allows for any extra Poisson variance, or overdispersion, by including a Gamma distributed error term in the Poisson model. This gives

$$\log \lambda_i = \beta \mathrm{X}_i + \xi_i \qquad \text{Equation 4.1.4}$$

Where ξ_i is the Gamma-distributed error term

The addition of the error term allows the mean to differ from the variance such that, (see Carson and Mannering (2001)),

$$\text{Var}\ [Y_i] = E\ [Y_i]\ [1+\text{k}E\ [Y_i]] \quad \text{Equation 4.1.5}$$

One of the major drawbacks of the NB distribution is that it can only be used to compensate for overdispersion and not underdispersion, (see Bosch and Ryan, (1998) and Dossou-Gbété and Mizère, (2006)).

4.2 Data Analysis using Poisson Regression.

The data under analysis covers the whole of England and Wales and is divided into forty-three Police Force Areas (PFA). Two PFA's have been excluded from the analysis, namely the Metropolitan Police and the City of London Police Force areas, due to their undue influence on the dataset.

A number of covariates have been dropped in order to prevent problems with multi-collinearity, see Table 4.2.1. From the STATS19 variables, column 1, Table 4.2.1, Killed and Seriously Injured (KSI) is the dependent variable in all Poisson Regression models detailed in these analyses.

Table 4.2.1: Variables included or dropped from Models

Variables Used in Analysis		
STATS19 Variables	**Socio-Demographic Variables**	**Police Enforcement Variables**
Driver Age	Geographical Area sq km	Fixed Penalty Notices (FPN's)
Driver Gender	Mean Index of Multiple Deprivation	Fixed Penalty Notices Group 16 (FPN_G16)
Junction Detail	Population Size	Prosecutions
Killed and Seriously Injured	Vehicle km billions	Vehicle Defect Rectification Notices (VDRN's)
Lighting Conditions	Percentage Motorway	Written Warnings (WW's)
Road Surface		
Speed Limit		
Vehicle Type		
Variables Dropped from Analysis		
Variable		**Reason**
Length of All Roads		Collinearity
Length of Trunk Motorway		Collinearity
Road Class		Collinearity
Road Type		Collinearity
Time,(Hour, Day)		Month is smallest time value
Total Accidents		Only Killed and Serious accidents used

Two different variables are used as offsets - Population Size and Vehicle km millions. Offsets are used when rates are being modelled. Here the dependent variable is the KSI rate with denominators of Population Size and Vehicle km millions. The denominator of the rate is transformed and included in the model as an independent variable and offset. Offsetting the variable means that its value is constrained, normally to one for ease of interpretation, (see Gelman and Hill (2007)), and is not estimated in the model. It is however included in the calculation for predicting the dependent variable. The offset variable is the log of the denominator, as the link function in any Poisson model is a log transformation. Each offset variable has been scaled for ease of interpretation in the final model analysis. Population size is scaled to units of 10 000 and Vehicle km millions are scaled to units of Vkm billions. All other variables are utilised as independent, or explanatory, variables. The Police Enforcement variables, column 3, Table 4.2.1, are simple explanatory variables, while all variables in column 1, Table 4.2.1, with the exception of KSI accidents are class type, categorical explanatory variables. A full description of the categorical explanatory variables is given in Table 4.2.2.

Table 4.2.2: Categorical Variables used in Analysis

Categorical Variables	Class Levels	Categories
AGE_GROUP	6	17 to 24; 25 to 34; 35 to 44; 45 to 54; 55 to 64; 65 Plus
GENDER	2	Female; Male
JUNCTION_DETAIL	3	Junction; > 20m from junction; Roundabout;
LIGHTING	2	Dark; Light
ROAD_SURFACE	4	Dry; Slippy; Snow; Wet
SPEED_LIMIT	5	30; 40; 50; 60; 70;
VEHICLE_TYPE	4	Car; HGV_LGV; Motor Cycle; Other

The five variables, Fixed Penalty Notices (FPN), Fixed Penalty Notices Group 16(FPN_G16), Prosecutions (Prosecutions), Vehicle Defect Rectification Notices (VDRN) and Written Warnings (WW), used as proxies for police enforcement are, by their nature, highly correlated with each other, especially FPN's and FPN_G16, as FPN_G16, which relates to speeding offences only, is a subset of all FPN's. This may present problems with multi-collinearity but each proxy represents a separate enforcement tool and needs to be treated as such. There will be no multi-collinearity problems relating to the FPN and FPN_G16 as they are used in different models.

4.3 Development of Poisson Regression Models

Poisson regression models are developed to investigate the relationship between the dependent variable, KSI, and the proxies for police enforcement, Fixed Penalty Notices (FPN), Fixed Penalty Notices Group 16 (FPN_G16), Prosecutions (Prosecutions), Vehicle Defect Rectification Notices (VDRN) and Written Warnings (WW). All proxy variables are scaled to units of 1000 to assist in the interpretation of parameter estimates from the final model results. Both annual accident data and quarterly annual accident data are investigated with contemporary and lagged time periods being considered. In relation to annual data the lag period is equal to one year, while for quarterly data there are two lag periods equal to one and two quarters. Each quarter represents a period of three months, therefore a lag of one quarter is equal to three months and a two quarter lag is equal to six months.

There are two different models developed for each contemporary and lagged time period. These consist of Poisson regression models where the only difference is the offset variable which is either lnpop or lnvkm. After an exploratory analysis of all data in which all extraneous data were removed, see Chapter 3, Section 3.4 for full details, models are developed for contemporary annual data followed by models for lagged annual data. In the first instance these models are developed using four of the proxy variables followed by models using only the proxy for speeding related offences, FPN_G16. The same procedure is then used to model the quarterly data.

4.3.1 Modelling Annual Accident Data

Poisson regression is used in order to determine the relationship, if any, between proxies for police enforcement, FPN's, FPN_G16's, Prosecutions, VDRN's and WW's, and KSI. The models will also control for Year, to allow for any improvement in safety, which may result due to technological advances and changes in legislation. Also included in the model are all categorical variables shown in Table 4.2.2 and the socio-demographic variables from Table 4.2.1. Annual data is modelled for both contemporary and lagged events, with the lag period being one year. Both annual and contemporary models are developed using two different offset variables – Population Size and Vehicle km's. In total there are four separate models dealing with annual data and the results from each model are discussed in the following sections.

4.3.2 Analysis of Annual Data

Initially annual data were to be modelled based on contemporary events with the Poisson regression based on annual data using four proxies for police enforcement activity, with models being developed separately for FPN's and FPN_G16. It should be noted that all proxy and socio-demographic variables have been standardised to enable proper comparison of effect sizes. This is done in every model analysis throughout this thesis. Also, the dependent variable, KSI, is the same in every model.

On considering the results of an exploratory investigation of the data, to determine suitability for Poisson regression modelling, it is apparent that the data is unsuitable for ordinary Poisson regression. The main reason for this is the lack of zeroes in the dataset and this represents a violation of distributional assumptions with respect to the Poisson distribution. The dataset lacks any zero counts as an event is only recorded if an accident occurs, therefore the probability of a zero count is zero. If Poisson regression is used the estimation procedure will try to fit a model which includes probabilities for values of zero. This will lead to incorrect model specification as a consequence of there being no zeroes in the dataset. The data are truncated at zero and, as such, alternative estimation procedures are necessary. In order to achieve a reliable model a procedure which deals with the zero truncation is required. Using STATA 10 (StataCorp, 2007), Zero Truncated Poisson (ZTP) models can be fitted. The ZTP procedure is designed to take into account the lack of zero values and adjusts the properties of the Poisson distribution accordingly (Simonoff, (2003)).

The adjusted probability distribution for the ZTP model can now be written as

$$P(Y = y)\frac{e^{-\mu}\mu^{y}}{y!(1-e^{-\mu})} \qquad y = 0,1,2... \qquad \text{Equation 4.3.2.1}$$

With mean and variance

$$E(Y) = \frac{\mu}{1-e^{-\mu}}, \qquad V(Y) = \left(\frac{\mu}{1-e^{-\mu}}\right)\left(1-\frac{\mu e^{-\mu}}{1-e^{-\mu}}\right)$$

4.3.3 Model Fitting

The initial model fitting was done using an aggregate of all proxy variables in order to establish the efficacy of the overall effect, in relation to the proxy variables. This aggregate variable was called All Penalties and was used in both contemporary and lagged form, with both offset variables used. For Population 10,000's the offset is named lnpop and for Vehicle km's (billions) it is lnvkm. This gives two models, contemporary and lagged, by one year, for each offset variable; a total of four different models in all for the initial analysis. In Table 4.3.3.1 the full output from the ZTP modelling, in relation to the aggregate proxy variable All Penalties, is given while Tables 4.3.3.2 to 4.3.3.4 give selected outputs. The full tables are shown in Appendix 4, Tables 1 to 4.

Table 4.3.3.1: Full Output from ZTP on Annual Data with Aggregate Proxy Variable and Offset lnpop

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Year	-0.0358	0.001	-27.84	0.0000	-0.0384	-0.0333
25 to 34	-0.0360	0.008	-4.74	0.0000	-0.0509	-0.0211
35 to 44	-0.3280	0.009	-38.14	0.0000	-0.3448	-0.3111
45 to 54	-0.6571	0.010	-63.10	0.0000	-0.6775	-0.6367
55 to 64	-1.0638	0.014	-76.28	0.0000	-1.0911	-1.0365
65 Plus	-0.8400	0.013	-66.45	0.0000	-0.8648	-0.8152
Female	-0.8332	0.008	-108.22	0.0000	-0.8483	-0.8181
speed limit 40	-1.4707	0.014	-107.15	0.0000	-1.4976	-1.4438
speed limit 50	-2.6508	0.048	-54.93	0.0000	-2.7454	-2.5562
speed limit 60	-0.2003	0.006	-30.89	0.0000	-0.2130	-0.1876
speed limit 70	-1.3127	0.014	-95.01	0.0000	-1.3398	-1.2857
HGV_LGV	-1.5239	0.015	-103.08	0.0000	-1.5528	-1.4949
Motorcycle	-1.0064	0.010	-104.71	0.0000	-1.0253	-0.9876
Other	-1.8850	0.020	-93.59	0.0000	-1.9244	-1.8455
Junction	0.0567	0.006	9.65	0.0000	0.0451	0.0682
Roundabout	-2.1875	0.094	-23.26	0.0000	-2.3718	-2.0031
Slippy	-2.4762	0.047	-52.20	0.0000	-2.5692	-2.3833
Snow	-4.4583	0.352	-12.68	0.0000	-5.1475	-3.7692
Wet	-0.5291	0.006	-82.21	0.0000	-0.5418	-0.5165
dark	-0.4618	0.006	-71.58	0.0000	-0.4744	-0.4491
Geographic Area sqkm	-0.0067	0.003	-2.03	0.0430	-0.0131	-0.0002
Mean Index of Multiple Deprivation	0.0518	0.003	15.39	0.0000	0.0452	0.0584
Percentage Motorway	-0.0238	0.003	-6.92	0.0000	-0.0306	-0.0171
All Penalties	-0.0699	0.003	-23.60	0.0000	-0.0757	-0.0641
Constant	63.0900	2.579	24.46	0.0000	58.0353	68.1446
lnpop	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
91504	-165143.4	-115061.7	25	230173.4	2.52	0.30

[1]AIC*n is the AIC reported by STATA 10

Table 4.3.3.2: Output from ZTP on Annual Lagged Data with Aggregate Proxy Variable and Offset lnpop

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Mean Index of Multiple Deprivation	0.0465	0.004	12.75	0.0000	0.0393	0.0536
Percentage Motorway	-0.0261	0.004	-6.99	0.0000	-0.0335	-0.0188
Lag1 All Penalties	-0.0653	0.003	-20.4	0.0000	-0.0715	-0.059
Constant	58.3151	3.208	18.18	0.0000	52.0285	64.6018
lnpop	(offset)					
	Model Information Criteria					
Number Obs	ll(null)	ll(model)	df	AIC*n[1]	AIC	Pseudo R^2
79663	-140825.8	-98860.2	25	197770	2.48	0.30

Table 4.3.3.3: Output from ZTP on Annual Data with Aggregate Proxy Variable and Offset lnvkm

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Geographic Area sqkm	-0.0481	0.003	-14.55	0.0000	-0.0546	-0.0416
Mean Index of Multiple Deprivation	0.1763	0.003	51.31	0.0000	0.1695	0.183
Percentage Motorway	-0.0964	0.003	-28.15	0.0000	-0.1031	-0.0897
All Penalties	-0.0176	0.003	-6.03	0.0000	-0.0234	-0.0119
Constant	92.2027	2.571	35.86	0.0000	87.1633	97.2421
lnvkm	(offset)					
	Model Information Criteria					
Number Obs	ll(null)	ll(model)	df	AIC*n[1]	AIC	Pseudo R^2
91504	-168158.1	-115046	25	230142	2.52	0.32

Table 4.3.3.4: Output from ZTP on Annual Lagged Data with Aggregate Proxy Variable and Offset lnvkm

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Geographic Area sqkm	-0.0487	0.004	-13.56	0.0000	-0.0558	-0.0417
Mean Index of Multiple Deprivation	0.1714	0.004	46.06	0.0000	0.1641	0.1787
Percentage Motorway	-0.0994	0.004	-26.68	0.0000	-0.1067	-0.0921
Lag1 All Penalties	-0.0138	0.003	-4.37	0.0000	-0.02	-0.0076
Constant	85.7288	3.196	26.82	0.0000	79.4648	91.9927
lnvkm	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
79663	-143292.6	-98876.9	25	197804	2.48	0.31

Considering the results, shown in Appendix 4, Tables 1 to 4, the values for all categorical variables are seen to be very similar across all four models. In all models there is a consistency of information which shows that a person is more likely to be in a KSI accident if they are a male driver, aged between 17 and 24 years, travelling in a car on a road with a fixed speed limit of 30 mph. The accident is most likely to happen at a junction, on a dry road during daylight hours.

All Penalties, the aggregate proxy variable, is shown to have a significant negative effect on the level of KSI accidents in all four models. In other words an increase in the level of police enforcement, as measured here by the aggregate proxy variable, is seen to be linked to a decrease in the number of KSI accidents. This effect is much stronger when the offset variable is population based, lnpop, than when it is based on vehicle km's travelled, lnvkm. The effect for contemporary data is almost four times greater for KSI rate by Population than for KSI rate by Vehicle km's and almost five times greater for the lagged effect.

Following on from the initial modelling stage the effects of the individual proxy variables, Prosecutions, FPN's - including speeding related FPN's as an individual proxy, VDRN's and WW's, are included in the models. Are they having the same effect, individually, on KSI accidents as the aggregate proxy?

There are four basic models to be fitted in relation to the annual data, incorporating the individual proxy variables, and these are as follows,

1. Contemporary Annual Data
2. Lagged Annual Data
3. Contemporary Annual Data with FPN_G16
4. Lagged Annual Data with FPN_G16

The distinction between models with and without FPN_G16 as one of the proxies for police enforcement is that those models without FPN_G16 use FPN's instead. The proxy FPN_G16 is a subset of FPN's and represents FPN's related only to speeding offences.

Every model is fitted for both of the previously mentioned offset variables – Population and Vehicle km's. For Population the offset is named lnpop and for Vehicle km's it is lnvkm. This gives a total of eight models in all derived from the original four basic models.

All categorical variables are compared to a reference or baseline category. The reference category for each variable is given in Table 4.3.3.5.

Table 4.3.3.5: Reference Categories for Categorical Variables

Variable Name	Reference Category
Age Group	17 to 24
Gender	Male
Speed Limit	30
Vehicle Type	Car
Junction Detail	> than 20m from junction
Road Surface	Dry
Lighting	Light

The reference categories are generated automatically by STATA 10 software and all categories, shown in Table 4.3.3.5, can be compared to their respective reference level in order to determine the relative importance of each level. Differentiation between the models used to analyse annual data are detailed in Table 4.3.3.6.

Table 4.3.3.6: Differentiation between Annual ZTP models.

ZTP Models	Dependent Variable	Offset Variable	Table number
Annual	KSI	Population (lnpop)	4.3.3.7
Annual	KSI	billions of vehicle km's travelled (lnvkm)	4.3.3.8
Annual Lagged	KSI	Population (lnpop)	4.3.3.9
Annual Lagged	KSI	billions of vehicle km's travelled (lnvkm)	4.3.3.10
Annual with Speeding related FPN_G16	KSI	Population (lnpop)	4.3.3.11
Annual with Speeding related FPN_G16	KSI	billions of vehicle km's travelled (lnvkm)	4.3.3.12
Annual Lagged with Speeding related FPN_G16	KSI	Population (lnpop)	4.3.3.13
Annual Lagged with Speeding related FPN_G16	KSI	billions of vehicle km's travelled (lnvkm)	4.3.3.14

Detailed in Table 4.3.3.7 is the full output from the ZTP regression on annual data with Tables 4.3.3.7 to 4.3.3.14 giving selected outputs relating to annual data. The full tables are shown in Appendix 4 Tables 5 to 12.

Table 4.3.3.7: Full Output from ZTP on Annual Data with Offset lnpop.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Year	-0.0439	0.001	-29.48	0.0000	-0.0468	-0.0409
25 to 34	-0.0360	0.008	-4.73	0.0000	-0.0509	-0.0211
35 to 44	-0.3279	0.009	-38.12	0.0000	-0.3447	-0.3110
45 to 54	-0.6573	0.010	-63.11	0.0000	-0.6777	-0.6369
55 to 64	-1.0649	0.014	-76.35	0.0000	-1.0923	-1.0376
65 Plus	-0.8410	0.013	-66.52	0.0000	-0.8658	-0.8162
Female	-0.8344	0.008	-108.36	0.0000	-0.8495	-0.8194
speed limit 40	-1.4719	0.014	-107.23	0.0000	-1.4988	-1.4450
speed limit 50	-2.6463	0.048	-54.85	0.0000	-2.7408	-2.5517
speed limit 60	-0.1981	0.006	-30.51	0.0000	-0.2108	-0.1854
speed limit 70	-1.3099	0.014	-94.77	0.0000	-1.3370	-1.2828
HGV_LGV	-1.5269	0.015	-103.27	0.0000	-1.5558	-1.4979
Motorcycle	-1.0075	0.010	-104.80	0.0000	-1.0263	-0.9886
Other	-1.8873	0.020	-93.71	0.0000	-1.9267	-1.8478
Junction	0.0567	0.006	9.65	0.0000	0.0452	0.0682
Roundabout	-2.1736	0.094	-23.12	0.0000	-2.3579	-1.9894
Slippy	-2.4806	0.047	-52.31	0.0000	-2.5736	-2.3877
Snow	-4.4606	0.352	-12.69	0.0000	-5.1497	-3.7714
Wet	-0.5302	0.006	-82.35	0.0000	-0.5428	-0.5175
dark	-0.4626	0.006	-71.69	0.0000	-0.4752	-0.4499
Mean Index of Multiple Deprivation	0.0473	0.004	12.89	0.0000	0.0401	0.0545
Percentage Motorway	-0.0287	0.003	-8.22	0.0000	-0.0356	-0.0219
Prosecutions	0.0034	0.004	0.95	0.3400	-0.0036	0.0104
FPN	-0.0720	0.004	-19.98	0.0000	-0.0791	-0.0649
VDRN	-0.0206	0.003	-6.45	0.0000	-0.0269	-0.0144
WW	-0.0265	0.004	-6.96	0.0000	-0.0339	-0.0190
Constant	79.1260	2.980	26.55	0.0000	73.2857	84.9663
lnpop	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n**[1]	**AIC**	**Pseudo R^2**
91504	-165143	-114962	28	229980	2.51	0.30

[1]AIC*n is the AIC reported by STATA 10

Table 5: Full Output from ZTP on Annual Data with Offset lnpop.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Year	-0.0439	0.001	-29.48	0.0000	-0.0468	-0.0409
25 to 34	-0.0360	0.008	-4.73	0.0000	-0.0509	-0.0211
35 to 44	-0.3279	0.009	-38.12	0.0000	-0.3447	-0.3110
45 to 54	-0.6573	0.010	-63.11	0.0000	-0.6777	-0.6369
55 to 64	-1.0649	0.014	-76.35	0.0000	-1.0923	-1.0376
65 Plus	-0.8410	0.013	-66.52	0.0000	-0.8658	-0.8162
Female	-0.8344	0.008	-108.36	0.0000	-0.8495	-0.8194
speed limit 40	-1.4719	0.014	-107.23	0.0000	-1.4988	-1.4450
speed limit 50	-2.6463	0.048	-54.85	0.0000	-2.7408	-2.5517
speed limit 60	-0.1981	0.006	-30.51	0.0000	-0.2108	-0.1854
speed limit 70	-1.3099	0.014	-94.77	0.0000	-1.3370	-1.2828
HGV_LGV	-1.5269	0.015	-103.27	0.0000	-1.5558	-1.4979
Motorcycle	-1.0075	0.010	-104.80	0.0000	-1.0263	-0.9886
Other	-1.8873	0.020	-93.71	0.0000	-1.9267	-1.8478
Junction	0.0567	0.006	9.65	0.0000	0.0452	0.0682
Roundabout	-2.1736	0.094	-23.12	0.0000	-2.3579	-1.9894
Slippy	-2.4806	0.047	-52.31	0.0000	-2.5736	-2.3877
Snow	-4.4606	0.352	-12.69	0.0000	-5.1497	-3.7714
Wet	-0.5302	0.006	-82.35	0.0000	-0.5428	-0.5175
dark	-0.4626	0.006	-71.69	0.0000	-0.4752	-0.4499
Mean Index of Multiple Deprivation	0.0473	0.004	12.89	0.0000	0.0401	0.0545
Percentage Motorway	-0.0287	0.003	-8.22	0.0000	-0.0356	-0.0219
Prosecutions	0.0034	0.004	0.95	0.3400	-0.0036	0.0104
FPN	-0.0720	0.004	-19.98	0.0000	-0.0791	-0.0649
VDRN	-0.0206	0.003	-6.45	0.0000	-0.0269	-0.0144
WW	-0.0265	0.004	-6.96	0.0000	-0.0339	-0.0190
Constant	79.1260	2.980	26.55	0.0000	73.2857	84.9663
lnpop	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
91504	-165143	-114962	28	229980	2.51	0.30

[1]AIC*n is the AIC reported by STATA 10

Table 4.3.3.8: Output from ZTP on Annual Data with Offset lnvkm.

ZTP Model D.V. = KSI	Parameter Estimates	Std. Error	z	P>z	95% Confidence Interval	
Geographic Area sqkm	-0.041	0.003	-11.91	0.000	-0.048	-0.034
Mean Index of Multiple Deprivation	0.176	0.004	46.73	0.000	0.169	0.183
Percentage Motorway	-0.103	0.004	-29.45	0.000	-0.110	-0.096
Prosecutions	0.032	0.004	9.07	0.000	0.025	0.039
FPN	-0.042	0.004	-11.79	0.000	-0.049	-0.035
VDRN	-0.022	0.003	-6.94	0.000	-0.028	-0.016
WW	-0.042	0.004	-11.03	0.000	-0.050	-0.035
Constant	113.563	2.949	38.5	0.000	107.782	119.340
lnvkm	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n1**	**AIC**	**Pseudo R2**
91504	-168158	-114884	28	229824	2.51	0.32

Table 4.3.3.9: Output from ZTP on Annual Lagged Data with Offset lnpop.

ZTP Model D.V. = KSI	Parameter Estimates	Std. Error	z	P>z	95% Confidence Interval	
Mean Index of Multiple Deprivation	0.046	0.004	11.45	0.000	0.038	0.054
Percentage Motorway	-0.030	0.004	-8	0.000	-0.038	-0.023
Lag Prosecutions	0.002	0.004	0.61	0.541	-0.005	0.010
Lag FPN	-0.064	0.004	-16.62	0.000	-0.072	-0.057
Lag VDRN	-0.027	0.003	-7.93	0.000	-0.034	-0.020
Lag WW	-0.030	0.004	-7.45	0.000	-0.038	-0.022
Constant	80.895	3.722	21.74	0.000	73.601	88.189
lnpop	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n1**	**AIC**	**Pseudo R2**
79663	-140826	-98773	28	197601	2.48	0.30

Table 4.3.3.10: Output from ZTP on Annual Lagged Data with Offset lnvkm.

ZTP Model D.V. = KSI	Parameter Estimates	Std. Error	z	P>z	95% Confidence Interval	
Geographic Area sqkm	-0.043	0.004	-11.52	0.000	-0.050	-0.036
Mean Index of Multiple Deprivation	0.176	0.004	42.98	0.000	0.168	0.184
Percentage Motorway	-0.105	0.004	-27.74	0.000	-0.113	-0.098
Lag Prosecutions	0.029	0.004	7.44	0.000	0.021	0.036
Lag FPN	-0.033	0.004	-8.77	0.000	-0.041	-0.026
Lag VDRN	-0.026	0.003	-7.85	0.000	-0.033	-0.020
Lag WW	-0.045	0.004	-11.02	0.000	-0.053	-0.037
Constant	113.279	3.676	30.81	0.000	106.074	120.484
lnvkm	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n1**	**AIC**	**Pseudo R2**
79663	-143293	-98741	28	197538	2.48	0.31

Table 4.3.3.11: Output from ZTP on Annual Data with Speeding Related FPN's (FPN_G16) and Offset lnpop.

ZTP Model D.V. = KSI	Parameter Estimates	Std. Error	z	P>z	95% Confidence Interval	
Mean Index of Multiple Deprivation	0.046	0.004	12.32	0.000	0.038	0.053
Percentage Motorway	-0.021	0.004	-5.84	0.000	-0.028	-0.014
Prosecutions	-0.025	0.003	-8.03	0.000	-0.031	-0.019
FPN G16	-0.056	0.003	-16.26	0.000	-0.062	-0.049
VDRN	-0.018	0.003	-5.75	0.000	-0.025	-0.012
WW	-0.036	0.004	-9.31	0.000	-0.043	-0.028
Constant	52.512	3.229	16.26	0.000	46.184	58.840
lnpop	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n1**	**AIC**	**Pseudo R2**
91504	-165143	-115027	28	230110	2.51	0.30

Table 4.3.3.12: **Output from ZTP on Annual Data with Speeding Related FPN's (FPN_G16) and Offset lnvkm.**

ZTP Model D.V. = KSI	Parameter Estimates	Std. Error	z	P>z	95% Confidence Interval	
Geographic Area sqkm	-0.040	0.003	-11.54	0.000	-0.046	-0.033
Mean Index of Multiple Deprivation	0.174	0.004	45.92	0.000	0.166	0.181
Percentage Motorway	-0.096	0.004	-27.15	0.000	-0.103	-0.089
Prosecutions	0.018	0.003	6.04	0.000	0.012	0.024
FPN G16	-0.043	0.003	-12.7	0.000	-0.050	-0.036
VDRN	-0.021	0.003	-6.62	0.000	-0.027	-0.015
WW	-0.047	0.004	-12.17	0.000	-0.054	-0.039
Constant	94.259	3.203	29.43	0.000	87.982	100.537
lnvkm	(offset)					
	Model Information Criteria					
Number Obs	ll(null)	ll(model)	df	AIC*n1	AIC	Pseudo R2
91504	-168158	-114871	28	229798	2.51	0.31

Table 4.3.3.13: **Output from ZTP on Annual Lagged Data with Speeding Related FPN's (FPN_G16) and Offset lnpop.**

ZTP Model D.V. = KSI	Parameter Estimates	Std. Error	z	P>z	95% Confidence Interval	
Mean Index of Multiple Deprivation	0.044	0.004	10.98	0.000	0.036	0.052
Percentage Motorway	-0.023	0.004	-5.95	0.000	-0.031	-0.015
Lag Prosecutions	-0.024	0.003	-7.2	0.000	-0.030	-0.017
Lag FPN 16	-0.049	0.004	-13.46	0.000	-0.056	-0.042
Lag VDRN	-0.024	0.003	-7.21	0.000	-0.031	-0.018
Lag WW	-0.037	0.004	-9.16	0.000	-0.045	-0.029
Constant	53.801	3.927	13.7	0.000	46.104	61.498
lnpop	(offset)					
	Model Information Criteria					
Number Obs	ll(null)	ll(model)	df	AIC*n1	AIC	Pseudo R2
79663	-140826	-98819	28	197693	2.48	0.30

Table 4.3.3.14: Output from ZTP on Annual Lagged Data with Speeding Related FPN's (FPN_G16) and Offset Invkm.

ZTP Model D.V. = KSI	Parameter Estimates	Std. Error	z	P>z	95% Confidence Interval	
Geographic Area sqkm	-0.0406	0.004	-10.89	0.000	-0.048	-0.033
Mean Index of Multiple Deprivation	0.1732	0.004	42.21	0.000	0.165	0.181
Percentage Motorway	-0.0986	0.004	-25.56	0.000	-0.106	-0.091
Lag Prosecutions	0.0178	0.003	5.46	0.000	0.011	0.024
Lag FPN 16	-0.0379	0.004	-10.5	0.000	-0.045	-0.031
Lag VDRN	-0.0255	0.003	-7.65	0.000	-0.032	-0.019
Lag WW	-0.0476	0.004	-11.7	0.000	-0.056	-0.040
Constant	94.6673	3.895	24.31	0.000	87.034	102.300
Invkm	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n1**	**AIC**	**Pseudo R2**
79663	-143293	-98723	28	197502	2.48	0.32

On inspection the values for all categorical variables are very similar regardless of the model chosen, see Tables 5 to12, Appendix 4. In each model there is once again a consistency of information which shows that a person is more likely to be in a KSI accident if they are male, aged between 17 and 24 years, travelling in a car on a road with a fixed speed limit of 30 mph. The accident is most likely to happen at a junction on a dry road during daylight hours. This is true, in respect to all the fitted models relating to annual data.

The main area of interest in this analysis relates to the effects of police enforcement on the number of KSI accidents and, to a lesser extent, the effect of the socio-demographic variables.

Both contemporary and lagged, by one year, effects are studied in relation to all proxy variables. This is done for models with and without FPN_G16 included giving four basic models each run with two different offset variables. The analysis begins by considering contemporary and lagged models with four proxy variables – Prosecutions, FPN's, VDRN's and WW's.

In general the effects of the proxy and the socio-demographic variables are smaller for the lagged data with the exception of VDRN's and WW's. Both VDRN's and WW's have significant negative effects in relation to KSI accidents, with the lagged effect for VDRN's being slightly stronger than the contemporary effect, see Tables 4.3.3.7 to 4.3.3.14. This may be due to the time given to respond to this type of penalty. VDRN's have to be complied with within a fourteen day period if the offender is to avoid prosecution. This would seem to provide sufficient incentive for compliance and the increase in effect size between contemporary and lagged VDRN's is suggestive of this.

Along with VDRN's and WW's it can be seen that FPN's have a significant negative effect on KSI accidents for both contemporary and lagged events. Prosecutions however are more difficult to interpret as their effect on KSI accidents varies, in both contemporary and lagged events, depending on the offset variable used in the ZTP regression. With the log of population (lnpop) as the offset Prosecutions are found to have no significant effect on KSI accidents when used along with the full set of FPN's. This changes when the offset is changed, with a significant positive effect associated with the log of Vehicle km's (lnvkm). It may be that this is related to increased police activity at accident blackspots which would naturally lead to an increase in the number of Prosecutions. The effects are slightly smaller with lagged events in both cases which seem to indicate that there is a small lagged effect.

The effects of the socio-demographic variables, Geographical Area sq km, Mean Index of Deprivation (IMD) and Percentage Motorway, are very similar across all models. Geographical Area sq km has no significant effects for any model using lnpop as the offset variable but has a significant negative effect for all models using lnvkm as the offset. This indicates that as area size increases there is an associated decrease in the number of KSI accidents when the level of vehicle kilometres travelled is held constant. Effectively this means that there are likely to be less KSI accidents in rural areas as opposed to urban areas. The positive effect associated with IMD is indicative of higher levels of KSI accidents in more deprived areas. This finding is in line with previous research (Abdalla et al., 1997). A higher percentage of motorways in each area are also associated with a decrease in the number of KSI accidents.

When speeding related fixed penalty notices are included in the analysis the results are very similar to those obtained using the full set of FPN's. These results are shown in Tables 4.3.3.11 and 4.3.3.14. The development of separate models which differentiate speeding related fixed penalties from other types allows for an investigation into the relative importance of speeding related offences, namely FPN_G16's. From the results, Tables 4.3.3.11 to 4.3.3.14., it can be seen that FPN_G16's have a significant negative effect on the number of KSI accidents. This is the case for both offset variables and mirrors the results from the models which use the full set of FPN's. These results suggest that the detection and punishment of speeding offenders is an important tool for enforcement agencies in the drive to reduce the number of KSI accidents.

The last two rows in each table, from 4.3.3.7 to 4.3.3.14, show the model information criteria. This is included mainly to show the equivalent of the R^2 measure used in ordinary regression to judge model goodness of fit. The equivalent measure for Zero Truncated Poisson (ZTP) regression is McFadden's Pseudo $R^{2,}$ which can be calculated from

$$R^2 = 1 - \frac{LL_{Model}}{LL_{Null}}$$

where LL_{Model} is the log likelihood of the current model
and LL_{Null} is the log likelihood of the null model.

This should not be interpreted in the same way as the R^2 index used in ordinary regression as values of McFadden's Pseudo R^2 lying between 0.2 and 0.4 are considered to be representative of an excellent fit (see McFadden (1977)). Using this criterion it can be seen that all ZTP regression models developed here can be considered to be an excellent fit to the data. In addition the models are logical, with no abnormality, which indicates reliability in the model. There is little to choose between the models but those with lnpop as the offset do seem to perform slightly better in terms of the effects of the proxy variables. The AIC value, Akaike's Information Criterion, is also used to compare models. The lower the value the better the model fits the data. The AIC can be calculated as follows

AIC = $d + 2p$ where

d = is the deviance = -2*log likelihood and

p = degrees of freedom/number of estimated parameters

4.4 Modelling Quarterly Accident Data

The initial step in modelling the quarterly accident data is identical to that used with the annual data, with aggregate proxy variables used to investigate any effect in relation to KSI accidents. Once again the aggregate variable is named All Penalties and four models will be generated dealing with both contemporary and lagged effects. Quarterly data are lagged by one and two quarters, three months and six months, and both offset variables are used. An example of the full output from the ZTP modeling of quarterly data is shown in Table 4.4.1, with selected outputs from the initial modelling of the quarterly data shown in Tables 4.4.2 to 4.4.4. Full output for all models is available in Appendix 4, Tables 13 to 16.

Table 4.4.1: Full Output from ZTP on Quarterly Data with Offset lnpop.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Year	-0.0212	0.004	-4.97	0.0000	-0.0296	-0.0129
Quarter 2	0.2616	0.018	14.58	0.0000	0.2264	0.2968
Quarter 3	0.2801	0.017	16.24	0.0000	0.2463	0.3139
Quarter 4	0.1441	0.018	8.16	0.0000	0.1095	0.1787
25 to 34	-0.0358	0.014	-2.53	0.0110	-0.0635	-0.0081
35 to 44	-0.2632	0.016	-16.35	0.0000	-0.2948	-0.2316
45 to 54	-0.6169	0.021	-29.67	0.0000	-0.6576	-0.5761
55 to 64	-1.0336	0.030	-35.02	0.0000	-1.0915	-0.9758
65 Plus	-0.7408	0.025	-29.60	0.0000	-0.7898	-0.6917
Female	-0.8318	0.016	-51.96	0.0000	-0.8632	-0.8004
speed limit 40	-1.4969	0.032	-46.94	0.0000	-1.5594	-1.4343
speed limit 50	-2.5752	0.115	-22.30	0.0000	-2.8016	-2.3489
speed limit 60	-0.0271	0.013	-2.13	0.0330	-0.0519	-0.0022
speed limit 70	-1.1194	0.030	-37.66	0.0000	-1.1777	-1.0612
HGV_LGV	-1.5587	0.035	-44.21	0.0000	-1.6278	-1.4896
Motorcycle	-0.7267	0.018	-41.05	0.0000	-0.7614	-0.6920
Other	-1.8083	0.046	-39.23	0.0000	-1.8987	-1.7180
Junction	0.0458	0.011	4.01	0.0000	0.0234	0.0681
Roundabout	-2.1986	0.070	-31.21	0.0000	-2.3367	-2.0606
Slippy	-1.9243	0.086	-22.26	0.0000	-2.0937	-1.7549
Snow	-3.5711	0.575	-6.21	0.0000	-4.6990	-2.4432
Wet	-0.3872	0.013	-30.34	0.0000	-0.4123	-0.3622
dark	-0.2936	0.012	-23.61	0.0000	-0.3180	-0.2692
Geographic Area sqkm	0.0027	0.006	0.42	0.6730	-0.0099	0.0153
Mean Index of Multiple Deprivation	0.0777	0.006	12.33	0.0000	0.0654	0.0901
Percentage Motorway	-0.0417	0.007	-6.37	0.0000	-0.0545	-0.0288
All Penalties	-0.0423	0.006	-7.11	0.0000	-0.0539	-0.0306
Constant	33.1262	8.558	3.87	0.0000	16.3520	49.9004
lnpop	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
77868	-76967.3	-53372.8	28	106801.7	1.37	0.31

[1]AIC*n is the AIC reported by STATA 10

Table 4.4.2: Output from ZTP on Quarterly Lagged Data with Offset lnpop.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Mean Index of Multiple Deprivation	0.083	0.006	13.18	0.000	0.071	0.096
Percentage Motorway	-0.040	0.006	-6.18	0.000	-0.053	-0.027
Lag1 All Penalties	-0.028	0.007	-4.02	0.000	-0.041	-0.014
Lag2 All Penalties	-0.023	0.007	-3.47	0.001	-0.036	-0.010
Constant	38.527	8.205	4.70	0.000	22.446	54.608
lnpop	(offset)					
	Model Information Criteria					
Number Obs	ll(null)	ll(model)	df	AIC*n[1]	AIC	Pseudo R^2
80584	-79432	-55112	29	110283	1.37	0.31

Table 4.4.3: Output from ZTP on Quarterly Data with Offset lnvkm.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Geographic Area sqkm	-0.038	0.006	-5.86	0.000	-0.051	-0.025
Mean Index of Multiple Deprivation	0.222	0.006	34.80	0.000	0.210	0.235
Percentage Motorway	-0.102	0.006	-15.68	0.000	-0.114	-0.089
All Penalties	-0.016	0.006	-2.77	0.006	-0.028	-0.005
Constant	65.024	8.533	7.62	0.000	48.300	81.749
lnvkm	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
77868	-77959	-53301	28	106657	1.37	0.32

Table 4.4.4: Output from ZTP on Quarterly Lagged Data with Offset lnvkm.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Geographic Area sqkm	-0.040	0.006	-6.23	0.000	-0.052	-0.027
Mean Index of Multiple Deprivation	0.224	0.006	34.98	0.000	0.212	0.237
Percentage Motorway	-0.101	0.006	-15.81	0.000	-0.114	-0.089
Lag1 All Penalties	-0.013	0.007	-1.92	0.055	-0.026	0.000
Lag2 All Penalties	-0.005	0.007	-0.72	0.470	-0.018	0.008
Constant	67.547	8.171	8.27	0.000	51.532	83.562
lnvkm	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
80584	-80467	-55042	29	110142	1.37	0.32

The results, shown in Appendix 4, Tables 13 to 16, show that, as with the annual data, the values for categorical variables are very similar for all models. In all models there is once more a general level of consistency which shows that a person is more likely to be in a KSI accident if they are male, aged between 17 and 24 years, travelling in a car on a road with a fixed speed limit of 30 mph. The accident is most likely to happen at a junction on a dry road during daylight hours.

The aggregated proxy variables are shown to have a significant negative effect on the level of KSI accidents in all four models, see Tables 4.4.1 to 4.4.4, with the effect being slightly stronger in models where the offset variable is lnpop. The weakest of the four models, see Table 4.4.4, relates to quarterly lagged data with lnvkm as the offset variable. In this model only the one quarter lagged proxy is significant, at the 10% level. However, the proxies, in the main, have a significant negative association with the level of KSI accidents thereby indicating that any increase in police enforcement activity is associated with a corresponding drop in the number of KSI accidents

As with the annual data models, based on aggregated proxy variables, the next step is to investigate the effects of the individual proxy variables - Prosecutions, FPN's VDRN's and WW's – to see if they are they having a similar effect on KSI accidents .

As with the modelling of the annual data there are four basic models to be fitted in relation to quarterly data and these are as follows,

1. Contemporary Quarterly Data
2. Lagged Quarterly Data
3. Contemporary Quarterly Data with FPN_G16
4. Lagged Quarterly Data with FPN_G16

The same procedures are used in modelling quarterly data as were used with annual data and all variables used in the previous analysis of annual data are used in the analysis of quarterly data. Once again the reference categories are generated automatically by STATA 10. All categories, as shown in Table 4.3.3.5, are repeated for the analysis of quarterly data with the addition of Quarter, with Quarter 1 used as the reference category.

Differentiation between the models used to analyse quarterly data are detailed in Table 4.4.5.

Table 4.4.5: Differentiation between Quarterly ZTP models.

ZTP Models	Dependent Variable	Offset Variable	Table number
Quarterly	KSI	Population (lnpop)	4.4.6
Quarterly	KSI	billions of vehicle km's travelled (lnvkm)	4.4.7
Quarterly Lagged	KSI	Population (lnpop)	4.4.8
Quarterly Lagged	KSI	billions of vehicle km's travelled (lnvkm)	4.4.9
Quarterly with Speeding related FPN_G16	KSI	Population (lnpop)	4.4.10
Quarterly with Speeding related FPN_G16	KSI	billions of vehicle km's travelled (lnvkm)	4.4.11
Quarterly Lagged with Speeding related FPN_G16	KSI	Population (lnpop)	4.4.12
Quarterly Lagged with Speeding related FPN_G16	KSI	billions of vehicle km's travelled (lnvkm)	4.4.13

The outputs from the ZTP regressions relating to quarterly data are detailed in Tables 4.4.6 to 4.4.13.

Table 4.4.6: Output from ZTP on Quarterly Data with Offset lnpop.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Mean Index of Multiple Deprivation	0.093	0.006	14.77	0.000	0.080	0.105
Percentage Motorway	-0.038	0.006	-5.96	0.000	-0.050	-0.025
Prosecutions	0.027	0.006	4.83	0.000	0.016	0.038
FPN	-0.057	0.006	-9.73	0.000	-0.069	-0.046
VDRN	-0.024	0.007	-3.63	0.000	-0.037	-0.011
WW	-0.071	0.006	-11.14	0.000	-0.083	-0.058
Constant	65.119	8.262	7.88	0.000	48.926	81.312
lnpop	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
86371	-85370	-58997	31	118056	1.37	0.31

Table 4.4.7: Output from ZTP on Quarterly Data with Offset lnvkm.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Geographic Area sqkm	-0.036	0.006	-5.61	0.000	-0.049	-0.024
Mean Index of Multiple Deprivation	0.241	0.006	37.92	0.000	0.229	0.254
Percentage Motorway	-0.103	0.006	-16.41	0.000	-0.115	-0.091
Prosecutions	0.027	0.006	4.94	0.000	0.016	0.038
FPN	-0.020	0.006	-3.48	0.000	-0.031	-0.009
VDRN	-0.041	0.007	-6.26	0.000	-0.054	-0.028
WW	-0.065	0.006	-10.29	0.000	-0.077	-0.052
Constant	99.998	8.209	12.18	0.000	83.908	116.087
lnvkm	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
86371	-86498	-58954	31	117969	1.37	0.32

Table 4.4.8: Output from ZTP on Quarterly Lagged Data with Offset lnpop.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Mean Index of Multiple Deprivation	0.086	0.007	12.91	0.000	0.073	0.099
Percentage Motorway	-0.037	0.007	-5.61	0.000	-0.050	-0.024
Lag 1 Prosecutions	0.016	0.006	2.88	0.004	0.005	0.027
Lag 1 FPN	-0.008	0.014	-0.61	0.542	-0.035	0.018
Lag 1 VDRN	-0.068	0.018	-3.85	0.000	-0.102	-0.033
Lag 1 WW	0.004	0.018	0.23	0.820	-0.032	0.040
Lag 2 Prosecutions	0.026	0.005	4.75	0.000	0.015	0.037
Lag 2 FPN	-0.054	0.014	-3.99	0.000	-0.081	-0.028
Lag 2 VDRN	-0.007	0.017	-0.43	0.668	-0.040	0.026
Lag 2 WW	-0.013	0.018	-0.74	0.459	-0.047	0.021
Constant	62.409	9.138	6.83	0.000	44.499	80.318
lnpop	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
80584	-79432	-54955	35	109980	1.36	0.31

Table 4.4.9 Output from ZTP on Quarterly Lagged Data with Offset lnvkm.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Geographic Area sqkm	-0.033	0.007	-4.94	0.000	-0.046	-0.020
Mean Index of Multiple Deprivation	0.235	0.007	34.63	0.000	0.222	0.248
Percentage Motorway	-0.104	0.007	-15.87	0.000	-0.117	-0.091
Lag 1 Prosecutions	0.015	0.005	2.74	0.006	0.004	0.026
Lag 1 FPN	0.002	0.014	0.13	0.896	-0.025	0.028
Lag 1 VDRN	-0.065	0.017	-3.77	0.000	-0.098	-0.031
Lag 1 WW	-0.004	0.019	-0.19	0.846	-0.040	0.033
Lag 2 Prosecutions	0.026	0.005	4.77	0.000	0.015	0.037
Lag 2 FPN	-0.026	0.014	-1.89	0.058	-0.052	0.001
Lag 2 VDRN	-0.005	0.016	-0.28	0.781	-0.037	0.027
Lag 2 WW	-0.028	0.018	-1.6	0.109	-0.063	0.006
Constant	100.360	9.068	11.07	0.000	82.588	118.132
lnvkm	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
80584	-80467	-54918	35	109906	1.36	0.32

Table 4.4.10: Output from ZTP on Quarterly Data with Speeding Related FPN's (FPN_G16) and Offset lnpop.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Mean Index of Multiple Deprivation	0.082	0.006	12.99	0.000	0.070	0.095
Percentage Motorway	-0.036	0.006	-5.56	0.000	-0.049	-0.023
Prosecutions	0.024	0.006	4.4	0.000	0.014	0.035
FPN G16	-0.049	0.006	-7.85	0.000	-0.062	-0.037
VDRN	-0.078	0.006	-12.32	0.000	-0.090	-0.065
WW	-0.030	0.007	-4.54	0.000	-0.043	-0.017
Constant	47.766	8.907	5.36	0.000	30.308	65.224
lnpop	(offset)					
	Model Information Criteria					
Number Obs	ll(null)	ll(model)	df	AIC*n[1]	AIC	Pseudo R^2
86371	-85370	-59013	31	118088	1.37	0.31

Table 4.4.11: Output from ZTP on Quarterly Data with Speeding Related FPN's (FPN_G16) and Offset lnvkm.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Geographic Area sqkm	-0.034	0.006	-5.37	0.000	-0.047	-0.022
Mean Index of Multiple Deprivation	0.236	0.006	36.87	0.000	0.223	0.248
Percentage Motorway	-0.098	0.006	-15.36	0.000	-0.111	-0.086
Prosecutions	0.028	0.006	5.01	0.000	0.017	0.038
FPN G16	-0.032	0.006	-5.24	0.000	-0.044	-0.020
VDRN	-0.065	0.006	-10.44	0.000	-0.077	-0.053
WW	-0.043	0.007	-6.54	0.000	-0.056	-0.030
Constant	85.378	8.848	9.65	0.000	68.036	102.720
lnvkm	(offset)					
	Model Information Criteria					
Number Obs	ll(null)	ll(model)	df	AIC*n[1]	AIC	Pseudo R^2
86371	-86498	-58946	31	117954	1.37	0.32

Table 4.4.12: Output from ZTP on Quarterly Lagged Data with Speeding Related FPN's (FPN_G16) and Offset lnpop.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Mean Index of Multiple Deprivation	0.076	0.007	11.16	0.000	0.062	0.089
Percentage Motorway	-0.037	0.007	-5.48	0.000	-0.050	-0.024
Lag 1 Prosecutions	0.016	0.006	2.8	0.005	0.005	0.026
Lag 1 FPN G16	-0.025	0.012	-2.06	0.039	-0.048	-0.001
Lag 1 VDRN	-0.066	0.018	-3.73	0.000	-0.100	-0.031
Lag 1 WW	0.000	0.019	-0.02	0.987	-0.037	0.036
Lag 2 Prosecutions	0.024	0.005	4.34	0.000	0.013	0.035
Lag 2 FPN G16	-0.019	0.012	-1.56	0.118	-0.043	0.005
Lag 2 VDRN	-0.018	0.017	-1.08	0.282	-0.051	0.015
Lag 2 WW	-0.019	0.018	-1.04	0.298	-0.053	0.016
Constant	45.412	9.816	4.63	0.000	26.173	64.651
lnpop	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
80584	-79432	-54986	35	110043	1.37	0.31

Table 4.4.13: Output from ZTP on Quarterly Lagged Data with Speeding Related FPN's (FPN_G16) and Offset lnvkm.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Geographic Area sqkm	-0.032	0.007	-4.94	0.000	-0.045	-0.020
Mean Index of Multiple Deprivation	0.229	0.007	33.46	0.000	0.216	0.243
Percentage Motorway	-0.101	0.007	-15.11	0.000	-0.114	-0.088
Lag 1 Prosecutions	0.016	0.005	2.84	0.005	0.005	0.026
Lag 1 FPN G16	-0.018	0.012	-1.5	0.132	-0.041	0.005
Lag 1 VDRN	-0.062	0.017	-3.61	0.000	-0.096	-0.028
Lag 1 WW	-0.006	0.019	-0.3	0.765	-0.042	0.031
Lag 2 Prosecutions	0.026	0.005	4.72	0.000	0.015	0.036
Lag 2 FPN G16	-0.008	0.012	-0.67	0.500	-0.032	0.015
Lag 2 VDRN	-0.009	0.016	-0.56	0.577	-0.041	0.023
Lag 2 WW	-0.030	0.018	-1.67	0.094	-0.064	0.005
Constant	87.677	9.736	9.01	0.000	68.594	106.760
lnvkm	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
80584	-80467	-54917	35	109904	1.36	0.32

The most likely scenario for a driver involved in a KSI accident, in relation to quarterly data and shown in Tables 4.4.6 to 4.4.13, is identical to that found in the analysis of annual data with the additional factor that for quarterly data a KSI accident is more likely to happen in Quarter 3, July to September of any given year, than at any other time.

The results of modelling the quarterly data using all proxies for police enforcement, using the full set of FPN's, are shown in Tables 4.4.6 to 4.4.9. For both contemporary and lagged events and regardless of which offset is used, Prosecutions are associated with a positive effect on KSI accidents. This would seem to suggest that an increase in the number of successful prosecutions is linked to an increase in the number of KSI accidents. However it is known that KSI accidents are decreasing year on year and it is more likely that the Prosecution effect is related to higher levels of police activity at sites with higher risk of KSI accidents, such as known accident blackspots.

When looking at the other proxy variables, FPN's, VDRN's and WW's, the results appear to be more easily interpretable. All are seen to be associated with a significant decrease in the number of KSI accidents, over both offsets, in relation to contemporary quarterly events. The size of the effect varies according to which offset is used, but any difference is minimal in terms of the effect associated with the KSI accidents. The results are noticeably different when examined for lagged quarterly data. The lag periods used are one and two quarters, three and six months. Quarterly lags were included to reflect the known changes in KSI accident levels between the different quarters. FPN's lagged by two quarters are approaching significance, on KSI accidents when lnvkm is used as the offset variable, see Table 4.4.9. This effect is even stronger when lnpop is used as the offset, see Table 4.4.8. There are no significant effects associated with FPN's lagged by one quarter. This suggests that there may be a diffusion effect at work whereby an increase in the level of FPN's issued by enforcement agencies has both an immediate significant effect and a slightly smaller, but still significant, effect six months later. In the case of VDRN's significant effects are found only for one quarter lags, regardless of offset variable. It is possible that this effect is related to the shorter compliance period associated with this type of penalty, typically fourteen days. There are no significant effects for WW's.

Selected results of the analysis using the FPN_G16 subset of FPN's are presented in Tables 4.4.10 to 4.4.13, with full output shown in Appendix 4, Tables 21 to 24. As with the annual data analysis, the results are very similar to those found using the full set of FPN's alongside all other proxy variables. For contemporary events all effects are in the same direction, negative and significant, and of similar magnitude over both offsets. In relation to quarterly lags there is very little difference between models when lnvkm is the offset except in the case of two quarter lagged FPN_G16s where there is no significant effect found. With lnpop as the offset it is now one quarter lagged FPN_G16's which have a significant negative effect rather than the two quarter lagged FPN's. While the effects of all socio-demographic variables are the same for the lagged data as they were for the contemporary data.

The effects of education strategies and engineering advances relating to road safety were considered as possible confounding factors. These are likely to have had an effect on both accident and KSI rates; however, as any effects are likely to be felt at a national level they are not thought to be prejudicial to the results given here.

The results presented here provide evidence that increased levels of enforcement, as measured by the proxy variables, leads to detectable reductions in KSI rates. Speeding related Fixed Penalty Notices, FPN_G16's, contemporary and lagged, treated in isolation are also seen to be associated with falling KSI rates indicating that excess speed is a significant factor in KSI accidents. The effects of Prosecutions on KSI rates are more difficult to interpret. As a result of the unknown time delay between any given accident and any subsequent prosecution we cannot be certain how contemporary or lagged the prosecutions actually are. The results from the models using lagged enforcement proxies suggest that the effects of increased levels of enforcement are not always immediately apparent but are often manifest one or two quarters, three to six months, later.

All the results discussed here are for models which do not include the Metropolitan police Force Area. Reasons for the exclusion of this PFA have been discussed previously, Section 3.1, page 32, but some further explanation may be worthwhile. The ZTP models for contemporary annual data, using both offsets, were run with the Metropolitan PFA included and these produced markedly different results from the models presented earlier.

Including the Metropolitan PFA in the models, see Appendix 4, Tables 25 and 26, has different effects depending on the offset used. For lnpop, the population based offset, Prosecutions are linked with a significant increase in accidents. For lnvkm, the vehicle kilometres travelled based offset, the same effect is found with the additional effect of FPN's linked to a significant increase in accidents. These results, especially related to the effect of FPN's, are counter intuitive to all other evidence and are no longer apparent when the Metropolitan PFA is removed from the models. Furthermore, 25 to 34 year olds now seem to be most likely to be involved in KSI accidents replacing the baseline age group, 17 to 24 year olds. Using this model obscures the true picture relating to the other forty-one PFA's and this is another reason for excluding the Metropolitan PFA from the analysis. Further investigation into the Metropolitan PFA would seem to be worthwhile, especially in relation to traffic flow throughout the area, but at this time is beyond the scope of this report.

Another area of investigation explored was the replacement of the socio-demographic variables, Geographical Area sq km, Mean Index of Deprivation (IMD) and Percentage Motorway, with PFA as a categorical dummy variable. It was thought that the effects of these variables could have been absorbed by PFA as a single categorical variable. The results from modelling this, with contemporary annual, data are given in Appendix 4, Tables 27 and 28. The results seem to be unreliable, when compared to previous results and known trends in the data and add no real insight.

5. Cluster Analysis

5.1 Introduction to Cluster Analysis.

The aim of cluster analysis is to identify groupings, or clusters, which are not immediately apparent within a data set. The procedure attempts to minimise variation within each cluster and also to maximise the variation between each cluster. Using hierarchical clustering methods the clusters are nested rather than mutually exclusive, which in general terms means that larger clusters may contain smaller clusters. There are two main choices of method available for hierarchical clustering, agglomerative and divisive. The divisive method starts by combining all variables into a single cluster and then subdivides into smaller clusters. The agglomerative method does the opposite; starting with each variable as an individual cluster and then combining these into larger clusters.

There are various algorithms available for hierarchical clustering and the main difference between them is in the linkage function used. The linkage function is used to calculate the difference or distance between each cluster. For the initial stage of cluster analysis the chosen algorithm is Ward's linkage (Ward, 1963). This differs from the other available methods in that it uses analysis of variance (ANOVA) to determine the distances between clusters by attempting to minimise the sum of squares between any two clusters that are formed at each step of the procedure. In general Ward's method is considered very efficient although it can produce clusters that are small in size.

Hierarchical clustering is used here for two reasons; to investigate the structure of the data and to provide a well defined set of clusters which can be used to produce multilevel models. By exposing the data to cluster analysis it is expected that clusters of PFA's with similar attributes will be identified thereby enhancing the understanding of the effects of enforcement on Killed and Seriously Injured (KSI) accidents. Furthermore, using the clusters identified by analysis to produce multilevel models will also give greater insight into the structure and nature of the data.

The use of hierarchical cluster analysis in accident analysis is quite well documented; see for example Karlaftis and Tarko (1998) and Wong et al., (2004), who both advocate the use of hierarchical clustering, employing Ward's linkage method and it is this method which is used here. Initially, data covering all KSI accidents for 2004 are used to develop the cluster analysis. The data are aggregated into forty one PFA's which are entered into the cluster analysis in order to produce distinct clusters of similar PFA's.

The choice of variables used to develop clusters is based on analysis done in Chapter 4, with results from the Zero Truncated Poisson regression analysis suggesting that the most suitable variables were KSI rates and the level of Fixed Penalty Notices (FPN's) issued and it is these variables that are used to develop the cluster groupings. Two distinct cluster analyses are produced using the KSI rates in conjunction with FPN_1000's. The first cluster analysis uses the KSI rate by Population and FPN_1000's while the second uses the KSI rate by Vkm and FPN_1000's. The software used for the cluster analysis is SPSS 16 (SPSS Inc., Chicago IL).

5.2 Ward Method Cluster Analyses on KSI Rate by Population and FPN_1000's

The results of the cluster analysis using KSI Rate by Population and FPN_1000's as the clustering variables are shown in Figure 5.2.1 and Table 5.2.1. All variables are standardised, by converting to z-scores, prior to analysis. Figure 5.2.2 shows a geographical representation of the clusters.

In Figure 5.2.1 a graphical representation of the developed clusters is shown. It should be noted that all variables were standardised, by converting to z-scores, prior to clustering to take into account the different measurement scales and to allow proper comparisons to be made. Examining Figure 5.2.1 it is apparent that a general trend exists which shows that lower KSI rates are associated with higher levels of FPN's. This trend is consistent with the results previously shown in chapter four.

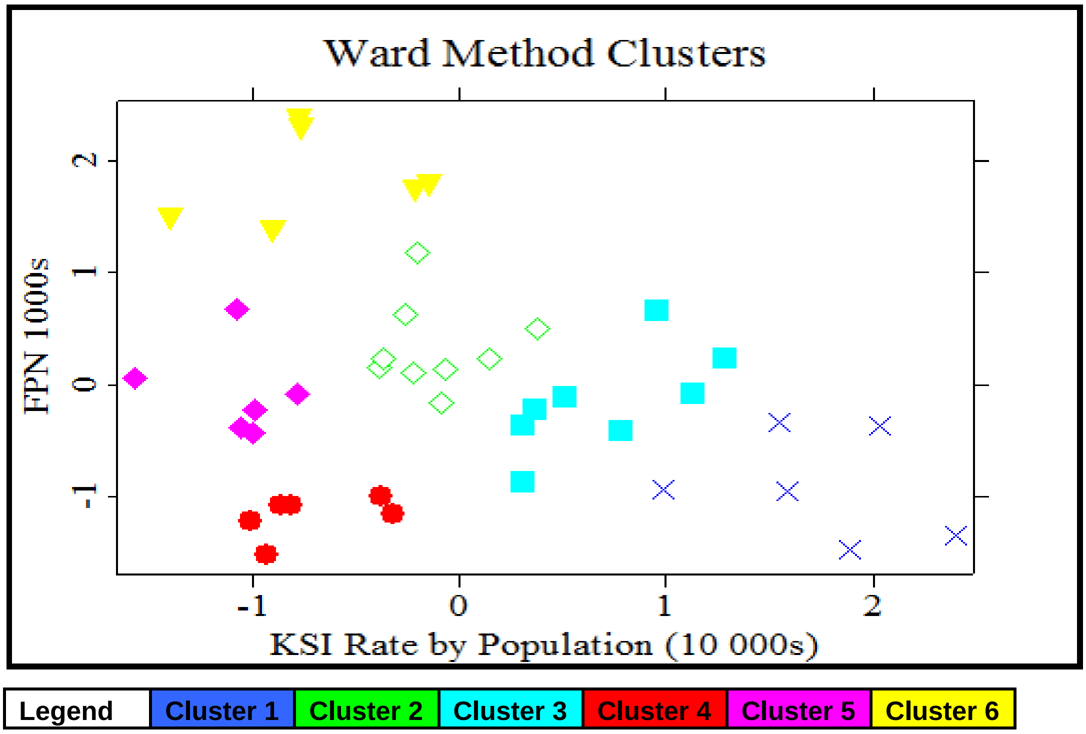
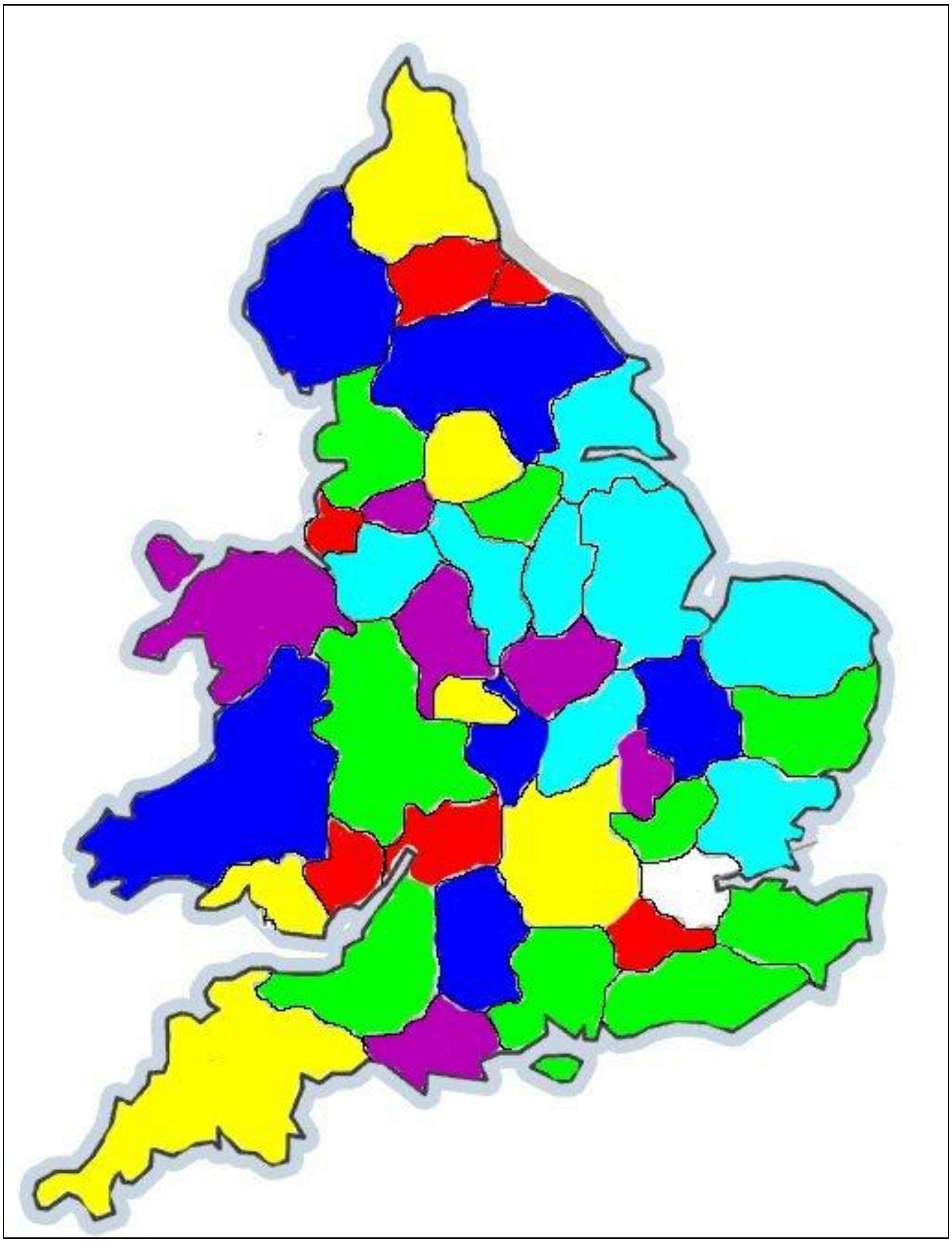


Figure 5.2.1: **Ward Method Clusters ZKSI Rate by Population and FPN_1000's**



Legend	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6

Figure 5.2.2: Map of Ward Method Clusters ZKSI Rate by Population and FPN_1000's

There is, however, one cluster which does not seem to fit this trend and this is easily seen in Figure 5.2.1, where Cluster 4 has low KSI rates and low levels of FPN's. Further information on the make up of each cluster is available in Table 5.2.1 where the cluster means, unstandardised, for all variables are shown.

Clusters 5 and 6 have low KSI rates and high levels of FPN's. Cluster 1 has by far the highest KSI rate and also has low levels of FPN's. In fact Cluster 1 has low levels across all variables, excepting the KSI rate and Geographical area. Cluster 1 is made up of relatively large, rural areas with low population and police strength numbers. It appears, from looking at the data, that this combination allied to the lower levels of police enforcement, as measured by the proxy variables, is responsible for the high KSI rate. There may be other factors at play here including the remoteness of accident sites which can effect the time taken for emergency services to reach the accident site, which may affect the outcome of the accident for those involved.

Table 5.2.1: Cluster Means, Unstandardised, for KSI Rate by Population and FPN_1000's

Ward Method Cluster Means	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
KSI Rate by Population	8.04	5.23	6.47	4.32	3.77	4.35
FPN_1000's	38.19	88.34	68.72	27.02	72.22	149.34
FPN_G16_1000's	24.06	57.38	45.55	7.69	48.47	75.17
VDRN_1000's	2.34	3.34	2.59	2.41	2.42	5.22
WW_1000's	1.75	1.51	0.27	1.20	1.17	2.95
GEOGRAPHIC AREA sqkm	4343.08	3757.28	3487.48	1292.54	2788.49	4933.18
MEAN IMD SCORE	15.76	17.36	19.21	22.66	18.36	22.06
PERCENT MOTORWAY	1.08	1.26	0.77	1.11	0.90	0.95

5.2.1 Analysis of Variance (ANOVA)

Having achieved a reasonable clustering of PFA's with similar attributes the next step was to test for significant differences between the cluster means, on each variable. This was done using Analysis of Variance (ANOVA), where the basic tenet is the derivation of two different estimates of the population variance. It is a necessary initial step, when running an ANOVA, to check for equal or unequal variance within each group. This is done using Levene's Test for Equality of Variance and the results indicated that all variables had equal variance

On running the ANOVA three variables - KSI Rate by Population, FPN_1000's and FPN_G16_1000's – were found to produce significant results. In relation to KSI Rate by Population only Clusters 1 and 3 are significantly different from all other clusters. Cluster 2 is not significantly different from Clusters 4 and 6, but is significantly different from all other clusters. No significant differences are reported between Clusters 4, 5 and 6. A graphical representation of this is shown in Figure 1, Appendix 5. For FPN_1000's, there are no significant differences between Clusters 1 and 4 or between Clusters 2, 3 and 5, with all other comparisons being significantly different from each other, see Figure 2, Appendix 5. In the case of FPN_G16_1000's, more than half the comparisons between clusters, eight out of fifteen, have no significant difference and this is shown graphically in Figure 3, Appendix 5.

In trying to interpret the significant differences between clusters, for each variable, it is informative to look at Table 5.2.1 which details the individual cluster means. From this it is possible to build a picture of what makes each cluster different; where significant differences actually exist. With respect to KSI Rate by Population, in Table 5.2.1, Clusters 4, 5 and 6 have similarly low levels of KSI rates which are not significantly different from each other. They are, however, significantly different, in fact significantly lower, than the KSI rates for Clusters 1 and 3. In turn, Cluster 1 has a significantly higher KSI rate than does Cluster 3. The main difference between Clusters 1 and 3 appears to be in the level of FPN_1000's where Cluster 3 has significantly higher numbers, see Table 5.2.1. Cluster 2 represents the mid level, falling between those clusters with high KSI rates and those with low KSI rates. This agrees with the findings from Chapter 4 where higher levels of police enforcement, as measured by the proxy variables, were linked to a decrease in KSI rates.

5.3 Ward Method Cluster Analyses on KSI Rate by Vkm and FPN_1000's

This section is a repeat of the previous analyses using different clustering variables. Here the KSI Rate by Vkm is used alongside FPN_1000's to develop the clusters. Identical procedures are used to develop and analyse the output of the Hierarchical Cluster Analysis. Table 5.3.1 and Figure 5.3.1 detail the output from the cluster analysis.

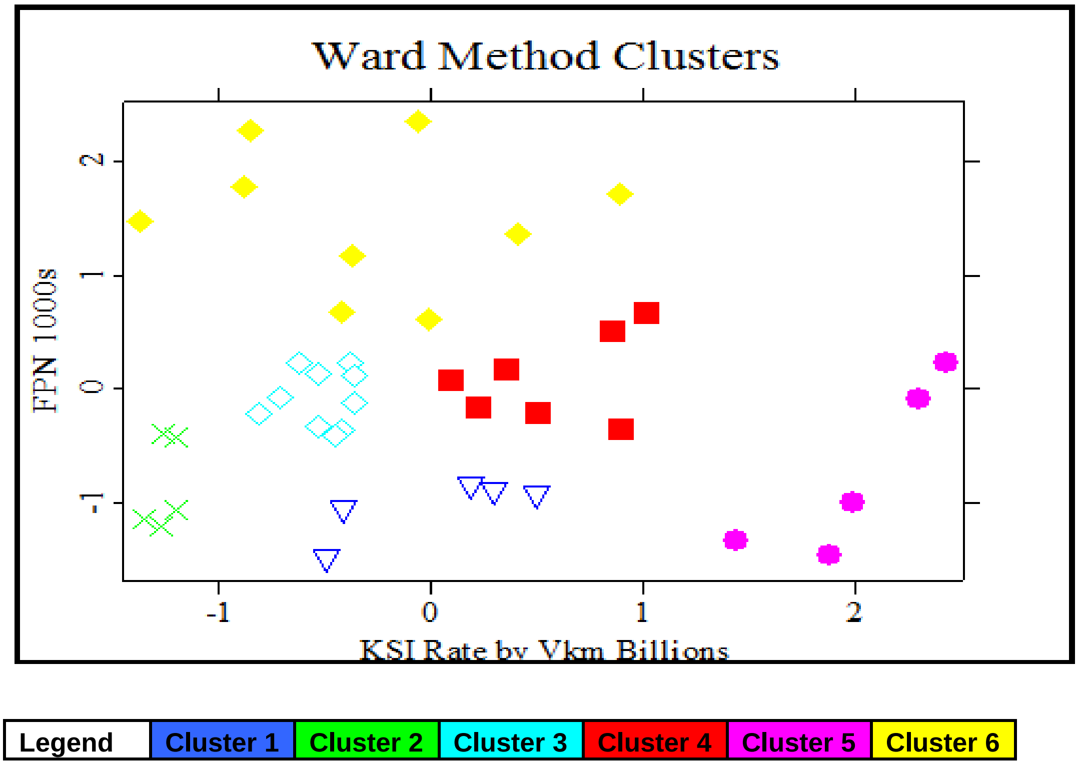


Figure 5.3.1: **Ward Method Clusters KSI Rate by Vkm and FPN_1000's**

Once again there appears to be a general trend, see Figure 5.3.1, where an increase in the level of FPN_1000's is associated with a decrease in the KSI rate. However, the trend is not as well defined in this instance, Table 5.3.1, and the cluster means, unstandardised, do not appear to fully support the trend. It may prove to be more illuminating to inspect the results of the ANOVA, for this analysis, where any significant differences will be more readily apparent.

Table 5.3.1: Cluster Means, Unstandardised for KSI Rate by Vkm and FPN_1000's

Ward Method Cluster Means	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
KSI Rate by Vkm	56.30	38.42	48.80	64.02	84.23	51.90
FPN 1000s	31.19	40.16	71.47	78.34	44.94	135.65
FPN G16 1000s	20.48	16.32	52.08	51.58	24.35	69.50
VDRN 1000s	2.11	1.94	2.74	3.44	1.94	4.86
WW 1000s	1.16	0.75	1.33	1.38	0.52	2.56
GEOGRAPHIC AREA sqkm	3721.19	1873.47	3449.16	3315.87	3342.72	4385.49
MEAN IMD SCORE	22.91	14.62	15.23	18.92	23.49	21.46
PERCENT MOTORWAY	0.63	1.38	1.39	0.76	0.65	1.02

5.3.1 Analysis of Variance for KSI RATE by Vkm and FPN_1000's

The results from Levene's Test for Equality of Variance indicate that three of the variables, KSI Rate by Vkm, FPN_1000's and FPN_G16_1000's, have unequal variance. Therefore it is useful to use, post-hoc, Dunnett's C test in the ANOVA for those variables.

Only three variables, KSI Rate by Vkm, FPN (1000s) and FPN G16 (1000s), displayed any significant differences between individual clusters. Graphical representations of this are shown in Figures 4, 5 and 6 Appendix 5.

For the KSI Rate by Vkm, one third of the cluster comparisons have no significant differences. It is apparent that Cluster 2 has the lowest KSI Rate by Vkm and is significantly different from all other clusters, when comparing only the KSI rate. With only two other variables showing any significant differences across clusters, FPN_1000's and FPN_G16_1000's, it would seem prudent to use these as further avenues of comparison. Cluster 2 is significantly different from only Cluster 6, with respect to FPN_1000's and FPN_G16_1000's, see Tables 4, 4a and 4b and also figures 4, 4a and 4b. A further examination of Table 5.3.1 suggests that there may be a link between KSI Rate by Vkm and the Mean IMD Score. It appears that low Mean IMD Scores are associated with low KSI levels there are, however, no statistically significant associations to be found. It may be worth noting that if multiple comparisons are carried out using Least Significant Difference (LSD) tests on Mean IMD Scores then there are significant differences found between clusters. The problem here is that the LSD test takes no account of the error rate for multiple comparisons and for this reason is omitted from the analysis proper. Cluster 5 is also significantly different from all other clusters, when comparing only KSI rates, having the highest level of KSI by Vkm and amongst the lowest level of enforcement.

There are many significant differences between the clusters but there is no discernible pattern to these differences. The clusters developed using the KSI Rate by Vkm are not as well defined as those produced using the KSI Rate by Population and this is readily apparent when comparing Figures 5.2.1 and 5.3.1. The trend of low KSI rates associated with high levels of police enforcement is much more visible in Figure 5.2.1.

In general the results from the hierarchical cluster analysis were mixed. There is a general trend which indicates that increasing police enforcement, measured here by the proxies for enforcement, is associated with a decrease in the KSI rates. This is better defined for the KSI Rate by Population than it is for the KSI Rate by Vkm. It may be that the aggregation of PFA's into distinctive clusters results in some loss of variation which, when added to the loss of variation already caused by the aggregation of local authority data into PFA data, makes it more difficult to define more tightly grouped clusters. One possible solution may be to try an alternative clustering method – Fuzzy C-means clustering.

5.4 Fuzzy C-means Cluster Analysis.

With results from the hierarchical cluster analysis being some what mixed, especially in relation to clusters based on the KSI Rate by Vkm further an alternative method of clustering was used in an attempt to produce further refinement of the clusters. The alternative method chosen was Fuzzy C-means clustering (FCM). FCM differs from Hierarchical Clustering in various ways with the main one of interest being that it allows for the possibility that data may belong to more than one cluster. The FCM method was first developed in 1973, (Dunn, 1973), and it is most commonly used in pattern recognition (Bezdek and Pal, 1992). The software used for fuzzy clustering is XploRe 4.8 (MD*TECH).

On running the FCM algorithm on the KSI Rate by Population a number of fuzzy points were generated. Fuzzy points are data whose cluster membership is ambiguous and the output is shown in Figure 5.4.1.

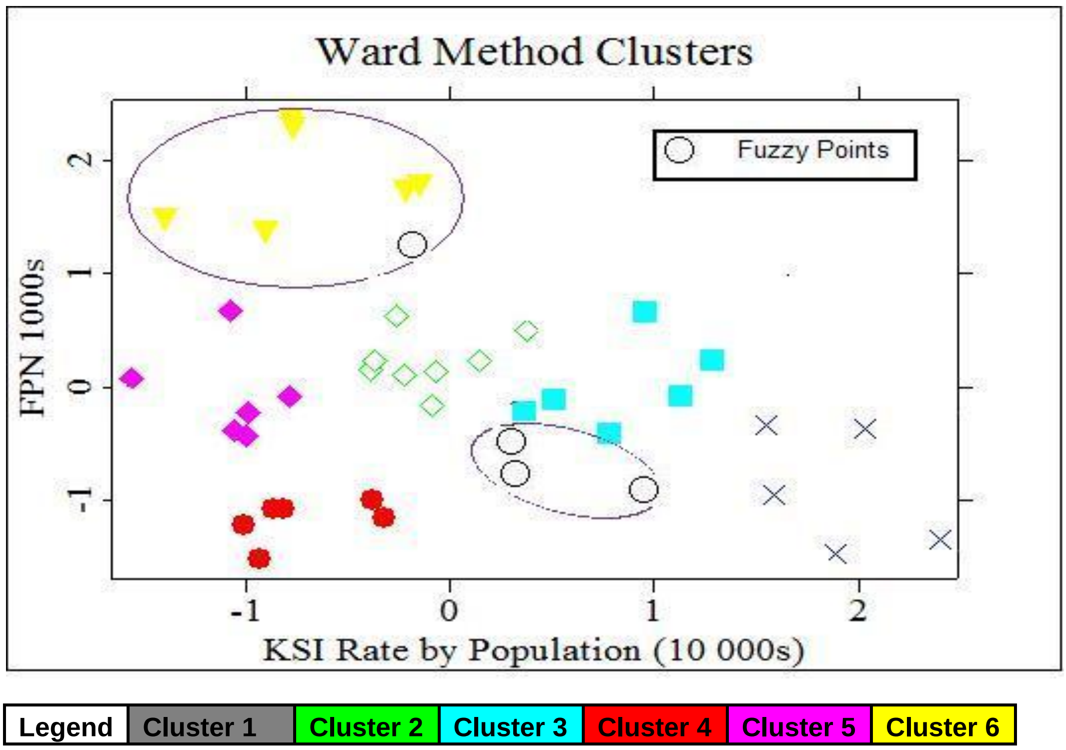
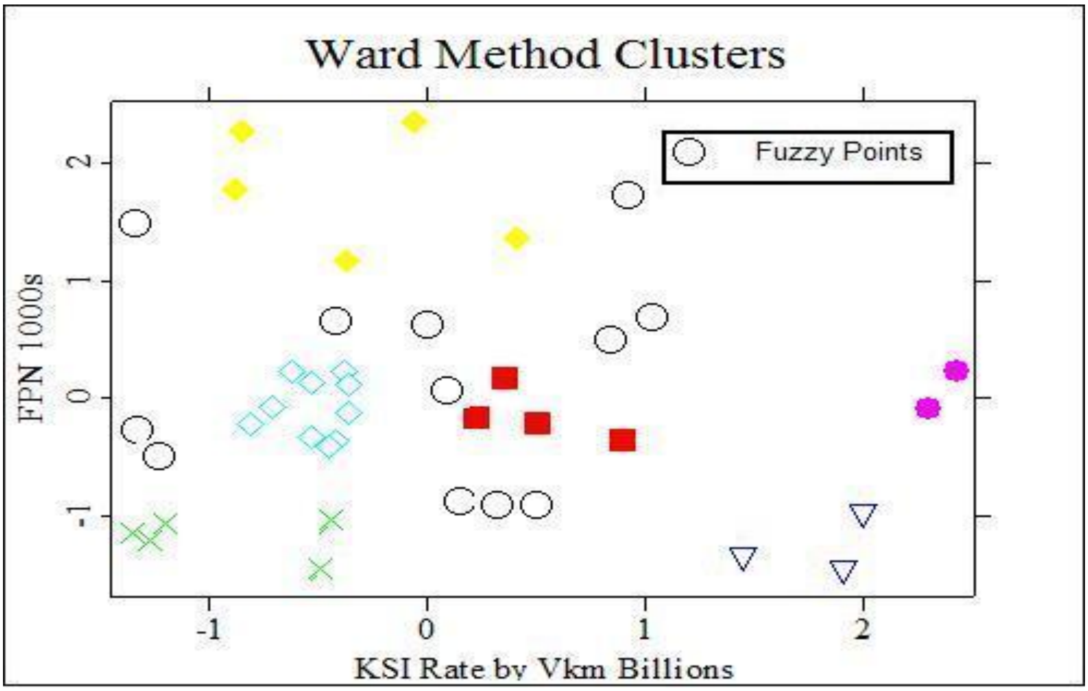


Figure 5.4.1: **Fuzzy C-means Clusters for KSI Rate by Population and FPN_1000's.**

A comparison of Figures 5.4.1 and 5.2.1 reveals that there are four fuzzy points of interest generated by the FCM method and these have been used to develop one new cluster and one adjusted cluster – circled in Figure 5.4.1. Although there is a slight change in the development of clusters obtained by the FCM method it would appear that little actual difference has been made to the overall outcome. Further evidence of this is provided by the output from an ANOVA of the new cluster configuration where there are no significant differences of any consequence between the FCM method and hierarchical clustering. In short there was no improvement on the original clustering.

The FCM method was also run on the KSI Rate by Vkm and this generated a number of fuzzy points, as shown in Figure 5.4.2.



Legend	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6

Figure 5.4.2: Fuzzy C-means Clusters for KSI Rate by Vkm and FPN_1000's.

There is no obvious way to improve the cluster groupings, compared to Figure 5.3.1, with the random scattering of fuzzy points reflecting the loose clustering of the original cluster set. Also Cluster 1 has now disappeared with two PFA's now allocated to Cluster2 and the remaining three classified as fuzzy. An ANOVA run on this set of data was also inconclusive and offered no improvement on the original.

Overall the attempt to define natural groupings of PFA's could be classed as successful only when using KSI Rate by Population and FPN_1000's as the main clustering variables. Six distinct clusters were generated, see Figure 5.2.1, and there is a general trend indicating an association between increased levels of police enforcement and lower KSI rates. This is in direct agreement with the results from chapter four and can be considered as further evidence that increasing the level of police enforcement, measured here by the proxy variables, is directly related to lower levels of KSI accident rates.

The main difficulty with this analysis is related to the aggregation of data. The original PFA data is aggregated up, from local authority level, in order to match the police enforcement data which, in its original form, is produced at PFA level. Inevitably there is a loss of information due to the upward aggregation and this is further compounded by the process of cluster analysis. Two possible solutions are either to have all data at the base level of aggregation, in this case local authority level, or use methods of analysis which may be able to better interpret the differing levels of information between successive levels of aggregation. One method suited to this is Multilevel Modelling and this will be used to model the data in chapter six.

6. Multilevel Modelling

6.1 Introduction to Multilevel Modelling

Multilevel models have generally been used in the fields of behavioural, social, and health sciences to analyse data with a hierarchical structure e.g. pupils within classes within schools would represent a three-level hierarchical or multilevel model (see Kreft and De Leeuw, 1998, Langford et al., 1998, Hox, 2002 and Goldstein, 2003). The application of multilevel modelling to road accident data is becoming more widespread but the literature related to this is still somewhat sparse. It may be that researchers are not aware of this technique (Kim et al., 2007) or it could be that the hierarchical nature of road accident data is commonly ignored by researchers (Jones and Jorgensen, 2003). The paper by Jones and Jorgensen seems to be the earliest application of multilevel modelling to road accident data and provides an in depth analysis and discussion on the use of this technique in relation to accident data and, in particular, the effects of crash severity. This was also the topic investigated by Lenguerrand et al. (2006). They found that multilevel modelling performed better than Generalised Estimating Equation modelling or logistic modelling, both of which tended to underestimate parameter values.

The main advantages of multilevel models are that, unlike traditional regression methods, they provide a more reliable set of results when applied to data which has a hierarchical structure, thereby allowing better understanding of where explanatory variables actually exert influence.

Multilevel models will be developed for both annual and quarterly data, For quarterly data there are two lag periods equal to one and two quarters. Each quarter represents a period of three months, therefore a lag of one quarter is equal to three months and a two quarter lag is equal to six months.

6.2 Multilevel Modelling of Accident Data

Having decided that multilevel models would provide the greatest insight, due to the hierarchical nature of the data under analysis, models were developed using *MLwiN 2.1* software (Rasbash et al., 2009). The models were initially based on the dataset developed in Chapter 5, Cluster Analysis, of this thesis. This dataset provided a hierarchical structure consisting of forty-one Police Force Areas (PFA's) in six derived clusters. Further models were developed also consisting of forty-one PFA's but grouped within nine distinct regional clusters. Both models analysed the effect of all Fixed Penalty Notices (FPN_1000's) and only speeding related Fixed Penalty Notices (FPN_G16_1000's) on the Killed and Seriously Injured (KSI) accident rate, the dependent variable in all models.

In developing the models one must be aware of distributional concerns. As the data under analysis are aggregated counts the preferred method of analysis is Poisson regression or Negative Binomial regression, as detailed in Chapter 4, Section 4.1. In this case there is significant overdispersion present in the Poisson models, therefore Negative Binomial models are used in order to account for the overdispersion.

6.2.1 Multilevel Models using FPN's

Two sets of clusters were used to develop two-level multilevel models, with PFA's as the level one variable and the derived clusters as the level two variable. In this section multilevel models based on derived clusters are presented. Two variables are used to construct multilevel models, ZFPN_1000's and ZFPN_G16_1000s, which represent standardised values of FPN_1000's and FPN_G16_1000's. In Table 6.2.1.1 the results of model development are shown – a null model, a variance components model and a third model, giving the effects of ZFPN_1000's on the KSI rate.

In the variance components model, Table 6.2.1.1, there is a statistically significant random variation, at the 5% level, between the derived clusters as well as a statistically significant fixed effect. The significance, for fixed effects, is derived by dividing the parameter estimate by its standard error. If the ratio is greater than 1.96 then the result is statistically significant. Significance tests for random effects, variances, follow the same calculation but the resulting p-value should be divided by two (see Snijders and Bosker, 1999). This does not apply to covariance which is simply the ratio of covariance estimate divided by the standard error estimate.

Table 6.2.1.1: Multilevel Negative Binomial Models of Effect of ZFPN_1000's on Derived Clusters

Models based on Derived Clusters	Null Model	S.E.	p-value	Variance Components Model	S.E.	p-value	NB Model	S.E.	p-value
Response Variable	**KSI**			**KSI**			**KSI**		
Fixed Effect									
Constant	-0.523	0.040	0.000	-0.588	0.079	0.000	-0.607	0.060	0.000
ZFPN_1000's							-0.345	0.057	0.000
Random Effect									
Level: CLUSTERS									
Constant				0.328	0.070	0.000	0.135	0.046	0.002
ZFPN_1000s							0.034	0.034	0.157
Covariance							-0.028	0.024	0.095

The third and final model, in Table 6.2.1.1, details the results when the effects of FPN's are added. From previous analysis it was expected that ZFPN_1000's would be associated with a decrease in the KSI rate and here it can be seen that this is indeed the case with a significant fixed effect associated with ZFPN_1000's. Here, as with the variance components model, there is significant random variation between clusters. The marked variation between clusters is expected as the clusters were developed in order to produce groups of Police Force Areas (PFA's) that have maximum variation between clusters and minimum variation within clusters. There is, however, no significant random variation, at the 5% level, between clusters associated with the effect of ZFPN_1000s.

The variation in the fixed effect of enforcement on different clusters is detailed in Figure 6.2.1.1. In general terms Figure 6.2.1.1 maps the variation between and within clusters. Each line represents the fixed effect of the enforcement variable, ZFPN, on the log of KSI rates for each individual cluster of PFA's and the position of each line, compared to all others, is a measure of the variation between clusters. The slope and gradient of each line is a measure of the variation, between PFA's, within each cluster. With the exception of Cluster 4 none of the other clusters has any significant effects at the 5% level, related to enforcement – see Table 6.2.1.2.

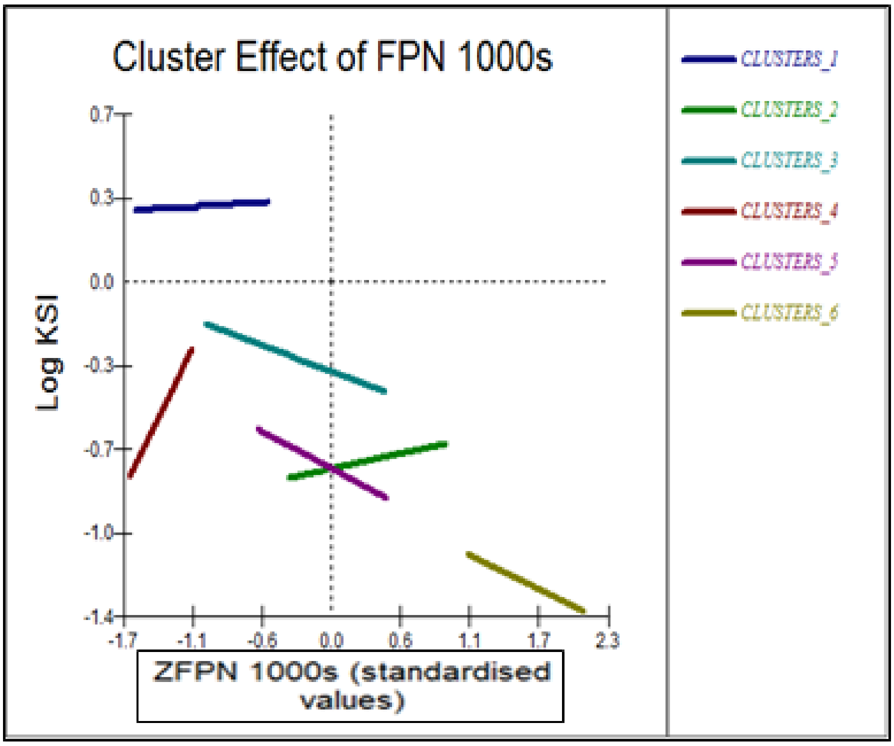


Figure 6.2.1.1: Effect of Enforcement – ZFPN_1000's – on Derived Clusters

This is not surprising as the clusters were developed using KSI rates and ZFPN_1000s and the lack of a statistically significant variation between clusters, in relation to ZFPN_1000s, indicates that the clusters are well defined and following the general trend identified in Chapter 4 – where increasing levels of police enforcement are linked to decreasing KSI rates. In Cluster 4 there is a statistically significant effect in relation to the effect of enforcement – ZFPN_1000's. This effect goes against the general trend of increased enforcement leading to decreasing KSI rates and is most probably an artefact of the clustering algorithm, see Figure 5.2.1 in Chapter 5, where a group of six PFA's has been clustered together. If Cluster 4 is grouped with Cluster 5 then this effect, which is counter-intuitive in light of all other evidence, disappears. Alternatively, as ZFPN's are at low levels, in Cluster 4, it may be that increasing ZFPN may be in response to increasing KSI accidents. This is an area requiring further investigation, which is beyond the scope of this thesis.

Table 6.2.1.2: Parameter Estimates and p-values for Fixed Effects of ZFPN_1000's on Derived Clusters

Models based on Derived Clusters	Fixed Effect Parameter Estimate	Standard Error	Parameter Estimate / Standard Error	p-value
Cluster 4 with ZFPN_1000's Effect	1.528	0.576	2.653	0.004
Cluster 6 with ZFPN_1000's Effect	-0.519	0.366	-1.418	0.080
Cluster 3 with ZFPN_1000's Effect	-0.297	0.281	-1.057	0.150
Cluster 2 with ZFPN_1000's Effect	0.078	0.181	0.431	0.334
Cluster 5 with ZFPN_1000's Effect	-0.094	0.404	-0.233	0.408
Cluster 1 with ZFPN_1000's Effect	0.034	0.362	0.094	0.462

6.2.2 Multilevel Models using ZFPN_G16_1000's

The methodology used, to develop the multilevel models in this section, is identical to that used in Section 6.2.1.1. Here the enforcement variable is ZFPN_G16_1000's, speeding related fixed penalty notices.

Table 6.2.2.1: Multilevel Negative Binomial Models of Effect of ZFPN_G16_1000's on Derived Clusters

Models based on Derived Clusters	Null Model	S.E.	p-value	Variance Components Model	S.E.	p-value	NB Model	S.E.	p-value
Response Variable	KSI			KSI			KSI		
Fixed Effect									
Constant	-0.713	0.04	0.000	-0.567	0.077	0.000	-0.591	0.067	0.000
ZFPN_1000's							-0.207	0.065	0.001
Random Effect									
Level: CLUSTERS									
Constant				0.297	0.066	0.000	0.187	0.056	0.001
ZFPN_G16_1000s							0.029	0.036	0.079
Covariance							-0.025	0.026	0.095

Once more three models are developed, see Table 6.2.2.1; a null model, a variance components model and a third model, looking at the effects of ZFPN_G16_1000's on the KSI rate. From the results of the variance components model one can see a statistically significant random variation, at the 5% level, between clusters in relation to KSI rates. When the effect of enforcement is added, ZFPN_G16_1000's, a significant fixed effect is found indicating an increase in the number of ZFPN_G16_1000's leads to a decrease in the KSI rates. No significant random variation, at the 5% level, between clusters is found relating to the effect of ZFPN_1000s.

Two clusters have a statistically significant fixed effect related to ZFPN_G16_1000's; Clusters 4 and 5 – see Table 6.2.2.2. There is significant variation between clusters and this is shown in Figure 6.2.2.1.

Table 6.2.2.2: Parameter Estimates and p-values for Fixed Effects of ZFPN_G16_1000's on Derived Clusters

Models based on Derived Clusters	Fixed Effect Parameter Estimate	S.E.	Parameter Estimate / Standard Error	p-value
Cluster 4 with ZFPN_G16_1000's Effect	0.952	0.421	2.261	0.012
Cluster 5 with ZFPN_G16_1000's Effect	0.379	0.214	1.771	0.038
Cluster 6 with ZFPN_G16_1000's Effect	-0.189	0.151	-1.252	0.106
Cluster 3 with ZFPN_G16_1000's Effect	-0.119	0.179	-0.665	0.253
Cluster 2 with ZFPN_G16_1000's Effect	0.083	0.133	0.624	0.266
Cluster 1 with ZFPN_G16_1000's Effect	0.018	0.234	0.077	0.469

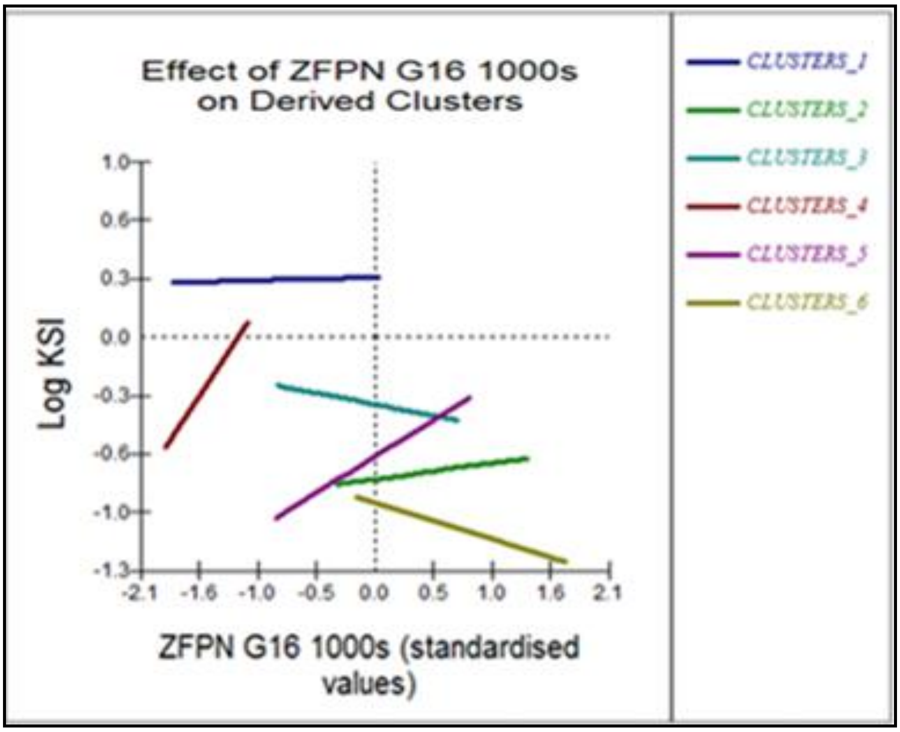


Figure 6.2.2.1: Effect of Enforcement – ZFPN_G16_1000's – on Derived Clusters

6.3 Multilevel Models based on Regional Clusters.

Having analysed the effect of police enforcement on the derived clusters and having gained further insight into the variation that exists, a new set of clusters were developed. Clusters based on regional groupings were produced and these are listed in Table 6.3.1. The development of the two-level multilevel models for the regional clusters follows the same procedure used for the derived clusters, with PFA's as the level one variable and regional clusters as the level two variable. Models are produced, separately, for ZFPN_1000's and ZFPN_G16_1000's.

Table 6.3.1: Regional Cluster Membership

REGIONAL CLUSTER	PFA	REGIONAL CLUSTER	PFA
East Anglia	Cambridgeshire	South East	Thames Valley
East Anglia	Norfolk	South East	Hampshire
East Anglia	Suffolk	South East	Surrey
East Anglia	Bedfordshire	South East	Kent
East Anglia	Hertfordshire	South East	Sussex
East Anglia	Essex	South West	Devon and Cornwall
East Midlands	Derbyshire	South West	Avon and Somerset
East Midlands	Nottinghamshire	South West	Gloucestershire
East Midlands	Lincolnshire	South West	Wiltshire
East Midlands	Leicestershire	South West	Dorset
East Midlands	Northamptonshire	Wales	North Wales
North East	Northumbria	Wales	Gwent
North East	Durham	Wales	South Wales
North East	Cleveland	Wales	Dyfed-Powys
North West	Cumbria	West Midlands	West Midlands
North West	Lancashire	West Midlands	Staffordshire
North West	Merseyside	West Midlands	West Mercia
North West	Greater Manchester	West Midlands	Warwickshire
North West	Cheshire	Yorkshire	North Yorkshire
		Yorkshire	West Yorkshire
		Yorkshire	South Yorkshire
		Yorkshire	Humberside

6.3.1 Multilevel Models using ZFPN_1000's on Regional Clusters

In Table 6.3.1.1 the results of multilevel model development, looking at the effect of ZFPN_1000's are detailed. As with models used to investigate the derived clusters there are three models produced - a null model, a variance components model and a third model examining the effects of ZFPN_1000's on the KSI rate. Table 6.3.1.1 highlights the results of model development.

Table 6.3.1.1: Multilevel Negative Binomial Models of Effect of ZFPN_1000's based on Regional Clusters

Models based on Regional Clusters	Null Model	S.E.	p-value	Variance Components Model	S.E.	p-value	NB Model	S.E.	p-value
Response Variable	KSI			KSI			KSI		
Fixed Effect									
Constant	-0.523	0.04	0.000	-0.483	0.099	0.000	-0.525	0.081	0.000
ZFPN_1000's							-0.306	0.071	0.000
Random Effect									
Level: CLUSTERS									
Constant				0.292	0.079	0.000	0.173	0.061	0.002
ZFPN_1000s							0.016	0.034	0.319
Covariance							-0.018	0.026	0.489

The variance components model, Table 6.3.1.1, has a statistically significant random variation between regional clusters. The NB model, Table 6.3.1.1, details the results when the effects of ZFPN_1000's are added. Here the fixed effect of ZFPN_1000's are statistically significant, showing that any increase in enforcement, as measured by ZFPN_1000's, leads to a decrease in the KSI rate. There is also evidence to support significant regional random variation between clusters but there is no significant random variation, at the 5% level, related to the effect of ZFPN_1000's.

The variation between regional clusters in relation to the effect of ZFPN_1000's, is shown in Figure 6.3.1.1. It is apparent that, for the regional clusters, there is a trend indicating lower KSI rates are associated with higher levels of ZFPN_1000's. This trend can be seen in all the regional clusters in Figure 6.3.1.1. The fixed effects of ZFPN_1000's are significant in four of the nine regional clusters, see Table 6.3.1.2, where clusters are ordered by ascending p-value. It is difficult to decipher this result as there are no consistent regional differences arising from the analysis. One possibility is that the four clusters in which a significant effect is found are more rural in make up than the others.

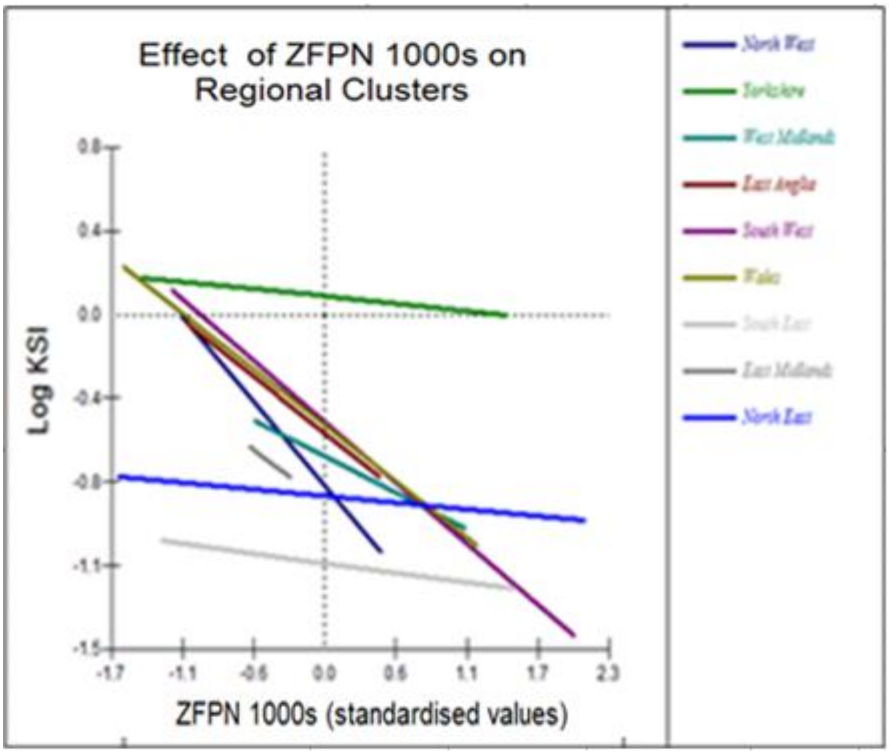


Figure 6.3.1.1: Effect of Enforcement – FPN 1000s – on Regional Clusters

Table 6.3.1.2: Parameter Estimates and p-values for Fixed Effects of ZFPN_1000's on Regional Clusters

Models based on Regional Clusters	Fixed Effect Parameter Estimate	Standard Error	Parameter Estimate / Standard Error	p-value
East Anglia with ZFPN_1000's Effect	-0.444	0.137	-3.241	0.000
South West with ZFPN_1000's Effect	-0.476	0.169	-2.817	0.003
North West with ZFPN_1000's Effect	-0.656	0.288	-2.278	0.012
Wales with ZFPN_1000's Effect	-0.436	0.200	-2.180	0.015
West Midlands with ZFPN_1000's Effect	-0.286	0.321	-0.891	0.187
East Midlands with ZFPN_1000's Effect	-0.415	0.673	-0.617	0.268
South East with ZFPN_1000's Effect	-0.075	0.182	-0.412	0.339
North East with ZFPN_1000'S Effect	-0.052	0.164	-0.317	0.375
Yorkshire with ZFPN_1000's Effect	-0.056	0.212	-0.264	0.396

6.3.2 Multilevel Models using ZFPN_G16_1000's

The methodology used here follows on from that used to develop the multilevel models in section 6.3.1 with the enforcement variable here being ZFPN_G16_1000's, speeding related fixed penalty notices.

Again three models are developed, see Table 6.3.2.1; the null model, the variance components model and a third model, looking at the effects of ZFPN_G16_1000's on the KSI rate in relation to regional clusters.
The results from the variance components model again detail significant random variation between clusters in relation to KSI rates. When ZFPN_G16_1000's are added to the model a significant fixed effect is found indicating an increase in the number of ZFPN_G16_1000's leads to a decrease in the KSI rates.

Table 6.3.2.1: Multilevel Negative Binomial Models of Effect of ZFPN_G16_1000's based on Regional Clusters

Models based on Regional Clusters	Null Model	S.E.	p-value	Variance Components Model	S.E.	p-value	NB Model	S.E.	p-value
Response Variable	KSI			KSI			KSI		
Fixed Effect									
Constant	-0.523	0.04	0.000	-0.483	0.099	0.000	-0.516	0.088	0.000
ZFPN_1000's							-0.216	0.072	0.003
Random Effect									
Level: CLUSTERS									
Constant				0.292	0.079	0.000	0.206	0.067	0.001
ZFPN G16_1000s							0.019	0.031	0.270
Covariance							-0.008	0.029	0.783

Only one of the nine clusters has any statistically significant fixed effect related to ZFPN_G16_1000's – East Anglia – see Table 6.3.2.2. There is significant regional variation between clusters and this is shown in Figure 6.3.2.1.

Table 6.3.2.2: Parameter Estimates and p-values for Fixed Effects of ZFPN_G16_1000's on Regional Clusters

Models based on Regional Clusters	Fixed Effect Parameter Estimate	Standard Error	Parameter Estimate / Standard Error	p-value
East Anglia with ZFPN_G16_1000's Effect	-0.367	0.120	-3.058	0.000
Wales with ZFPN_G16_1000's Effect	-0.470	0.300	-1.567	0.059
West Midlands with ZFPN_G16_1000's Effect	-0.963	0.663	-1.452	0.073
South West with ZFPN_G16_1000's Effect	-0.284	0.199	-1.427	0.079
North West with ZFPN_G16_1000's Effect	-0.475	0.345	-1.377	0.084
North East with ZFPN_G16_1000's Effect	0.101	0.209	0.483	0.315
South East with ZFPN_G16_1000'S Effect	-0.034	0.160	-0.213	0.417
East Midlands with ZFPN_G16_1000'S Effect	0.044	0.249	0.177	0.429
Yorkshire with ZFPN_G16_1000's Effect	0.006	0.304	0.020	0.496

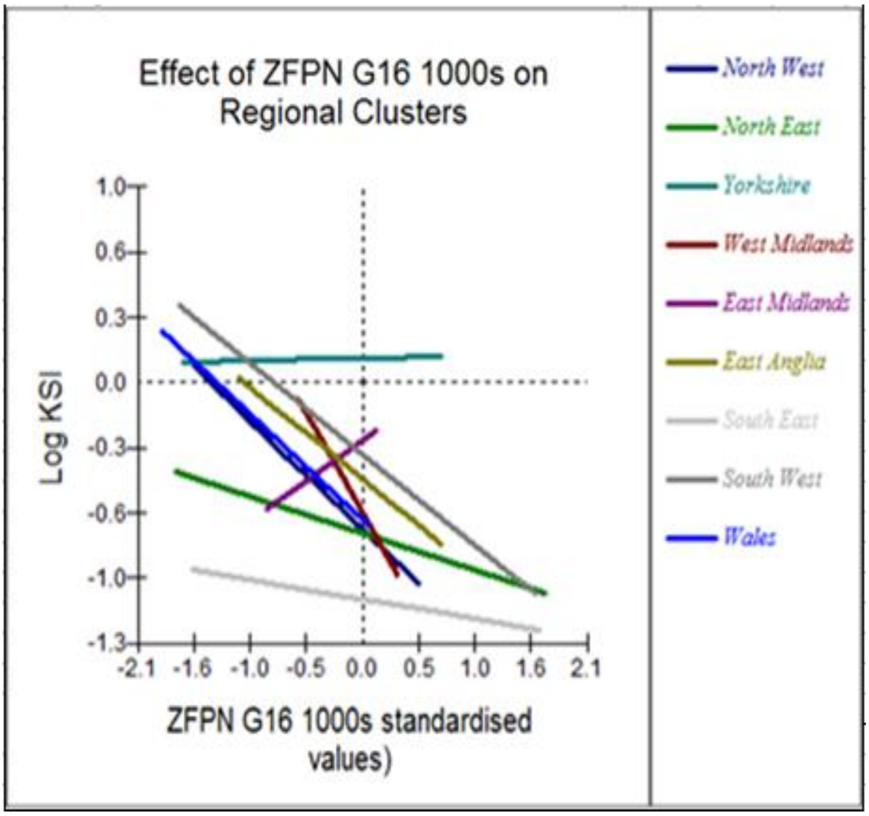


Figure 6.3.2.1: Effect of Enforcement – ZFPN G16 1000s – on Regional Clusters

6.4 Discussion of Results relating to Annual Data

In this part of the analysis the effect of police enforcement, as measured by the proxy variables ZFPN_1000's and ZFPN_G16_1000's, is examined in relation to the annual data.

The effect of the proxy variables on the derived clusters showed there were significant fixed effects for both ZFPN_1000's and ZFPN_G16_1000's. These effects suggest that an increase in the level of police enforcement leads to a decrease in the overall KSI rate. However, no significant random variation, at the 5% level, between clusters, relating to the effect of enforcement, was found. As the derived clusters were based on the KSI rate and enforcement proxies, this result is not unexpected if the clusters are well defined. In light of this result it would be fair to say that the derived clusters are well defined in relation to the enforcement variables, hence the lack of variation between clusters in this respect. The variation relating to the fixed effects of enforcement on the derived clusters is shown in Figure 6.2.1.1, where the intercepts represent the constant term and the slopes represent the effect of police enforcement – ZFPN_1000's. The picture presented is slightly misleading as there are three clusters showing enforcement linked to an increase in the KSI rate. This is an artefact of the cluster grouping and this is highlighted in Figures 6.4.1 and 6.4.2.

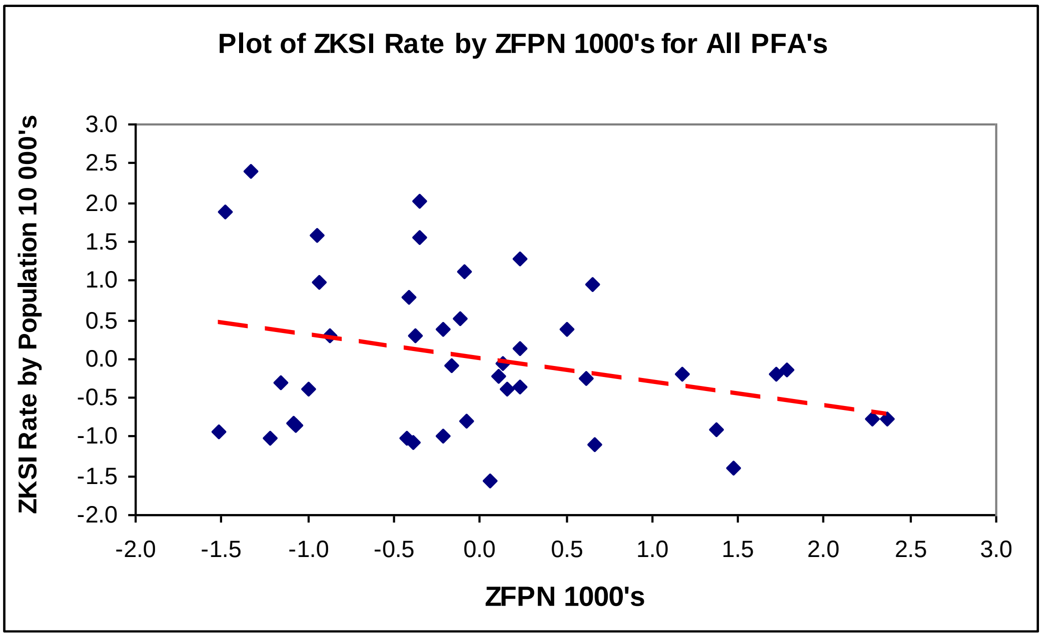


Figure 6.4.1: ZKSI Rate by ZFPN_1000's for All PFA's

Figure 6.4.1 highlights the general trend across all PFA's. It is clear that the trend indicates that an increase in FPN's leads to a decrease in the KSI rate. Figure 6.4.2 displays the same data with the cluster groupings shown. If this is compared with Figure 6.2.1.1, where clusters 1, 2 and 4 suggest that enforcement is linked to an increase in the KSI rate. Only in cluster 4 is this effect found to be statistically significant – see Table 6.2.1.2. It seems that even though three of the derived six clusters suggest increasing KSI rates are linked to increased enforcement, the overall trend indicates that increased enforcement leads to a fall in KSI rates.

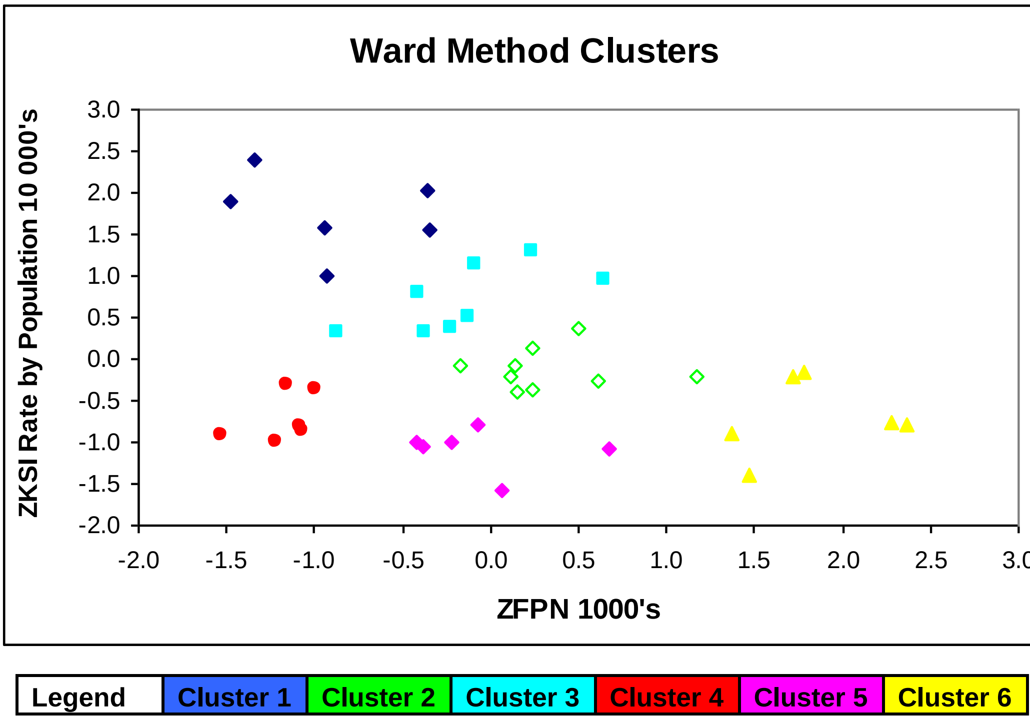


Figure 6.4.2: Ward Method Clusters ZKSI Rate and ZFPN 1000's

The results for ZFPN_G16_1000's, when the variation between clusters is examined with respect to police enforcement, are very similar to those found for ZFPN_1000's. Clusters 4 and 5 are the only clusters to have a statistically significant effect, see Figure 6.2.2.2. It should be noted that the fixed effect of enforcement for ZFPN_G16_1000's is smaller that the effect associated with ZFPN_1000's. This is expected as ZFPN_G16_1000's are a subset of ZFPN_1000's.

The effects associated with the regional clusters are similar to the effects found for the derived clusters. The same proxy variables are used here, ZFPN_1000's and ZFPN_G16_1000's, to construct the models. Again both proxy variables have a significant fixed effect on the KSI rate which is indicative of increased enforcement leading to lower KSI rates. In both models a significant regional variation between clusters is found, but no significant variation, at the 5% level, between clusters in relation to the enforcement variables.

The regional variation in the effect of enforcement for regional clusters is shown in Figure 6.3.1.1 and 6.3.2.1 for ZFPN_1000's and ZFPN_G16_1000's respectively. For ZFPN_1000's, Figure 6.3.1.1, the trend in all regional clusters indicates that increased enforcement leads to lower KSI rates, with four of the nine regional clusters being statistically significant in this respect, Table 6.3.1.1. Further investigation of the make up of the regional clusters found no easily explainable or consistent differences, or similarities, to account for this. One possible explanation may be that the four statistically significant clusters contained a higher proportion of rural areas than other clusters.

With regard to the regional variation associated with the fixed effect of ZFPN_G16_1000's seven of the nine regional clusters follow the trend associated with ZFPN_1000's while the remaining two clusters have an opposite effect. Only one regional cluster, however, is statistically significant with respect to enforcement. Again it may be related to the higher proportion of rural areas within this cluster or, in this case, the higher average percentage of ZFPN_G16_1000's issued in this cluster than in others.

In general the results indicate that higher levels of police enforcement are effective in reducing the level of KSI rates. No significant random variation, at the 5% level, was found between clusters, derived or regional, relating to the effect of enforcement for either proxy variable. However, there was significant variation found between clusters in relation to KSI rates.

6.5 Multilevel Modelling of Quarterly Data

Multilevel modelling of the quarterly data generally follows the same procedure used when modeling the annual data. Models are produced for both derived cluster data and regional cluster data over two separate quarters, Quarter 3 and Quarter 4, from the year 2003. This is the most recent data available in a quarterly format.

As with the annual data the derived clusters are modelled first, beginning with Quarter 3. For each quarter models are produced for FPN_1000's and

FPN_G16_1000's. Models are also produced for FPN_1000's and FPN_G16_1000's, lagged by one and two quarters, three and six months, in order to investigate any effect relating to time lags of police enforcement. The response variable for all models is KSI road traffic accidents.

6.5.1 Quarter 3 Multilevel Models using ZFPN_1000's

The results of model development, a null model, a variance components model and a Negative Binomial model, are shown in Table 6.5.1.1.

Table 6.5.1.1: Multilevel Negative Binomial Models of Effect of ZFPN_1000's on Derived Clusters in Quarter 3

Models Based on Derived Clusters	Null Model	Standard Error	p-value	Variance Components Model	Standard Error	p-value	NB Model ZFPN	Standard Error	p-value
Response	KSI			KSI			KSI		
Fixed Part									
Constant	-1.830	0.040	0.000	-1.808	0.088	0.000	-1.880	0.076	0.000
Zfpn_1000s							-0.231	0.075	0.000
Random Effect									
Level: CLUSTERS									
Constant				0.262	0.068	0.000	0.152	0.055	0.000
Zfpn_1000s							0.041	0.039	0.147
Covariance							-0.029	0.029	0.076

From Table 6.5.1.1, it can be seen, across all models, that there is a significant variation between clusters in relation to both fixed and random effects. This is to be expected as the clusters were developed in order to produce maximum variation between clusters. There is a significant fixed effect associated with ZFPN_1000's but this is not repeated in the random effects. The variation in the fixed effect of ZFPN_1000's on different clusters, for Quarter 3, is shown in Figure 6.5.1.1. Only Cluster 3 has any significant effect related to enforcement, in the form of ZFPN_1000's – see Table 6.5.1.2.

Table 6.5.1.2: Parameter Estimates and p-values for Fixed Effects of ZFPN_1000's on Derived Clusters in Quarter 3

Models based on Derived Clusters	Fixed Effect Parameter Estimate	Standard Error	Parameter Estimate / Standard Error	p-value
Cluster 3 with ZFPN_1000's Effect	-0.276	0.137	-2.015	0.022
Cluster 2 with ZFPN_1000's Effect	-0.085	0.103	-0.825	0.205
Cluster 4 with ZFPN_1000's Effect	0.765	1.186	0.645	0.260
Cluster 5 with ZFPN_1000's Effect	0.116	0.127	0.913	0.274
Cluster 6 with ZFPN_1000's Effect	-0.259	0.534	-0.485	0.314
Cluster 1 with ZFPN_1000's Effect	-0.078	0.478	-0.163	0.435

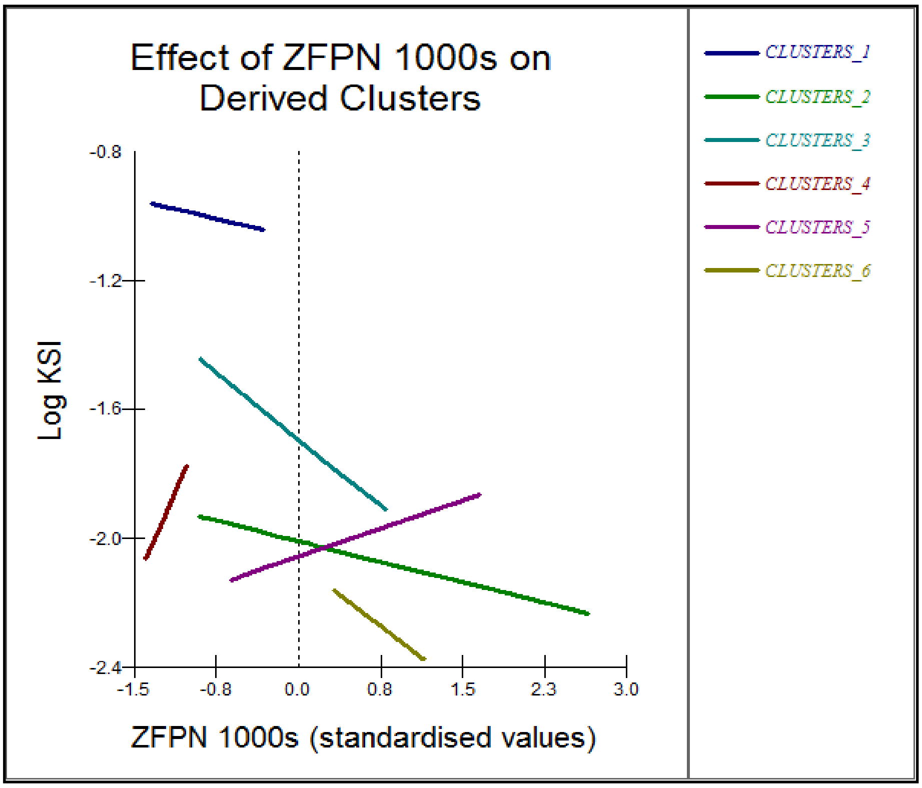


Figure 6.5.1.1: Effect of Enforcement, ZFPN_1000's, on Derived Clusters in Quarter 3

6.5.2. Quarter 3 Multilevel Models using ZLag1FPN_1000's and ZLag1_FPN_1000's

Lagged multilevel models are developed using identical procedures to the model produced in Section 6.5.1. Here the proxies for enforcement are ZLag1_FPN_1000's and ZLag2_FPN_1000's, which are equivalent to ZFPN_1000's lagged by one and two quarters respectively. The results of model development, for both lagged variables, are shown in Table 6.5.2.1. The null model is omitted as it is identical to that shown in Table 6.5.1.1.

Table 6.5.2.1: Multilevel Negative Binomial Models of Effect of ZLag1_FPN_1000's and ZLag2_FPN_1000's on Derived Clusters in Quarter 3

Models Based on Derived Clusters	Variance Components Model	Standard Error	p-value	NB Model ZLag1 FPN	Standard Error	p-value	NB Model ZLag2 FPN	Standard Error	p-value
Response	KSI			KSI			KSI		
Fixed Effect									
Constant	-1.808	0.088	0.000	-1.878	0.074	0.000	-1.866	0.079	0.000
Zlag1_fpn_1000s				-0.261	0.075	0.000			
Zlag2_fpn_1000s							-0.312	0.092	0.000
Random Effect									
Level: CLUSTERS									
Constant	0.262	0.068	0.000	0.141	0.053	0.002	0.125	0.063	0.012
Zlag1_fpn_1000s				0.049	0.043	0.127			
Covariance Lag1				-0.044	0.029	0.065			
Zlag2_fpn_1000s							0.100	0.077	0.044
Covariance Lag2							-0.062	0.040	0.620

It is apparent, from looking at Table 6.5.2.1, that, for fixed effects, there are significant effects to be found for all variables, with both lagged variables having a significant effect on the KSI rate. However, for random effects only ZLag2_FPN_1000's has a significant effect.

The variation in the fixed effect of the lagged proxy variables on each cluster is shown in Figures 6.5.2.1 and 6.5.2.2. For ZLag1_FPN_1000's a significant effect is found in both Clusters 3 and 4, see Table 6.5.2.2, with Cluster 6 significant at the 10% level. The effect in Cluster 3 is associated with a decrease in the KSI rate and this follows the general trend that has been found throughout this report. The effect found in Cluster 4 is similar to that found with the annual data, see Figure 6.2.1.1 and is explained in the paragraph following Figure 6.2.1.1. In relation to ZLag2_FPN_1000's only Cluster 3 has any significant fixed effect, see Table 6.5.2.3.

Table 6.5.2.2: Parameter Estimates and p-values for Fixed Effects of ZLag1_FPN_1000's on Derived Clusters in Quarter 3

Models based on Derived Clusters	Fixed Effect Parameter Estimate	Standard Error	Parameter Estimate / Standard Error	p-value
Cluster 3 with ZLag1_FPN_1000's Effect	-0.428	0.184	-2.326	0.010
Cluster 4 with ZLag1_FPN_1000's Effect	2.139	1.279	1.672	0.047
Cluster 6 with ZLag1_FPN_1000's Effect	-0.556	0.407	-1.366	0.086
Cluster 5 with ZLag1_FPN_1000's Effect	-0.133	0.566	-0.235	0.407
Cluster 2 with ZLag1_FPN_1000's Effect	-0.007	0.082	-0.085	0.466
Cluster 1 with ZLag1_FPN_1000's Effect	0.019	0.331	0.057	0.477

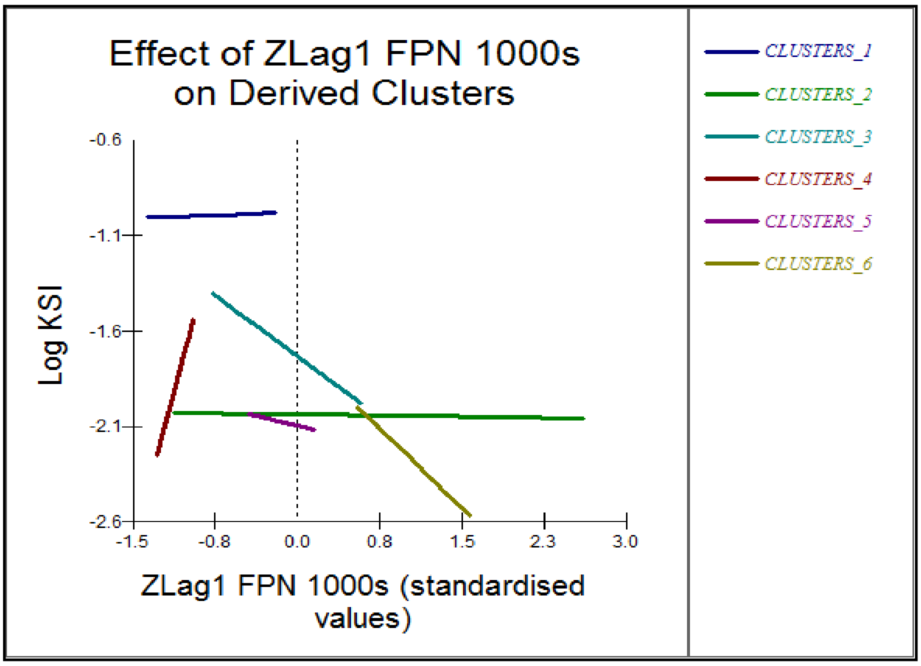


Figure 6.5.2.1: Effect of Enforcement, ZLag2_FPN_1000's, on Derived Clusters in Quarter 3

Table 6.5.2.3: Parameter Estimates and p-values for Fixed Effects of ZLag2_FPN_1000's on Derived Clusters in Quarter 3

Models based on Derived Clusters	Fixed Effect Parameter Estimate	Standard Error	Parameter Estimate / Standard Error	p-value
Cluster 3 with ZLag2_FPN_1000's Effect	-0.552	0.236	-2.339	0.001
Cluster 4 with ZLag2_FPN_1000's Effect	2.030	1.280	1.586	0.056
Cluster 6 with ZLag2_FPN_1000's Effect	-0.592	0.373	-1.587	0.056
Cluster 2 with ZLag2_FPN_1000's Effect	-0.053	0.098	-0.541	0.294
Cluster 5 with ZLag2_FPN_1000's Effect	-0.222	0.454	-0.489	0.312
Cluster 1 with ZLag2_FPN_1000's Effect	-0.040	0.411	-0.097	0.461

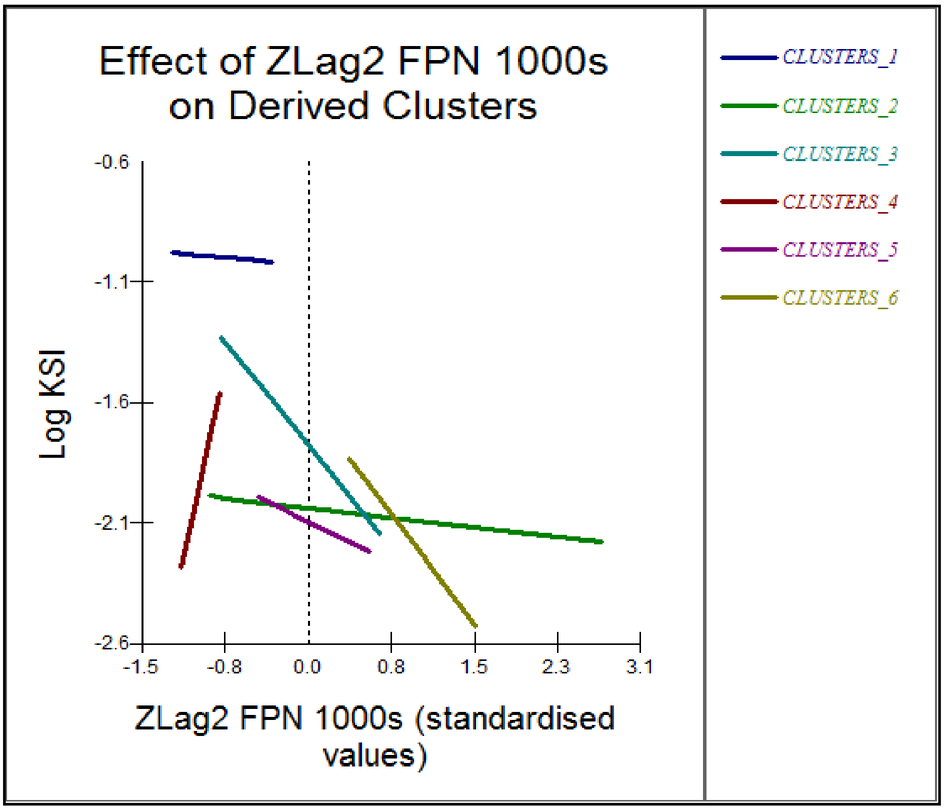


Figure 6.5.2.2: Effect of Enforcement, ZLag2_FPN_1000's, on Derived Clusters in Quarter 3

6.5.3 Quarter 3 Multilevel Models using ZFPN_G16_1000's

The methodology used, to develop multilevel models in this section, is identical to that used previously. The proxy for enforcement used here is ZFPN_G16_1000's, speeding related fixed penalty notices. Again three models are produced - see Table 1, Appendix 6a. In the variance components model significant variation is found between clusters in relation to KSI rates. The variation in the fixed effects between clusters can be seen in Figure 1, Appendix 6b. When the effect of enforcement is added, ZFPN_G16_1000's in the NB model, a significant fixed effect is found where an increase in the number of ZFPN_G16_1000's leads to a decrease in the KSI rates. There is however no significant variation, at the 5% level, between clusters in relation to ZFPN_G16_1000's. The parameter estimates for the fixed effects of ZFPN_G16_1000's are shown in Table 1, Appendix 6c, where only Cluster 3 has any significant effect related to enforcement, in the form of ZFPN_G16_1000's.

6.5.3.1 Quarter 3 Multilevel Models using ZLag1_FPN_G16_1000's and ZLag2_FPN_G16_1000's

Table 2, Appendix 6a, details the results from modelling with the lagged proxy variables, ZLag1_FPN_G16_1000's and ZLag2_FPN_G16_1000's. The results from the variance components model are identical, as it is the same model, and there are similar results for the fixed effect part of both models where both lagged variables have a significant effect linked to a decrease in KSI rates. For random effects neither lagged variable has any significant effect at the 5% level, although the two quarter lagged proxy, ZLag2_FPN_G16_1000's, is approaching significance. Once again there is significant variation between clusters, as defined by the Constant in each model, in both the fixed and random part of the models. This is expected as the clusters were developed in order to produce maximum variation between clusters and minimum variation within clusters in relation to KSI rates. The variation between clusters in relation to fixed effects is shown in Figures 2 and

3, Appendix 6b, with the parameter estimates shown in Tables 2 and 3, Appendix 6c. Once again it is Cluster 3 which has significant effects in relation to the enforcement variables.

6.5.4 Quarter 4 Multilevel Models using ZFPN_1000's

The results of model development for Quarter 4 data follow the methods used previously and are shown in Table 6.5.4.1. As before a null model, a variance components model and a Negative Binomial model are produced.

Table 6.5.4.1: Multilevel Negative Binomial Models of Effect of ZFPN_1000's on Derived Clusters in Quarter 4

Models Based on Derived Clusters	Null Model	Standard Error	p-value	Variance Components Model	Standard Error	p-value	NB Model ZFPN	Standard Error	p-value
Response	KSI			KSI			KSI		
Fixed Effect									
Constant	-1.866	0.040	0.000	-1.850	0.089	0.000	-1.907	0.077	0.000
ZFPN_1000s							0.255	0.070	0.011
Random Effect									
Level: CLUSTERS									
Constant				0.270	0.070	0.000	0.172	0.057	0.000
ZFPN_1000s							0.025	0.033	0.110
Covariance							0.037	0.028	0.093

In Table 6.5.4.1, it can be seen, across all models, that there is significant variation between clusters in relation to both fixed and random effects. There is also a significant fixed effect associated with ZFPN_1000's in the NB model but no significant effect, at the 5% level, in the random part of the model. Only Cluster 3 has any significant effect related to enforcement, at the 5% level, with Cluster 6 significant at the 10% level, shown in Table 6.5.4.2. Variation in the fixed effect of ZFPN_1000's, for Quarter 4, is shown in Figure 6.5.4.1.

Table 6.5.4.2: Parameter Estimates and p-values for Fixed Effects of ZFPN_1000's on Derived Clusters in Quarter 4

Models based on Derived Clusters	Fixed Effect Parameter Estimate	Standard Error	Parameter Estimate / Standard Error	p-value
Cluster 3 with ZFPN_1000's Effect	-0.418	0.190	-2.200	0.014
Cluster 6 with ZFPN_1000's Effect	-0.767	0.477	-1.608	0.054
Cluster 4 with ZFPN_1000's Effect	1.682	1.155	1.456	0.073
Cluster 5 with ZFPN_1000's Effect	-0.085	0.138	-0.616	0.269
Cluster 2 with ZFPN_1000's Effect	-0.080	0.134	-0.597	0.275
Cluster 1 with ZFPN_1000's Effect	-0.109	0.431	-0.253	0.400

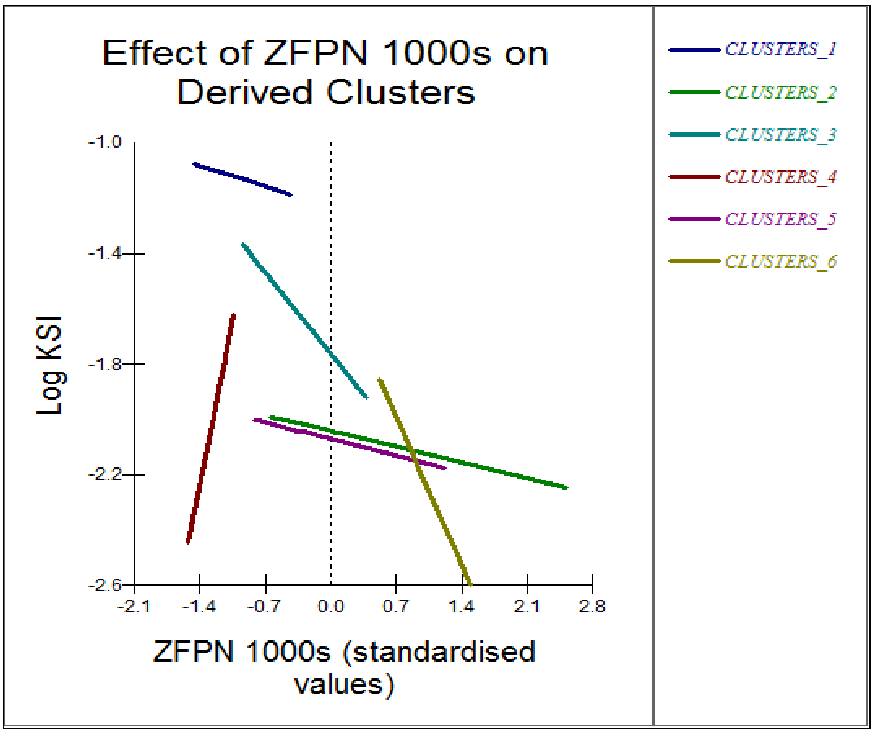


Figure 6.5.4.1: Effect of Enforcement, ZFPN _1000's, on Derived Clusters in Quarter 4

6.5.4.1 Quarter 4 Multilevel Models using ZLag1FPN_1000's and ZLag1_FPN_1000's

Lagged multilevel models were developed for Quarter 4 data with the proxies for enforcement ZLag1_FPN_1000's and ZLag2_FPN_1000's. The results of model development, for both lagged variables, are shown in Table 3, Appendix 6a.

In Table 3, Appendix 6a, for fixed effects, there are significant effects to be found for both lagged variables in relation to the KSI rate. However, for random effects neither proxy variable has any significant effect, at the 5% level. There is also significant variation between clusters in relation to both fixed and random effects.

The variation between clusters relating to the fixed effect of the lagged proxy variables is shown in Figures 4 and 5, Appendix 6b. For ZLag1_FPN_1000's only Cluster 3 has any significant effect, see Table 4, Appendix 6c. The effect in Cluster 3 is associated with a decrease in the KSI rate. With ZLag2_FPN_1000's Clusters 3, 4 and 6 all have a significant effect on the KSI rate, see Table 5, Appendix 6c. The effect in Clusters 3 and 6 is associated with a decrease in the KSI rate while the effect in Cluster 4 is associated with an increase in the KSI rate.

6.5.5 Quarter 4 Multilevel Models using ZFPN_G16_1000's

The proxy for enforcement used in this section is ZFPN_G16_1000's. Once more three models are produced and the results can be seen in Table 4, Appendix 6a. In the variance components model there is a significant variation between clusters in relation to KSI rates. This variation in the fixed effects between clusters can be seen in Figure 6, Appendix 6b. When the effect of enforcement is taken into account in the NB model, Table 4, Appendix 6a, there is a significant fixed effect relating an increase in the number of ZFPN_G16_1000's to a decrease in the KSI rates. There is however no significant random variation, at the 5% level, between clusters in relation to

ZFPN_G16_1000's. The parameter estimates for the fixed effects of ZFPN_G16_1000's are shown in Table 6, Appendix 6c, where Clusters 3 and 6 both have a significant effect related to enforcement, in the form of ZFPN_G16_1000's.

6.5.5.1 Quarter 4 Multilevel Models using ZLag1_FPN_G16_1000's and ZLag2_FPN_G16_1000's

Results from modelling with the lagged proxy variables are shown in Table 5, Appendix 6a, where for fixed and random effects significant variation between clusters is found. This variation is shown in Figures 7 and 8, Appendix 6b. Both lagged variables have a significant effect linked to a decrease in KSI rates. There are also significant random effects associated with both ZLag1_FPN_G16_1000's and ZLag2_FPN_G16_1000's, see Table 5, Appendix 6a, with the proxy lagged by one quarter having a slightly stronger effect.

Parameter estimates for the effect of ZLag1_FPN_G16_1000's and ZLag2_FPN_G16_1000's on individual clusters are given in Tables 7 and 8, Appendix 6c. This time, as with the same models using the Quarter 3 data, it is only Cluster 3 which has a significant effect related to the enforcement proxies.

6.6 Multilevel Models on Regional Clusters

Having analysed the effect of the enforcement proxy variables on the derived clusters and having gained further insight into the variation that exists, the analysis now moves on to look at the effects of enforcement on the regional clusters. Regional groupings were produced and these are listed in Table 6.3.1. The two-level multilevel models for regional clusters follow the same procedures used for the derived clusters, with PFA's as the level one variable and regional clusters, rather than derived clusters, as the level two variable.

6.6.1 Quarter 3 Multilevel Models using ZFPN_1000's on Regional Clusters

In Table 6.6.1.1 the results of multilevel model development on regional clusters are detailed. The methodology follows that used to investigate the derived clusters producing initially three models - a null model, a variance components model and a third model examining the effects of ZFPN_1000's on the KSI rate. Detailed in Table 6.6.1.1 are the results of these models.

Table 6.6.1.1: Multilevel Negative Binomial Models of Effect of ZFPN_1000's on Regional Clusters in Quarter 3

Models Based on Regional Clusters	Null Model	Standard Error	p-value	Variance Components Model	Standard Error	p-value	NB Model ZFPN	Standard Error	p-value
Response	KSI			KSI			KSI		
Fixed Effect									
Constant	-1.830	0.040	0.000	-1.813	0.114	0.000	-1.850	0.107	0.000
ZFPN_1000s							-0.288	0.053	0.000
Random Effect									
Level: REGIONAL CLUSTER NAME									
Constant				0.103	0.055	0.015	0.091	0.048	0.015
ZFPN_1000s							0.013	0.011	0.060
Covariance							0.002	0.017	0.453

The variance components model, Table 6.6.1.1, has a significant variation between regional clusters. Detailed in the NB model are the results when the effects of ZFPN_1000's are added. Here the fixed effect of ZFPN_1000's are statistically significant, showing that any increase in enforcement, as measured by ZFPN_1000's, leads to a decrease in the KSI rate. There is also significant regional variation between clusters but there is no significant random variation, at the 5% level, related to the effect of ZFPN_1000's, although it is approaching significance with a P = 0.06.

The variation between regional clusters relating to the effect of ZFPN_1000's, is shown in Figure 6.6.1.1. This suggests that, for the regional clusters, there is a trend suggesting lower KSI rates are associated with higher levels of enforcement.

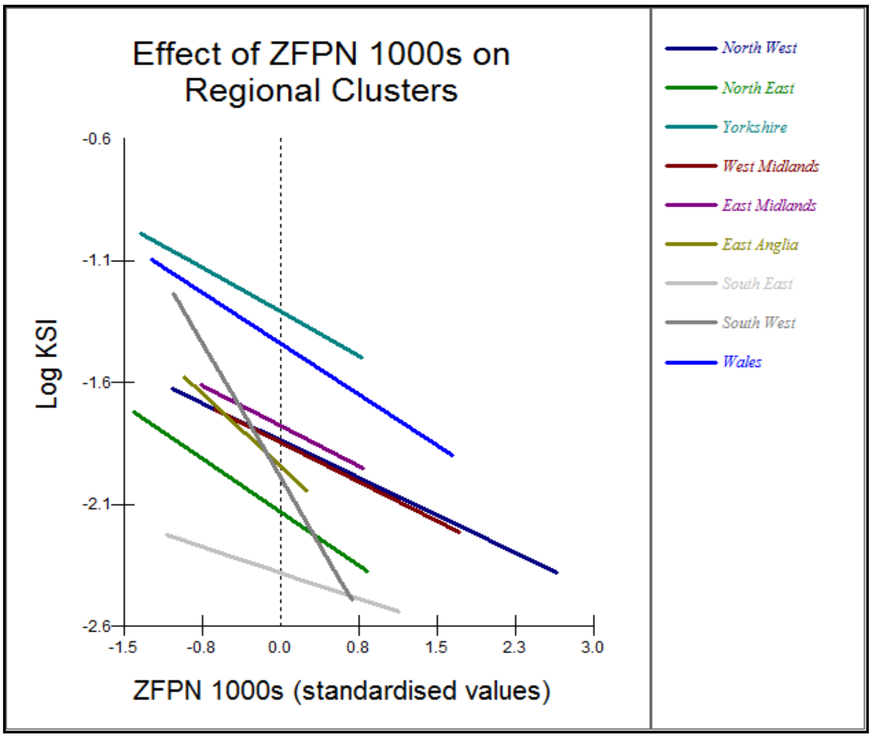


Figure 6.6.1.1: Effect of Enforcement, ZFPN _1000's, on Regional Clusters in Quarter 3

The fixed effects of ZFPN_1000's are significant in seven of the nine regional clusters, see Table 6.6.1.2, where clusters are ordered by ascending p-value. The clusters which do not have significant effects, at the 5% level, would be significant at the 10% level and allied to the significance of the other seven regional clusters suggests that there is a general trend associating an increase in police enforcement with a decrease in KSI rates.

Table 6.6.1.2: Parameter Estimates and p-values for Fixed Effects of ZFPN_1000's on Regional Clusters in Quarter 3

Models based on Regional Clusters	Fixed Effect Parameter Estimate	Standard Error	Parameter Estimate / Standard Error	p-value
North West with ZFPN_1000’s Effect	-0.204	0.059	-3.458	0.000
South West with ZFPN_1000’s Effect	-0.735	0.129	-5.698	0.000
Wales with ZFPN_1000’s Effect	-0.279	0.095	-2.937	0.002
North East with ZFPN_1000’S Effect	-0.291	0.117	-2.487	0.006
East Anglia with ZFPN_1000’s Effect	-0.396	0.162	-2.444	0.007
West Midlands with ZFPN_1000’s Effect	-0.215	0.100	-2.150	0.016
Yorkshire with ZFPN_1000’s Effect	-0.240	0.136	-1.765	0.039
South East with ZFPN_1000’s Effect	-0.143	0.097	-1.474	0.070
East Midlands with ZFPN_1000’s Effect	-0.222	0.158	-1.405	0.080

6.6.2. Quarter 3 Multilevel Models using ZLag1_FPN_1000’s and ZLag1_FPN_1000’s on Regional Clusters

Lagged multilevel models are developed on the regional clusters with the proxies for enforcement being ZLag1_FPN_1000’s and ZLag2_FPN_1000’s, equivalent to ZFPN_1000’s lagged by one and two quarters respectively. The results of model development, for both lagged variables, are shown in Table 6.6.2.1. Here it can be seen that there are significant fixed and random effects to be found for all proxy variables, with both lagged variables having a significant effect on the KSI rate.

Table 6.6.2.1: Multilevel Negative Binomial Models of Effect of ZLag1_FPN_1000's and ZLag2_FPN_1000's on Regional Clusters in Quarter 3

Models Based on Regional Clusters	Variance Components Model	Standard Error	p-value	NB Model ZLag1 FPN	Standard Error	p-value	NB Model ZLag2 FPN	Standard Error	p-value
Response	KSI			KSI			KSI		
Fixed Effect									
Constant	-1.813	0.114	0.000	-1.856	0.098	0.000	-1.852	0.097	0.000
Zlag1_FPN_1000s				-0.284	0.063	0.000			
Zlag2_FPN_1000s							-0.309	0.064	0.000
Random Effect									
Level: REGIONAL CLUSTER NAME									
Constant	0.103	0.055	0.015	0.075	0.041	0.017	0.073	0.040	0.017
Zlag1_FPN_1000s				0.021	0.016	0.047			
Covariance Lag1				-0.025	0.020	0.106			
Zlag2_FPN_1000s							0.023	0.017	0.044
Covariance Lag2							-0.020	0.020	0.159

The variation in the fixed effect of the lagged proxy variables on each cluster is shown in Figures 9 and 10, Appendix 6b.

The fixed effects relating to both lagged variables are shown in Tables 9 and 10, Appendix 6c. For both variables seven out nine clusters are associated with significant effects of increased enforcement which is linked to a decrease in the KSI rate. This adds to the evidence suggesting a general trend associating an increase in police enforcement with a decrease in KSI rates.

6.6.3 Quarter 3 Multilevel Models using ZFPN_G16_1000's on Regional Clusters

The proxy for enforcement used in this section is ZFPN_G16_1000's. Once more three models are produced – see Table 6, Appendix 6a. In the variance components model significant variation is found between clusters in relation to KSI rates. When the effect of enforcement is added, ZFPN_G16_1000's in the NB model, a significant fixed effect is seen where an increase in the number of ZFPN_G16_1000's leads to a decrease in the KSI rates. The variation in the fixed effects between clusters is shown in Figure 11, Appendix 6b. There is however no significant variation, at the 5% level, between clusters in relation to ZFPN_G16_1000's. The parameter estimates for the fixed effects of ZFPN_G16_1000's are shown in Table 11, Appendix 6c, where all but one of the nine clusters have significant effects related to enforcement.

6.6.3.1 Quarter 3 Multilevel Models using ZLag1_FPN_G16_1000's and ZLag2_FPN_G16_1000's on Regional Clusters

Detailed results from modelling with the lagged proxy variables ZLag1_FPN_G16_1000's and ZLag2_FPN_G16_1000's, are given in Table 7, Appendix 6a. For the fixed effect part of both models, both lagged variables have a significant effect linked to a decrease in KSI rates. For random effects neither lagged variable has any significant effect, at the 5% level,. Once again there is significant variation between clusters, in both the fixed and random part of the models. This is not unexpected as the clusters were developed in order to produce maximum variation between clusters. The variation between clusters in relation to fixed effects can be seen in Figures 12 and 13, Appendix 6b, and the parameter estimates showing the effect of the proxy variables are given in Tables 12 and 13, Appendix 6c. Both lagged proxy variables have a significant effect in seven out of nine clusters although the effect is seen in different clusters for each proxy.

6.6.4 Quarter 4 Multilevel Models using ZFPN_1000's on Regional Clusters

Model development for regional clusters Quarter 4 data follows the same procedure as for derived cluster Quarter 4 data. As before a null model, a variance components model and a Negative Binomial model are produced and results are given in Table 6.6.4.1. In Table 6.6.4.1, across all models, there is significant variation between clusters in relation to both fixed and random effects. There is also a significant fixed effect associated with ZFPN_1000's in the NB model and significant variation across clusters in the effect of ZFPN_1000's.

Table 6.6.4.1: Multilevel Negative Binomial Models of Effect of ZFPN_1000's on Regional Clusters in Quarter 4

Models Based on Regional Clusters	Null Model	Standard Error	p-value	Variance Components Model	Standard Error	p-value	NB Model ZFPN	Standard Error	p-value
Response	KSI			KSI			KSI		
Fixed Effect									
Constant	-1.866	0.040	0.000	-1.850	0.112	0.000	-1.884	0.106	0.000
ZFPN_1000s							-0.273	0.062	0.000
Random Effect									
Level: REGIONAL CLUSTER NAME									
Constant				0.100	0.053	0.015	0.090	0.048	0.015
ZFPN_1000s							0.020	0.015	0.046
Covariance							-0.003	0.020	0.440

This variation between clusters is shown in Figure 14, Appendix 6b. The parameter estimates and associated p-values are given in Table 6.6.4.2, where six of nine clusters have a significant effect indicating that enforcement is linked to decreasing KSI rates.

Table 6.6.4.2: Parameter Estimates and p-values for Fixed Effects of ZFPN_1000's on Regional Clusters in Quarter 4

Models based on Regional Clusters	Fixed Effect Parameter Estimate	Standard Error	Parameter Estimate / Standard Error	p-value
North West with ZFPN_1000's Effect	-0.208	0.060	-3.467	0.000
South West with ZFPN_1000's Effect	-0.509	0.081	-6.284	0.000
Wales with ZFPN_1000's Effect	-0.425	0.096	-4.427	0.000
North East with ZFPN_1000'S Effect	-0.250	0.111	-2.252	0.012
East Anglia with ZFPN_1000's Effect	-0.334	0.169	-1.976	0.024
West Midlands with ZFPN_1000's Effect	-0.282	0.201	-1.403	0.080
East Midlands with ZFPN_1000's Effect	-0.470	0.225	-2.089	0.180
South East with ZFPN_1000's Effect	-0.058	0.081	-0.716	0.237
Yorkshire with ZFPN_1000's Effect	0.013	0.123	0.106	0.458

6.6.4.1 Quarter 4 Multilevel Models using ZLag1FPN_1000’s and ZLag1_FPN_1000’s on Regional Clusters

Results for multilevel models using Quarter 4 data, with variables ZLag1_FPN_1000’s and ZLag2_FPN_1000’s, are shown in Table 8, Appendix 6a. In this table, for fixed and random effects, both lagged variables are significant in relation to the KSI rate. There is also significant variation between clusters in relation to both fixed and random effects. The variation between clusters relating to the fixed effect of the lagged proxy variables is shown in Figures 15 and 16, Appendix 6b. For ZLag1_FPN_1000’s has a significant effect on seven out of nine regional clusters, see Table 14, Appendix 6c. The variable ZLag2_FPN_1000’s has a significant effect on the KSI rate in six out of the nine clusters; this is shown in Table 15, Appendix 6c. The effect in for both variables is associated with a decrease in the KSI rate.

6.6.5 Quarter 4 Multilevel Models using ZFPN_G16_1000’s on Regional Clusters

Following the methodology of previous sections three models are developed using the proxy for enforcement ZFPN_G16_1000’s and the results can be seen in Table 9, Appendix 6a. There is a significant variation between clusters in the variance components model and this fixed effect between clusters can be seen in Figure 17, Appendix 6b. When the effect of enforcement is added, in the NB model, Table 9, Appendix 6a, this also has a significant fixed effect, relating an increase in the number of ZFPN_G16_1000’s to a decrease in the KSI rates. There is no significant random variation found between clusters, at the 5% level, in relation to ZFPN_G16_1000’s. Parameter estimates for the fixed effects of ZFPN_G16_1000’s are shown in Table 16, Appendix 6c, where seven of the nine clusters have a significant effect related to enforcement.

6.6.5.1 Quarter 4 Multilevel Models using ZLag1_FPN_G16_1000's and ZLag2_FPN_G16_1000's

The results from the final set of models, using the lagged proxy variables ZLag1_FPN_G16_1000's and ZLag2_FPN_G16_1000's are shown in Table 6.6.5.1.

Table 6.6.5.1: Multilevel Negative Binomial Models of Effect of ZLag1_FPN_G16_1000's and ZLag2_FPN_G16_1000's on Regional Clusters in Quarter 4

Models Based on Regional Clusters	Variance Components Model	Standard Error	p-value	NB Model ZFPN Lag1 G16	Standard Error	p-value	NB Model ZLag2 FPN G16	Standard Error	p-value
Response	KSI			KSI			KSI		
Fixed Effect									
Constant	-1.850	0.112	0.000	-1.832	0.107	0.000	-1.891	0.097	0.000
Zlag1_FPN_G16_1000s				-0.283	0.065	0.000			
Zlag2_FPN_G16_1000s							-0.214	0.048	0.000
Random Effect									
Level: REGIONAL CLUSTER NAME									
Constant	0.100	0.053	0.015	0.085	0.045	0.015	0.074	0.040	0.015
Zlag1_FPN_G16_1000s				0.045	0.029	0.030			
Covariance Lag1				0.003	0.032	0.463			
Zlag2_FPN_G16_1000s							0.007	0.008	0.085
Covariance Lag2							-0.017	0.015	0.129

Here, for both fixed and random effects, there is significant variation between clusters. This variation is shown in Figures 18 and 19, Appendix 6b. Both lagged variables have significant fixed effects linked to a decrease in KSI rates. However, only ZLag1_FPN_G16_1000's has a significant random effect. Parameter estimates for the effect of ZLag1_FPN_G16_1000's and ZLag2_FPN_G16_1000's on individual clusters are given in Tables 17 and 18, Appendix 6c, and in both cases six of the nine clusters have significant effects related to the enforcement proxies.

6.7 Discussion of Results relating to Quarterly Data

6.7.1 Results from Analysis of Derived Clusters

In this section the effect of police enforcement on quarterly data is discussed. Here results from the derived cluster data over two separate quarters, Quarter 3 and Quarter 4, from the year 2003 are discussed.

For the derived clusters there are significant fixed effects for all proxy variables in both Quarter 3 and Quarter 4. These effects are further evidence that an increase in the level of police enforcement leads to a decrease in the overall KSI rate. Significant variation between clusters, as represented by the value for the Constant in each model, was also found in all models. Variation between clusters, relating to the effect of the proxy variables, differed for each model. For Quarter 3 only the effect of ZLag2_FPN_ 1000's had significant variation between clusters, while in Quarter 4 only the effects of ZLag1_FPN_G16_1000's and ZLag2_FPN_G16_1000's varied significantly between clusters.

Significant variation, relating to the fixed effect of the proxy variables, was found in a number of clusters in both Quarters 3 and 4. This effect was found in Cluster 3 for all proxy variables in both quarters, in Cluster 4 for both ZLag1_FPN_ 1000's in Quarter 3 and ZLag2_FPN_ 1000's in Quarter 4, and in Cluster 6 for ZLag2_FPN_ 1000's and ZFPN_G16_1000's.

6.7.2 Results from Analysis of Regional Clusters

The analysis on regional clusters follows the same procedure used with the derived clusters. The same variables are used to develop models based on regional clusters as were used with the derived clusters. Once again all proxy variables have significant fixed effects on the KSI rate, in both quarters, where an increase in enforcement is related to a decrease in the KSI rate.

In relation to random effects in Quarter 3, only ZLag1_FPN_1000's and ZLag2_FPN_1000's have any significant effect between clusters although all other proxy variables would have produced significant effects if the significance level had been set at 10%. In Quarter 4 twice as many proxy variables were found to have a significant effect with only ZFPN_G16_1000's and ZLag2_FPN_G16_1000's having no significant effect, at the 5% level.

Regarding the regional variation associated with the fixed effect of the proxy variables, in the majority of cases, there is a significant effect to be found. In Quarter 3 five of the six models have only two clusters, from nine, where no significant effect was found at the 5% level, while in the remaining model only one cluster is not statistically significant, at the 5% level, with respect to enforcement. Similarly, for Quarter 4, the majority of clusters are found to have significant effects in all models.

The results from the regional cluster data, both annually and quarterly, provide further evidence of a strong trend linking an increase in enforcement with a decrease in the KSI rate. This trend appears stronger in the regional data than in the derived cluster data and suggests that there is indeed a link between increased police enforcement and decreasing KSI rates. The trend is somewhat masked by the construction of the derived clusters but when looked at as a whole, see Figure 6.4.2, the trend is clear.

7 Discussion and Conclusions

7.1 Introduction

The main focus of this study was to investigate the effects of police enforcement on Road Traffic Accidents (RTA's), specifically the level of Killed and Seriously Injured (KSI) accidents. It has been well documented by previous researchers (Zaidel, 2002, Elliott and Broughton, 2004) that increased levels of police enforcement generally lead to a decrease in the number of accidents and in turn, a higher level of safety for all road users.

Police enforcement can be a difficult measure to quantify and in this report measures of enforcement are represented by proxy variables. The proxy variables were,

- Fixed Penalty Notices (FPN's)
- Prosecutions (Pros)
- Written Warnings (WW)
- Vehicle Defect Rectification Notices (VDRN's)

A subset of FPN's, FPN_G16, representing speeding related violations was also used a proxy variable. This subset is used due to the high level of FPN's issued for speeding offences and the ongoing debate surrounding the efficacy of police enforcement in relation to speed violations.

The effect of police enforcement on KSI accident rates is analysed across forty one Police Force Areas (PFA's) covering England and Wales. There are forty three PFA's in England and Wales but, for reasons covered earlier in this report, both the City of London and Metropolitan PFA's have been omitted from all analyses. For meaningful comparisons to me made between PFA's, on the effect of enforcement, KSI accident rates are used as the independent variable in all analyses.

7.2 Discussion of Results

Three methods of analyses were used investigate the effect of police enforcement on the KSI accident rates across all PFA's. The results from each method will be discussed and a summary of the findings will then be presented.

7.2.1 Results from Zero Truncated Poisson Regression

Initially, as the data were classed as count data, regression models were to be developed based on the Poisson distribution. However, results from exploratory modelling showed that ordinary Poisson regression was unsuitable for modelling the data due to a lack of zero counts. This violates the distributional assumptions of the Poisson distribution which allows for zero counts and, as a result, if Poisson regression was to be used it would produce incorrectly specified models. As the data were truncated at zero an alternative estimation procedure was needed to achieve reliable models. Fortunately a procedure which deals with the zero truncated count data is available: Zero Truncated Poisson (ZTP) regression. The ZTP procedure adjusted the properties of the Poisson distribution to take into account the lack of zero values.

The initial ZTP model fitting was done using an aggregate variable, All Penalties, constructed by summing all proxy variables and was used in both contemporary and lagged form. Two offset variables were also used, *lnpop* which is population based and *lnvkm* which is based on vehicle kilometres travelled. In total two models, one contemporary and one lagged by a year, for each offset variable; a total of four different models in all were created for the initial analysis.

Results from this analysis are given in Appendix 4, Tables 1 to 4, and one can see that all categorical variables have very similar values across all four models. The results, from all models, indicate that a person is more likely to be in a KSI accident if they are male, aged between 17 and 24 years, travelling in a car on a road with a fixed speed limit of 30 mph. The accident is more likely to take place at a junction, on a dry road during daylight hours.

A significant negative effect is found in all four models, linking an increase in the level of police enforcement, as measured here by the aggregate proxy variable, with a decrease in the number of KSI accidents. This effect is stronger when the offset is population based; approximately four times stronger for contemporary data and five times for lagged data.

After the analysis using the proxy All Penalties was complete further analysis examining the effect of individual proxies was undertaken. Four models were designed incorporating the individual proxy variables, with each model fitted for both offsets, giving a total of eight models.

- Contemporary Annual Data
- Lagged Annual Data
- Contemporary Annual Data with FPN_G16
- Lagged Annual Data with FPN_G16

The only difference between models with FPN_G16 and those without is that those without use FPN's instead. The proxy FPN_G16 is a subset of FPN's and represents speeding offences.

Again, values for all categorical variables, regardless of the model chosen, are very similar, Tables 5 to12, Appendix 4. Every model indicates that males, aged between 17 and 24 years, travelling in a car on a road with a speed limit of 30 mph are more likely to be in a KSI accident. The accident is most likely to happen at a junction on a dry road during daylight hours

The effects of all proxy variables on the KSI rates, across all eight models, are given in Tables 7.2.1.1 and 7.2.1.2.

Table 7.2.1.1: Selected Output from Annual Data detailing Effect of Proxy Variables on KSI Rates

Proxy Variables for Police Enforcement	Annual Data with Offset Inpop.	Annual Data with Offset Invkm	Annual Lagged Data with Offset Inpop.	Annual Lagged Data with Offset Invkm
Prosecutions	Non-Significant	Significant +ve Effect		
Lagged Prosecutions			Non-Significant	Significant +ve Effect
FPN	Significant -ve Effect	Significant -ve Effect		
Lagged FPN			Significant -ve Effect	Significant -ve Effect
VDRN	Significant -ve Effect	Significant -ve Effect		
Lagged VDRN			Significant -ve Effect	Significant -ve Effect
WW	Significant -ve Effect	Significant -ve Effect		
Lagged WW			Significant -ve Effect	Significant -ve Effect

Table 7.2.2.1: Selected Output from Annual Data, including Speeding Related FPN's, detailing Effect of Proxy Variables on KSI Rates

Proxy Variables for Police Enforcement	Annual Data with Speeding Related FPN's (FPN_G16) and Offset Inpop.	Annual Data with Speeding Related FPN's (FPN_G16) and Offset Invkm	Annual Lagged Data with Speeding Related FPN's (FPN_G16) and Offset Inpop.	Annual Lagged Data with Speeding Related FPN's (FPN_G16) and Offset Invkm
Prosecutions	Significant -ve Effect	Significant +ve Effect		
Lagged Prosecutions			Significant -ve Effect	Significant +ve Effect
FPN G16	Significant -ve Effect	Significant -ve Effect		
Lagged FPN G16			Significant -ve Effect	Significant -ve Effect
VDRN	Significant -ve Effect	Significant -ve Effect		
Lagged VDRN			Significant -ve Effect	Significant -ve Effect
WW	Significant -ve Effect	Significant -ve Effect		
Lagged WW			Significant -ve Effect	Significant -ve Effect

FPN's have a significant negative effect on KSI accidents, both contemporary and lagged across all models. In this case the contemporary effect is stronger than the lagged effect, see Chapter 4, Tables 4.3.3.7 to 4.3.3.10. VDRN's and WW's, in all models, have a significant negative effect on KSI accidents. The lagged effect for VDRN's is slightly stronger than the contemporary effect, see Chapter 4, Tables 4.3.3.7 to 4.3.3.14. The lagged effect of VDRN's may have a stronger deterrent effect due to increased compliance, with this type of penalty, leading to vehicles becoming more roadworthy and less likely to be involved in a road traffic accident.

The interpretation of the effect of Prosecutions is more complex as it varies between models depending on which offset is used. Prosecutions are found to have no significant effect on KSI accidents with *lnpop* as the offset variable when modelled alongside the full set of FPN's. However, when the offset is lnvkm a significant positive effect is found. One reason for this may be related to increasing police enforcement at accident blackspots leading to higher levels of prosecutable offences being recorded.

The effects of the socio-demographic variables, Geographical Area sq km, Mean Index of Deprivation (IMD) and Percentage Motorway, are very similar across all models. When *lnvkm* is the offset Geographical Area sq km has a significant negative effect in all models, suggesting that increasing area size is associated with decreasing KSI accidents, resulting in fewer accidents in rural areas than in urban areas. The strong effect IMD has is evidence of higher levels of KSI accidents in more deprived areas and this finding is further evidenced by previous research (Abdalla et al., 1997). The results also indicate that the higher the percentage of motorway in each area then the lower the level of KSI accidents is likely to be.

In Table 7.2.1.2, selected results from modelling the annual data, with speeding related FPN's included, are very similar to those obtained using the full set of FPN's, see Table 7.2.1.1. Using the speeding related subset FPN_G16's allows an analysis of the relative importance, if any, of speeding related offences. Results from this analysis indicate that FPN_G16's have a significant negative effect on the number of KSI accidents in all four models mirroring the results for the full set of FPN's. It should be noted that fixed penalties issued for speeding related offences are mainly those issued by speed cameras.

Modelling of the quarterly accident data follows the same procedure as with the annual data. Aggregate proxy variables are initially used to investigate any effects of enforcement in on KSI accidents. The same aggregate variable, All Penalties, is used and four models are developed to analyse both contemporary and lagged effects and both offset variables are used. Quarterly data are lagged by one and two quarters, equal to three months and six months respectively.

Results from the analysis, Appendix 4, Tables 13 to 16, give values for categorical variables that are similar for all models. Once again the most likely accident scenario is to be male, aged between 17 and 24 years, travelling in a car on a road with a fixed speed limit of 30 mph, with the accident most likely to happen at a junction on a dry road during daylight hours.

The aggregate proxy variable has significant negative effects on KSI accidents for all four models and is slightly stronger in models offset *lnpop*. The weakest models relates to quarterly lagged data with lnvkm as the offset. In this model none of the proxies are significant at the 5% level. However, the proxies generally have a significant negative effect on KSI accidents, indicating any increase in police enforcement leads to lower levels of KSI accidents.

In Tables 7.2.1.3 and 7.2.1.4, selected outputs from analysis of the quarterly data, detailing the effect of the proxies for police enforcement on the level of KSI accidents, are presented.

Table 7.2.1.3: Selected Output from Quarterly Data Detailing Effect of Proxy Variables on KSI Rates

Proxy Variables for Police Enforcement	Quarterly Data with Offset Inpop.	Quarterly Data with Offset Invkm	Quarterly Lagged Data with Offset Inpop.	Quarterly Lagged Data with Offset Invkm
Prosecutions	Significant +ve Effect	Significant +ve Effect		
Lag 1 Prosecutions			Significant +ve Effect	Significant +ve Effect
Lag 2 Prosecutions			Significant +ve Effect	Significant +ve Effect
FPN	Significant -ve Effect	Significant -ve Effect		
Lag 1 FPN			Non-Significant	Non-Significant
Lag 2 FPN			Significant -ve Effect	Non-Significant
VDRN	Significant -ve Effect	Significant -ve Effect		
Lag 1 VDRN			Significant -ve Effect	Significant -ve Effect
Lag 2 VDRN			Non-Significant	Non-Significant
WW	Significant -ve Effect	Significant -ve Effect		
Lag 1 WW			Non-Significant	Non-Significant
Lag 2 WW			Non-Significant	Non-Significant

Table 7.2.1.4: Selected Output from Quarterly Data, including Speeding Related FPN's, Detailing Effect of Proxy Variables on KSI Rates

Proxy Variables for Police Enforcement	Quarterly Data with Speeding Related FPN's (FPN_G16) and Offset Inpop.	Quarterly Data with Speeding Related FPN's (FPN_G16) and Offset Invkm.	Quarterly Lagged Data with Speeding Related FPN's (FPN_G16) and Offset Inpop.	Quarterly Lagged Data with Speeding Related FPN's (FPN_G16) and Offset Invkm
Prosecutions	Significant +ve Effect	Significant +ve Effect		
Lag 1 Prosecutions			Significant +ve Effect	Significant +ve Effect
Lag 2 Prosecutions			Significant +ve Effect	Significant +ve Effect
FPN G16	Significant -ve Effect	Significant -ve Effect		
Lag 1 FPN G16			Significant -ve Effect	Non-Significant
Lag 2 FPN G16			Non-Significant	Non-Significant
VDRN	Significant -ve Effect	Significant -ve Effect		
Lag 1 VDRN			Significant -ve Effect	Significant -ve Effect
Lag 2 VDRN			Non-Significant	Non-Significant
WW	Significant -ve Effect	Significant -ve Effect		
Lag 1 WW			Non-Significant	Non-Significant
Lag 2 WW			Non-Significant	Non-Significant

In all quarterly models Prosecutions have a significant positive effect on KSI accidents suggesting that increasing numbers of successful prosecutions is associated with an increase in the number of KSI accidents. As it is known that KSI accidents are decreasing year on year then it is more likely that the effect of Prosecutions is a result of higher levels of police activity at sites with higher risk of KSI accidents.

The results for FPN's, VDRN's and WW's indicate they are all associated with decreasing numbers of KSI accidents, for contemporary quarterly events. The effect size varies depending on the offset however the differences are minimal in terms of their effect on KSI accidents. For lagged quarterly data the results are different. In relation to FPN's the two quarter lag has a significant effect, at $P < 0.10$, with offset lnvkm. With offset lnpop, FPN's lagged by two quarters are significant at $P < .05$. No significant effects are found with the one quarter lag FPN's. The evidence from the analysis points to a diffusion effect where increasing enforcement activity, by means of FPN's, has not only an immediate significant effect on the level of KSI accidents but also a lagged effect two quarters, six months, later. Significant effects are found for VDRN's with a one quarter lag. This is possibly related to the shorter compliance period of VDRN's, typically within fourteen days of the offence. There were no significant effects for WW's.

Results from the analysis using FPN_G16s are very similar to those found using the full set of FPN's. All contemporary effects are negative and significant, and of a similar magnitude for both offset variables. For both lagged variables little difference is found between models with offset *lnvkm*, except for FPN_G16s, lagged by two quarters, which is non-significant. One quarter lagged FPN_G16's, with lnpop as the offset, have a significant negative effect and the effects of the socio-demographic variables for the lagged data are unchanged.

The results presented here are evidence that detectable reductions in KSI accidents can be achieved by increasing the level of police enforcement, as measured by the proxy variables. Of particular interest, considering the current climate, are the results relating to speeding related offences where it appears that an increase in the number of penalties issued is linked to a decrease in the number of KSI accidents. This is further evidence that enforcement strategies, aimed at detecting and punishing offenders who violate speed limits, play an important role in the drive to reduce the number of KSI accidents.

The real effect of enforcement, measured by Prosecutions, on accident rates is difficult to estimate. The extent of the delay between offence and successful prosecution is an unknown factor and adds a degree of uncertainty to any conclusion based on results derived from this proxy variable.

It is likely that advances in road safety engineering and continuing education strategies had some effect on the general downward trend in road traffic accidents. However, as these are national programmes any effects would be felt nationwide and are not thought to be prejudicial to this analysis.

7.2.2 Discussion of Results from Cluster Analysis

In choosing to use Cluster Analysis methods the aim was to identify groupings, or clusters, which were not immediately apparent in the dataset. Clusters were developed based on analysis done in Chapter 4, indicating the most suitable variables were KSI rates and the level of Fixed Penalty Notices (FPN's). Two distinct cluster analyses, using KSI rates based on population and vehicle kilometres travelled variables were produced.

Cluster analysis using KSI Rate by Population and FPN's as the clustering variables produced the cluster groupings detailed in Figure 7.2.2.1. Both variables were standardised prior to clustering to allow proper comparisons to be made. In Figure 7.2.2.1, one can see a general trend indicating that decreasing KSI rates are associated with increasing FPN's.

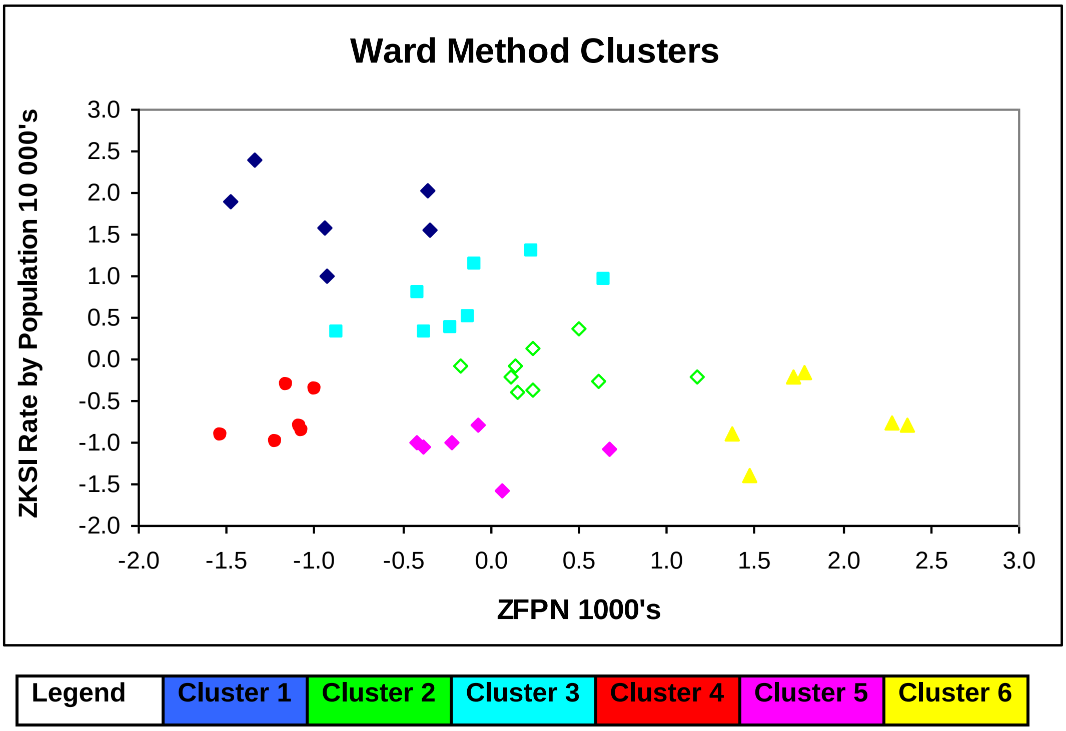


Figure 7.2.2.1: Ward Method Clusters ZKSI Rate and ZFPN 1000's

Having developed the clusters it is interesting to see how they compare across all proxy and socio-demographic variables. Cluster means for each proxy and socio-demographic variable are detailed in Table 7.2.2.1.

In attempting to identify differences between clusters it is informative to look at Table 7.2.2.1.

Table 7.2.2.1: Cluster Means for KSI Rate by Population and FPN (1000s)

Ward Method Cluster Means	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
KSI Rate by Population (10 000s)	8.04	5.23	6.47	4.32	3.77	4.35
FPN (1000s)	38.19	88.34	68.72	27.02	72.22	149.34
FPN G16 (1000s)	24.06	57.38	45.55	7.69	48.47	75.17
VDRN (1000s)	2.34	3.34	2.59	2.41	2.42	5.22
WW (1000s)	1.75	1.51	0.27	1.20	1.17	2.95
GEOGRAPHIC AREA sqkm	4343.08	3757.28	3487.48	1292.54	2788.49	4933.18
MEAN IMD SCORE	15.76	17.36	19.21	22.66	18.36	22.06
PERCENT MOTORWAY	1.08	1.26	0.77	1.11	0.90	0.95

Clusters 4, 5 and 6 have the lowest KSI rates and there is no significant difference between them in this respect. However, they do have significantly lower KSI rates when compared to Clusters 1 and 3. Cluster 1, in turn, has a significantly higher KSI rate than all other clusters. Another difference between Clusters 1 and 3 is in the level of FPN's with Cluster 3 having significantly higher numbers. Cluster 2 falls between clusters with high and low KSI rates. The findings here, where higher levels of enforcement, as measured by the proxy variables, are associated with lower KSI rates is in line with the results from Chapter 4. Clusters developed using vehicle kilometres travelled, *lnvkm,* were poorly defined although the trend of increasing enforcement linked to decreasing levels of KSI accidents was still apparent.

Overall, results from the cluster analysis were mixed with clusters derived from population based KSI rates more clearly defined than those developed from vehicle kilometres travelled based rates. The trend, identified earlier, which links increasing police enforcement, measured here by the proxy variables, with a decrease in the KSI rates is still apparent. Further refinement of the derived clusters was attempted using Fuzzy C-means (FCM) clustering. The main advantage of FCM clustering over other clustering techniques is that it is possible for data to be allocated to more than one cluster. It was thought that this might produce better defined clusters, especially in relation to KSI rates based on vehicle kilometres travelled. However, this was not the case, even though the FCM method identified some data which could be placed in alternative clusters the end result was no better than the existing cluster definitions. Another consideration, in relation to clustering, is the effect of Edge effects. Edge effects may lead to complications in statistical tests based on spatial processes. Tests, such as cluster analysis, can be affected by the finite size of the area of interest and this may be a topic worth further investigation.

7.3 Multilevel Modelling

Previous analyses have not been able to take into account the hierarchical nature of the data under analysis. Multilevel Modelling is ideally suited for this type of analysis and the results from this analysis are discussed below

7.3.1 Discussion of Multilevel Modelling Results

Significant fixed effects were found for both ZFPN's and ZFPN_G16's in relation to the derived clusters, linking an increase in enforcement to a decrease in the overall KSI rate. There is also significant random variation between clusters, but no significant random variation between clusters associated with either proxy variable. Significant variation of the fixed effect of enforcement for each cluster is only found in Cluster 4, relating to the effect of ZFPN's and Clusters 4 and 5, relating to the effect of ZFPN_G16. This general lack of variation is not an unexpected result as the clusters were developed to have minimum variation within clusters, and this result indicates that the clusters are well defined in this respect. The effect found in Cluster 4 goes against the trend of increasing enforcement leading to decreasing KSI rates and can be considered as an artefact of the clustering algorithm.

Multilevel modelling of the regional clusters found similar effects to those found for the derived clusters with both proxies having significant fixed effects on the rate of KSI accidents. Significant random variation was found between clusters, in respect to KSI rates, there was, however, no significant random variation between clusters in relation to the effect of enforcement.

All regional clusters followed the trend indicating that increased enforcement, ZFPN's here, leads to lower KSI rates, with four of the nine regional clusters being statistically significant in this respect. With regard to the fixed effect of ZFPN_G16's seven of nine regional clusters follow the trend associated with ZFPN_1000's.However, only one cluster is statistically significant with respect to enforcement.

Results from the multilevel modelling of the annual data provide further evidence that increased police enforcement is an effective tool in helping to reduce the level of KSI rates. No significant random variation for either proxy variable was found between clusters, derived or regional. However, there was significant variation found between clusters in relation to KSI rates.

The analysis of the effect of enforcement on derived clusters found significant fixed effects for all proxy variables in both Quarters 3 and 4, further evidence linking increasing enforcement with decreasing KSI rates. Significant variation between clusters was also found in all models. Significant random variation between clusters was found only for the effect of ZLag2_FPN in Quarter 3. In Quarter 4 the effects of ZLag1_FPN and ZLag2_FPN varied significantly between clusters. Significant variation in the fixed effect of enforcement was found in a number of clusters in both Quarters. This effect was found in Cluster 3 for all proxy variables in both quarters, in Cluster 4 for both ZLag1_FPN's in Quarter 3 and ZLag2_FPN's in Quarter 4, and in Cluster 6 for ZLag2_FPN_ 1000's and ZFPN_G16's.

The analysis of regional clusters found that all proxy variables had significant fixed effects on the KSI rate, in both quarters. In relation to random effects in Quarter 3, only ZLag1_FPN's and ZLag2_FPN's have any significant effect between clusters although all other proxy variables would be significant if the significance level was set at 0.10. In Quarter 4 only ZFPN_G16's and ZLag2_FPN_G16's had no significant random effect. The regional variation associated with the fixed effect of the proxy variables is, in the majority of cases, seen to have a significant effect. In Quarter 3 five of the six models have seven of nine clusters with significant fixed effects with respect to enforcement, while in the remaining model only one cluster is not statistically significant. Similarly in Quarter 4 the majority of clusters are found to have significant effects across all models.

The results from the analysis of the regional cluster data, both annual and quarterly, provide yet more evidence that effect of increased enforcement reduces the level of KSI rates. These results follow the trend noted in previous chapters and there seems little doubt that increased levels of police enforcement are instrumental in reducing the number of KSI accidents.

In summary the results from the statistical analyses confirm findings from previous research that increased enforcement is associated with a reduction in RTA's, see, for instance Summala et al, (1980) and Davis et al. (2006). The most important question asked at the start of this project was,

'Does police enforcement activity have any real effect on levels of KSI road traffic accidents?'

The findings from the present research indicate that, yes, enforcement does have an effect on the level of KSI accidents. The results presented in this research provide strong evidence that increasing enforcement activity results in reduced levels of KSI accidents

7.4 Limitations

In any piece of research there will be limitations exposed. In this respect this research is no different. The main limitation is related to the data, or to be more precise, the depth of the data. The data used here has been aggregated up to

Police Force Area (PFA) level and inherent in this aggregation is a loss of information. Accident data is available at lower levels than PFA but had to be aggregated to match the classification of the enforcement data. The enforcement data was supplied at PFA level but is collected at lower levels of aggregation and it would have been beneficial to this investigation if the data had been supplied at these lower levels of aggregation. This is especially true in the case of multilevel modelling where the analysis was restricted to two-level models. Other limitations would include the lack of data relating to other enforcement activities carried out by individual PFA's and information on how each PFA applies national enforcement and road safety policy within its own area. Chief amongst these would be the lack of information on the use of mass media outlets in publicising national and local road safety initiatives. If data were collated, and made available, it would allow interested parties to measure the level of accidents before, during and after such campaigns thereby allowing the real effects, good and bad, of such initiatives to be evaluated. This problem also applies to engineering improvements relating to road safety. The effect of engineering initiatives, on the safety of the road infrastructure, should be monitored and full details made available alongside accident statistics. This would provide an opportunity, not only for engineers and other interested parties, but also for road users to gain a better understanding of the process that aims to provide a safer road infrastructure.

7.5 Contribution to Knowledge

Despite the limitations, detailed in Section 7.4, this thesis has made a number of important contributions to knowledge which are

- The combining of different data sets – STATS19 data, Home Office Penalty data and Socio-Demographic data – into one database allowing for a fuller investigation into the effects of police enforcement on KSI accidents
- Significant contribution to the debate on improving road safety, particularly to the debate on the efficacy of speed cameras, as measured in this thesis by speeding related FPN's

- Methodological advancement in the analysis of police enforcement in Great Britain, using Cluster Analysis and Multilevel Modelling

7.6 Recommendations

In this thesis the effects of police enforcement on the level of KSI accidents have been considered. In light of the findings some recommendations for practitioners and policy makers are suggested. Recommendations for future research are also put forward.

7.6.1 Recommendations for Practice and Policy

- There needs to be more cooperation between national and local agencies in the production of data and statistics relating to RTA's
- As with data production more cooperation is needed in the evaluation of road safety initiatives
- To properly evaluate the effect of prosecutions, relating to road traffic laws, the date of offence, not the date of prosecution, needs to be made available.
- New enforcement and road safety initiatives need to take account of specific local needs. Again, higher levels of consultation between national and local agencies can improve the success of new strategies.

7.6.2 Recommendations for Further Research

- Data should be made available to all interested parties at the lowest level of aggregation. This would further increase the accuracy of any analyses
- A wider range of data relating to enforcement activities should be made available, again, this would be beneficial to any analyses and improved understanding of the processes at work.
- More research should take advantage of Multilevel Modelling to fully explore the inherent variation present in the study of RTA's

7.7 Conclusions

The range of enforcement strategies available to the police, local authorities and national government are many and varied and in this research the effects of enforcement on the level of KSI accidents has been investigated. There would seem to be little doubt, based on results presented here, that higher levels of police enforcement lead to decreasing numbers of KSI accidents. In the present research results have consistently found a link between increased enforcement and a decrease in the number of KSI accidents and these findings are consistent with previous research in the field; see Summala et al, (1980), Zaal (1994) Blais and Dupont (2005).

Results relating to the effect of the enforcement proxy FPN_G16, speeding related fixed penalties, should be of particular interest to advocates, and critics, of speed cameras. The great majority of fixed penalties issued for speeding come from speed cameras and the findings in this research provide strong evidence that increasing the number of fixed penalties for speeding, as measured by FPN_G16's, leads to measurable reductions in KSI accidents, providing considerable benefits in the fields of public health and road safety.

Any future research based on the data used here would benefit from the addition of other, relevant variables and more localised data. This would allow a more in depth examination of the effects of enforcement, at national and local level, and, dependent on findings, may allow for road safety strategies to be tailored for specific situations and implemented locally. At the present time national strategies appear to be working but these fail to fully address local situations that may require a different approach.

Appendices

Appendix 3

Table 1 Details and sources of all variable names

Variable Names	Full Description of Variable Name	Data Source
YEAR	YEAR	STATS19
PFA	PFA Identification Code	ONS
PFA NAME	PFA Name	ONS
FPN	Fixed Penalty Notices	Home Office
FPN_G16	Speeding related FPN's	Home Office
PROSECUTIONS	PROSECUTIONS	Home Office
VDRN	Vehicle Defect Rectification Notices issued	Home Office
WW	Written Warnings	Home Office
POPULATION_10000s	Population of PFA in units of 10,000	ONS
Vkm_Billions	Vehicle km travelled in units of one billion	ONS
IMD	Index of Multiple Deprivation	www.wales.gov.uk; www.odpm.gov.uk
Geographical Area sqkm	Geographical area of each PFA	www.policecouldyou.co.uk
Percent Motorway	Percentage of total motorway in each PFA	www.dft.gov.uk

Figure 1: Annual Trends in Accident Rates by 10 000 population 1991 to 2004 for individual Police Force Areas

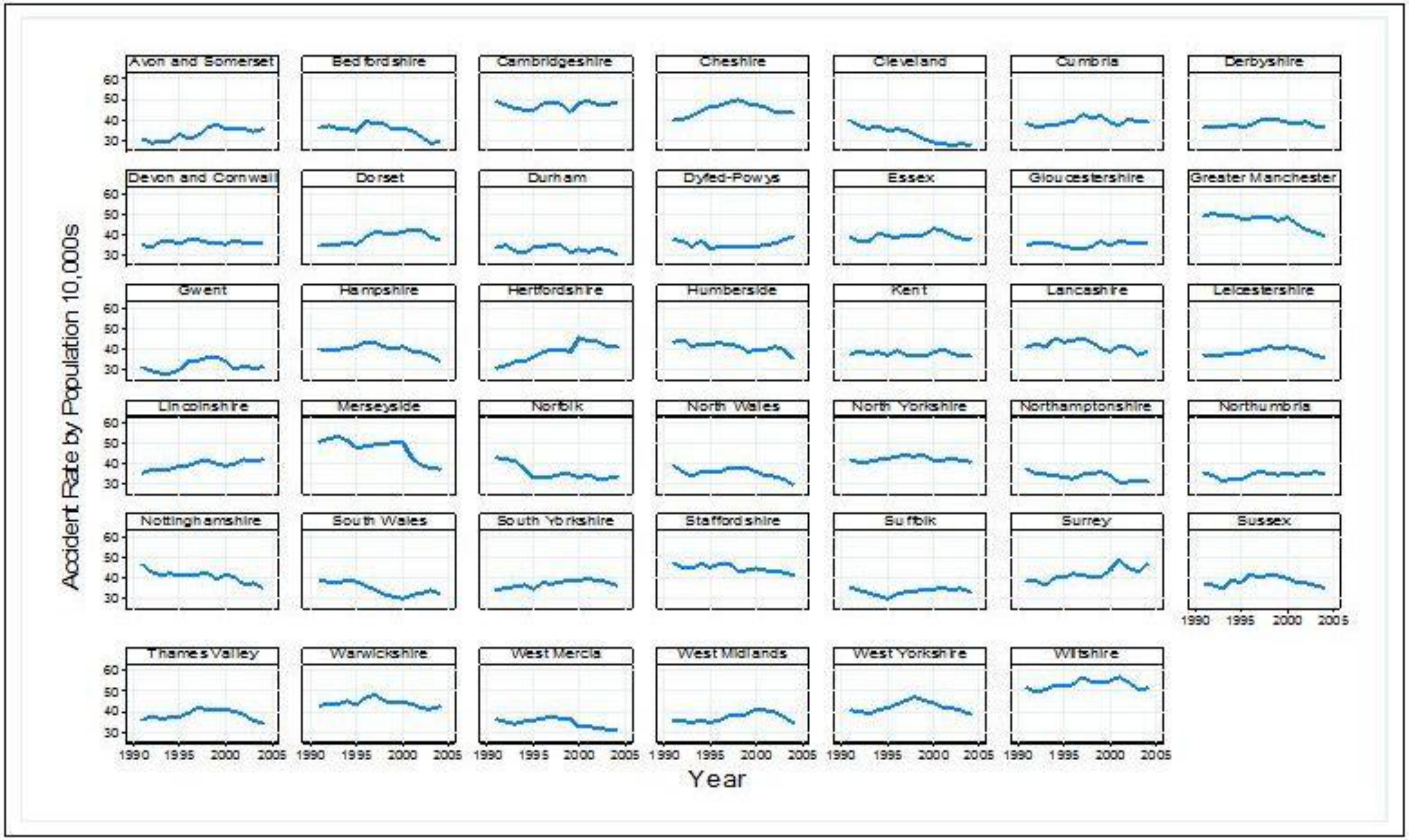


Figure 2: Annual Trends in KSI Rates by 10 000 population 1991 to 2004 for Individual Police Force Areas

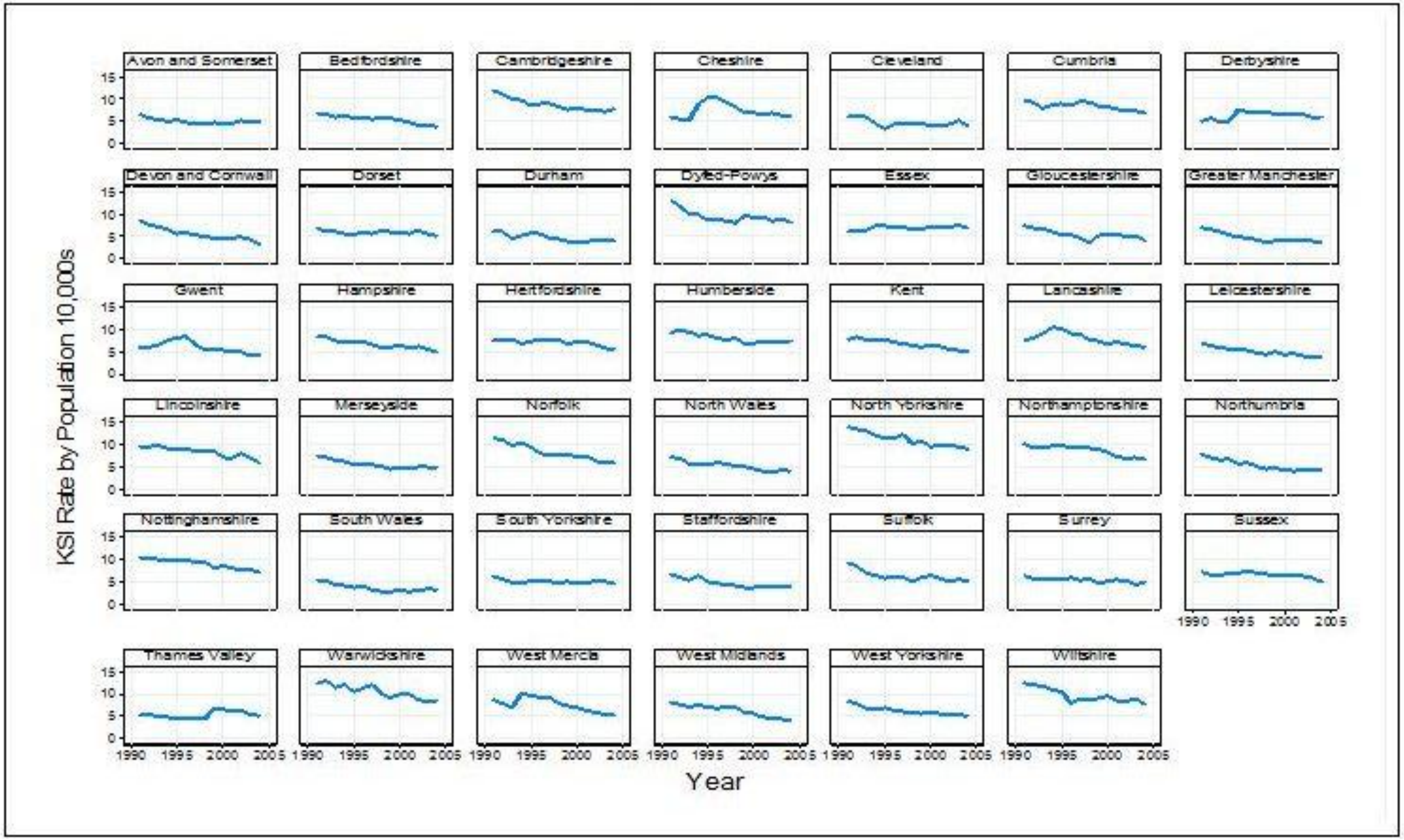


Figure 3: Annual Trend in Prosecutions by PFA 1997 to 2004

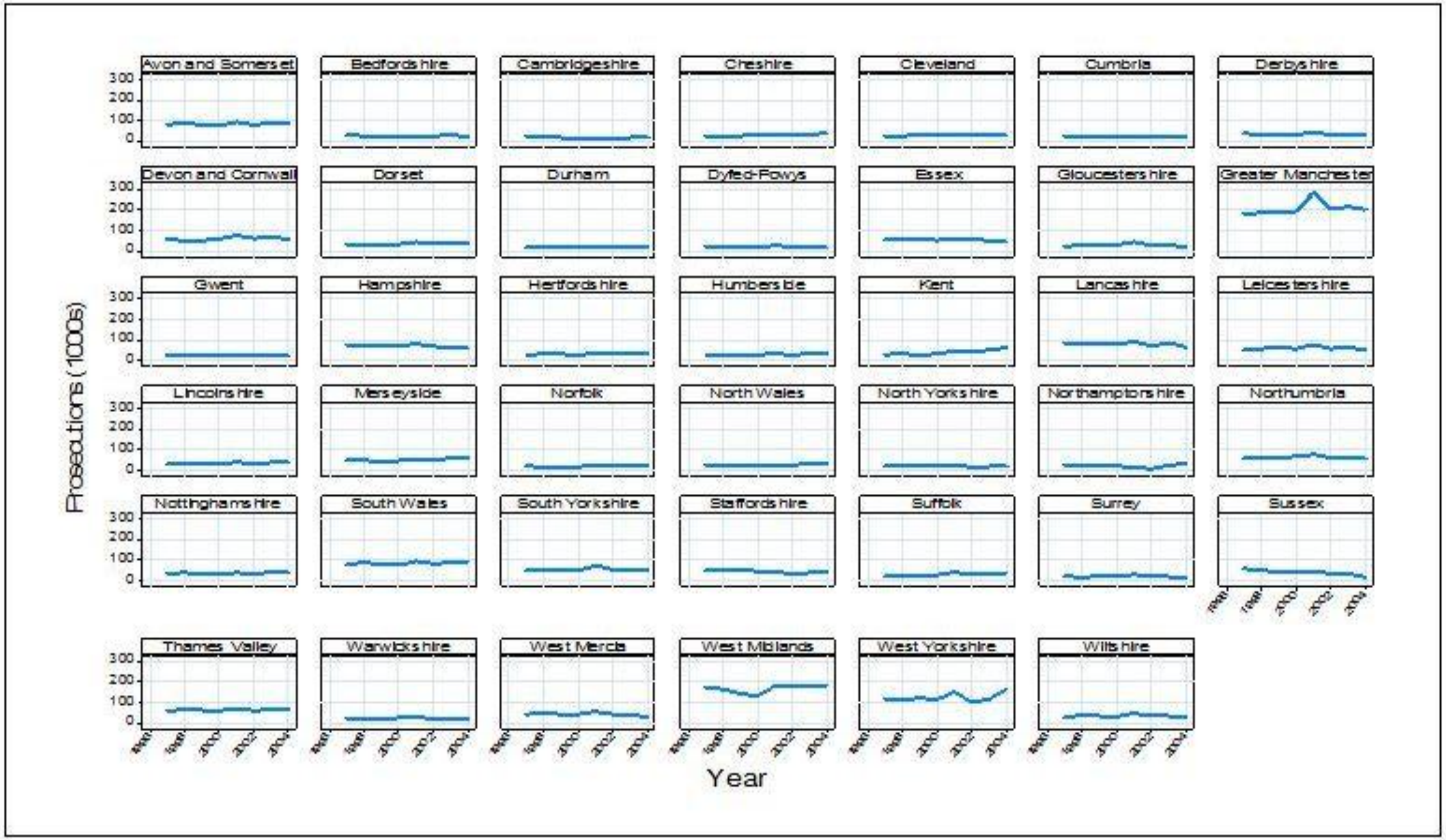


Figure 4: Annual Trend in FPN's by PFA 1997 to 2004

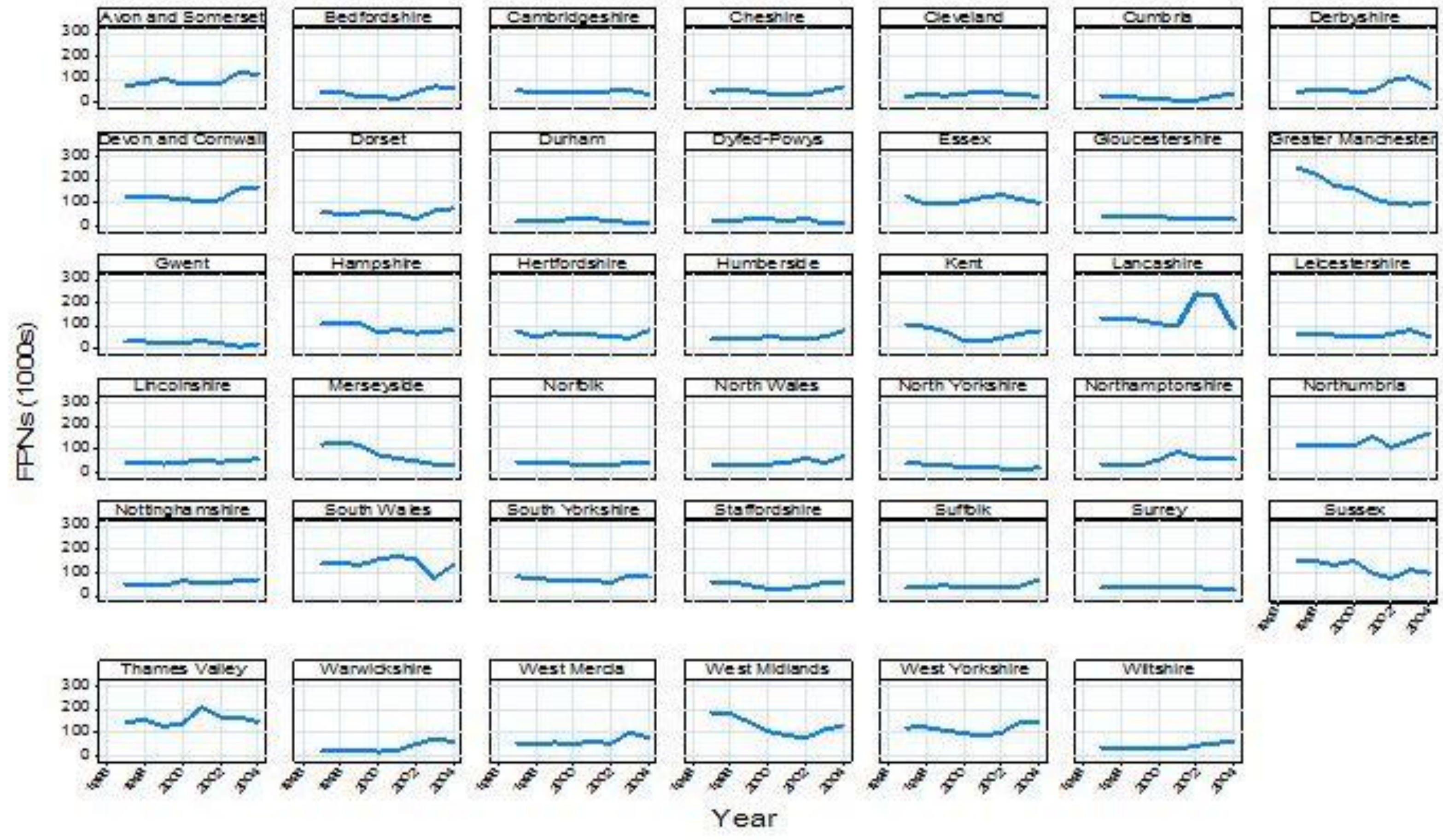


Figure 5: Annual Trend in VDRN's by PFA 1997 to 2004

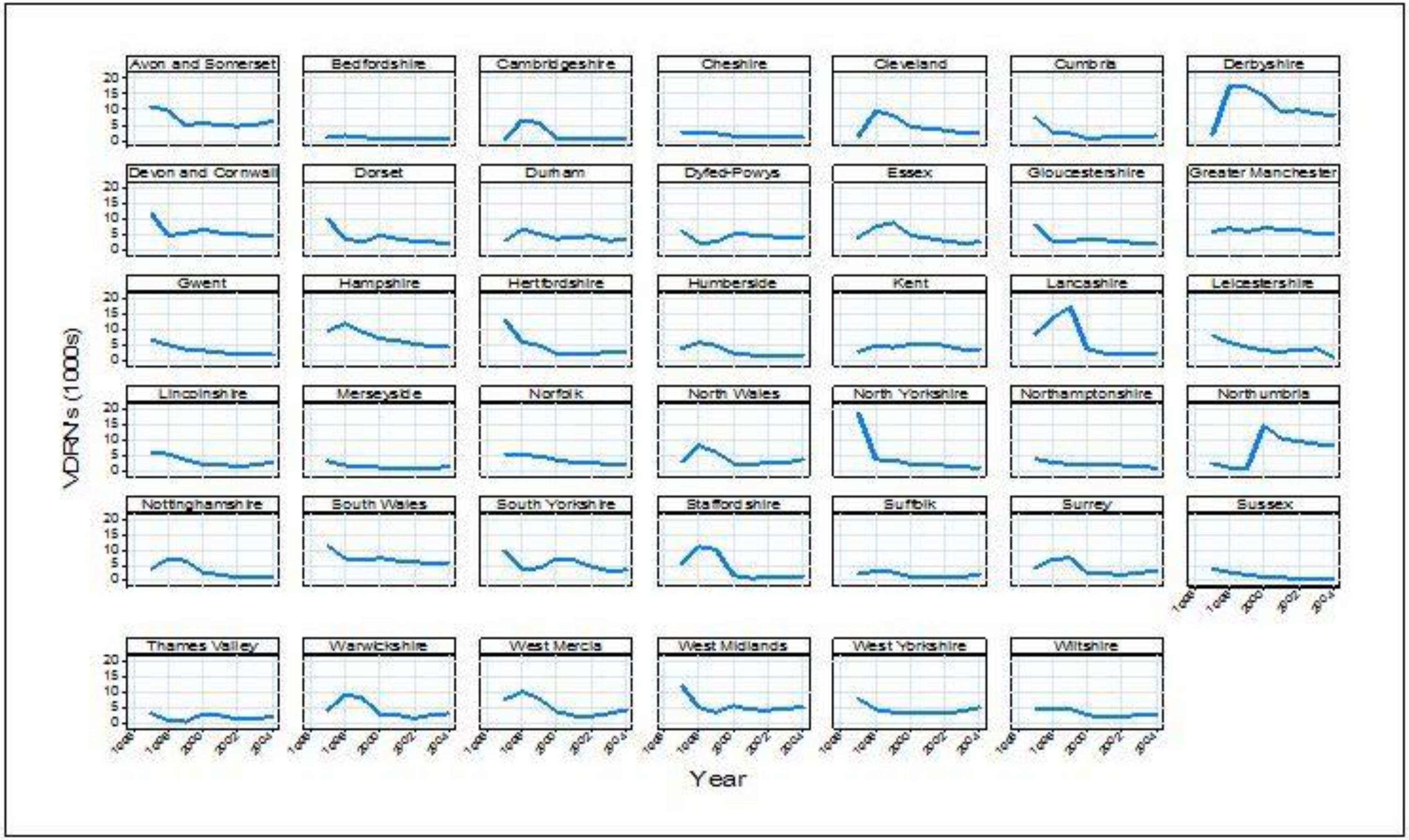
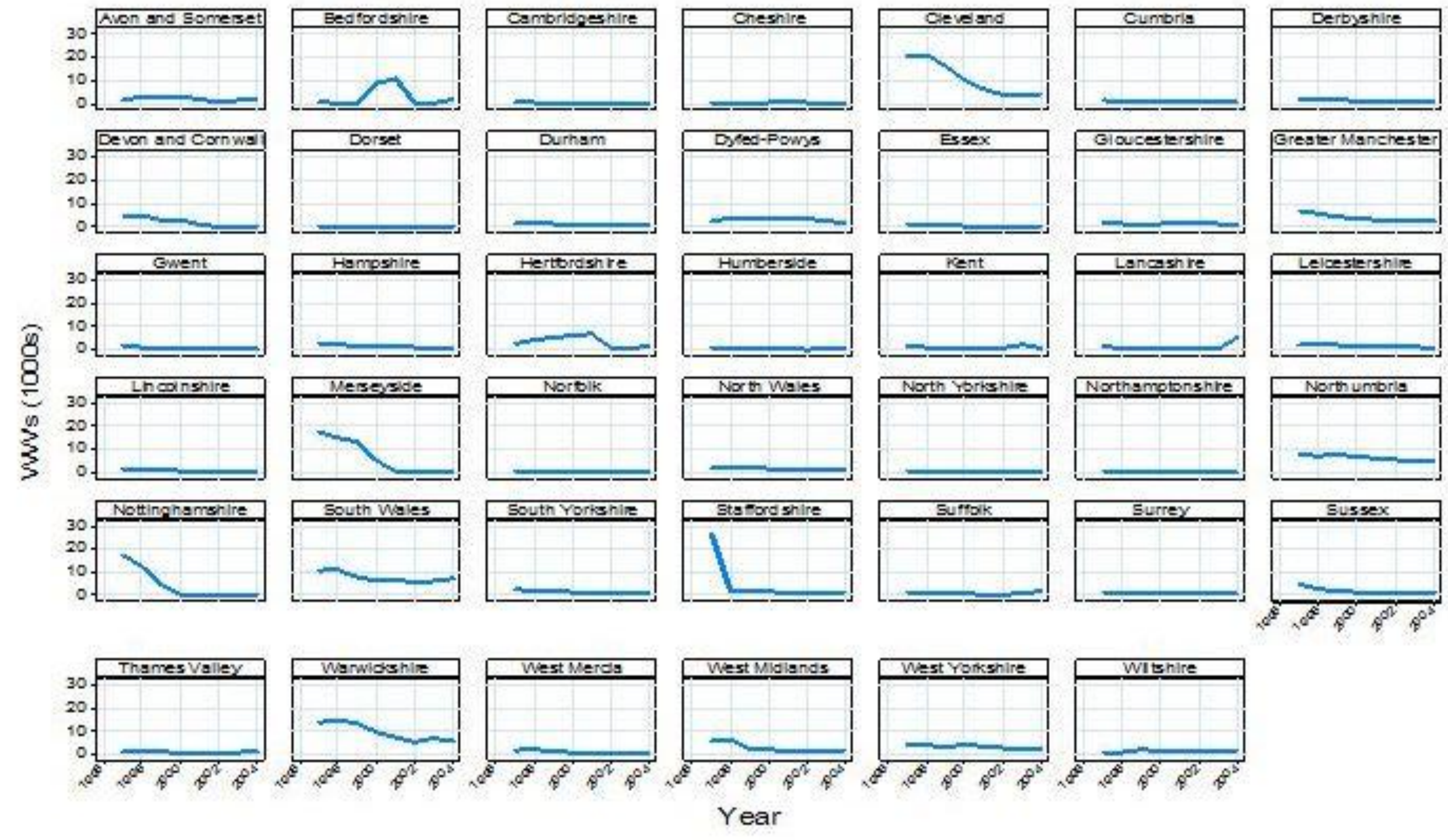


Figure 6: Annual Trend in WW's by PFA 1997 to 2004



Appendix 4:

Output from Annual Data

Table 1: Full Output from ZTP on Annual Data with Aggregate Proxy Variable and Offset lnpop

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Year	-0.0358	0.001	-27.84	0.0000	-0.0384	-0.0333
25 to 34	-0.0360	0.008	-4.74	0.0000	-0.0509	-0.0211
35 to 44	-0.3280	0.009	-38.14	0.0000	-0.3448	-0.3111
45 to 54	-0.6571	0.010	-63.10	0.0000	-0.6775	-0.6367
55 to 64	-1.0638	0.014	-76.28	0.0000	-1.0911	-1.0365
65 Plus	-0.8400	0.013	-66.45	0.0000	-0.8648	-0.8152
Female	-0.8332	0.008	-108.22	0.0000	-0.8483	-0.8181
speed limit 40	-1.4707	0.014	-107.15	0.0000	-1.4976	-1.4438
speed limit 50	-2.6508	0.048	-54.93	0.0000	-2.7454	-2.5562
speed limit 60	-0.2003	0.006	-30.89	0.0000	-0.2130	-0.1876
speed limit 70	-1.3127	0.014	-95.01	0.0000	-1.3398	-1.2857
HGV_LGV	-1.5239	0.015	-103.08	0.0000	-1.5528	-1.4949
Motorcycle	-1.0064	0.010	-104.71	0.0000	-1.0253	-0.9876
Other	-1.8850	0.020	-93.59	0.0000	-1.9244	-1.8455
Junction	0.0567	0.006	9.65	0.0000	0.0451	0.0682
Roundabout	-2.1875	0.094	-23.26	0.0000	-2.3718	-2.0031
Slippy	-2.4762	0.047	-52.20	0.0000	-2.5692	-2.3833
Snow	-4.4583	0.352	-12.68	0.0000	-5.1475	-3.7692
Wet	-0.5291	0.006	-82.21	0.0000	-0.5418	-0.5165
dark	-0.4618	0.006	-71.58	0.0000	-0.4744	-0.4491
Geographic Area sqkm	-0.0067	0.003	-2.03	0.0430	-0.0131	-0.0002
Mean Index of Multiple Deprivation	0.0518	0.003	15.39	0.0000	0.0452	0.0584
Percentage Motorway	-0.0238	0.003	-6.92	0.0000	-0.0306	-0.0171
All Penalties	-0.0699	0.003	-23.60	0.0000	-0.0757	-0.0641
Constant	63.0900	2.579	24.46	0.0000	58.0353	68.1446
lnpop	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n**[1]	**AIC**	**Pseudo R^2**
91504	-165143.4	-115061.7	25	230173.4	2.52	0.30

[1]AIC*n is the AIC reported by STATA 10

Table 2: Full Output from ZTP on Annual Lagged Data with Aggregate Proxy Variable and Offset lnpop

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Year	-0.0334	0.002	-20.87	0.0000	-0.0366	-0.0303
25 to 34	-0.0484	0.008	-5.83	0.0000	-0.0647	-0.0321
35 to 44	-0.3093	0.009	-33.36	0.0000	-0.3275	-0.2912
45 to 54	-0.6448	0.011	-57.15	0.0000	-0.6670	-0.6227
55 to 64	-1.0558	0.015	-69.71	0.0000	-1.0855	-1.0261
65 Plus	-0.8267	0.014	-60.44	0.0000	-0.8535	-0.7999
Female	-0.8342	0.008	-99.37	0.0000	-0.8506	-0.8177
speed limit 40	-1.4503	0.015	-97.81	0.0000	-1.4794	-1.4212
speed limit 50	-2.6093	0.051	-51.13	0.0000	-2.7094	-2.5093
speed limit 60	-0.1919	0.007	-27.21	0.0000	-0.2057	-0.1781
speed limit 70	-1.2815	0.015	-86.28	0.0000	-1.3106	-1.2524
HGV_LGV	-1.5282	0.016	-93.77	0.0000	-1.5601	-1.4962
Motorcycle	-0.9696	0.010	-94.66	0.0000	-0.9897	-0.9495
Other	-1.8600	0.022	-85.18	0.0000	-1.9027	-1.8172
Junction	0.0504	0.006	7.89	0.0000	0.0379	0.0629
Roundabout	-2.1913	0.094	-23.28	0.0000	-2.3757	-2.0068
Slippy	-2.4215	0.049	-49.46	0.0000	-2.5174	-2.3255
Snow	-4.3085	0.351	-12.26	0.0000	-4.9973	-3.6196
Wet	-0.5317	0.007	-75.86	0.0000	-0.5454	-0.5179
dark	-0.4539	0.007	-64.79	0.0000	-0.4677	-0.4402
Geographic Area sqkm	-0.0074	0.004	-2.09	0.0370	-0.0144	-0.0005
Mean Index of Multiple Deprivation	0.0465	0.004	12.75	0.0000	0.0393	0.0536
Percentage Motorway	-0.0261	0.004	-6.99	0.0000	-0.0335	-0.0188
Lag1 All Penalties	-0.0653	0.003	-20.40	0.0000	-0.0715	-0.0590
Constant	58.3151	3.208	18.18	0.0000	52.0285	64.6018
lnpop	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
79663	-140825.8	-98860.22	25	197770.4	2.48	0.30

[1]AIC*n is the AIC reported by STATA 10

Table 3: Full Output from ZTP on Annual Data with Aggregate Proxy Variable and Offset lnvkm

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Year	-0.0492	0.001	-38.33	0.0000	-0.0517	-0.0467
25 to 34	-0.0364	0.008	-4.78	0.0000	-0.0513	-0.0215
35 to 44	-0.3275	0.009	-38.09	0.0000	-0.3443	-0.3106
45 to 54	-0.6566	0.010	-63.06	0.0000	-0.6770	-0.6362
55 to 64	-1.0632	0.014	-76.23	0.0000	-1.0905	-1.0359
65 Plus	-0.8376	0.013	-66.26	0.0000	-0.8624	-0.8128
Female	-0.8315	0.008	-108.00	0.0000	-0.8466	-0.8164
speed limit 40	-1.4676	0.014	-106.90	0.0000	-1.4945	-1.4407
speed limit 50	-2.6537	0.048	-54.98	0.0000	-2.7483	-2.5591
speed limit 60	-0.2069	0.006	-31.92	0.0000	-0.2196	-0.1942
speed limit 70	-1.3170	0.014	-95.28	0.0000	-1.3441	-1.2899
HGV_LGV	-1.5236	0.015	-103.03	0.0000	-1.5525	-1.4946
Motorcycle	-1.0030	0.010	-104.35	0.0000	-1.0219	-0.9842
Other	-1.8819	0.020	-93.42	0.0000	-1.9214	-1.8424
Junction	0.0565	0.006	9.62	0.0000	0.0450	0.0680
Roundabout	-2.1888	0.094	-23.27	0.0000	-2.3732	-2.0044
Slippy	-2.4789	0.047	-52.24	0.0000	-2.5719	-2.3859
Snow	-4.4725	0.352	-12.72	0.0000	-5.1617	-3.7832
Wet	-0.5290	0.006	-82.19	0.0000	-0.5416	-0.5163
dark	-0.4598	0.006	-71.27	0.0000	-0.4724	-0.4471
Geographic Area sqkm	-0.0481	0.003	-14.55	0.0000	-0.0546	-0.0416
Mean Index of Multiple Deprivation	0.1763	0.003	51.31	0.0000	0.1695	0.1830
Percentage Motorway	-0.0964	0.003	-28.15	0.0000	-0.1031	-0.0897
All Penalties	-0.0176	0.003	-6.03	0.0000	-0.0234	-0.0119
Constant	92.2027	2.571	35.86	0.0000	87.1633	97.2421
lnvkm	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
91504	-168158.1	-115046.1	25	230142.3	2.52	0.32

[1]AIC*n is the AIC reported by STATA 10

Table.4: Full Output from ZTP on Annual Lagged Data with Aggregate Proxy Variable and Offset lnvkm

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Year	-0.0459	0.002	-28.79	0.0000	-0.0491	-0.0428
25 to 34	-0.0488	0.008	-5.87	0.0000	-0.0650	-0.0325
35 to 44	-0.3091	0.009	-33.34	0.0000	-0.3273	-0.2910
45 to 54	-0.6444	0.011	-57.12	0.0000	-0.6665	-0.6223
55 to 64	-1.0555	0.015	-69.69	0.0000	-1.0852	-1.0258
65 Plus	-0.8245	0.014	-60.27	0.0000	-0.8513	-0.7977
Female	-0.8324	0.008	-99.16	0.0000	-0.8489	-0.8160
speed limit 40	-1.4473	0.015	-97.58	0.0000	-1.4764	-1.4182
speed limit 50	-2.6132	0.051	-51.20	0.0000	-2.7132	-2.5132
speed limit 60	-0.1986	0.007	-28.17	0.0000	-0.2124	-0.1847
speed limit 70	-1.2857	0.015	-86.53	0.0000	-1.3148	-1.2565
HGV_LGV	-1.5274	0.016	-93.69	0.0000	-1.5594	-1.4955
Motorcycle	-0.9665	0.010	-94.35	0.0000	-0.9866	-0.9464
Other	-1.8570	0.022	-85.03	0.0000	-1.8998	-1.8142
Junction	0.0501	0.006	7.86	0.0000	0.0376	0.0626
Roundabout	-2.1967	0.094	-23.33	0.0000	-2.3812	-2.0122
Slippy	-2.4223	0.049	-49.46	0.0000	-2.5183	-2.3264
Snow	-4.3194	0.351	-12.29	0.0000	-5.0083	-3.6305
Wet	-0.5316	0.007	-75.85	0.0000	-0.5453	-0.5178
dark	-0.4517	0.007	-64.47	0.0000	-0.4655	-0.4380
Geographic Area sqkm	-0.0487	0.004	-13.56	0.0000	-0.0558	-0.0417
Mean Index of Multiple Deprivation	0.1714	0.004	46.06	0.0000	0.1641	0.1787
Percentage Motorway	-0.0994	0.004	-26.68	0.0000	-0.1067	-0.0921
Lag1 All Penalties	-0.0138	0.003	-4.37	0.0000	-0.0200	-0.0076
Constant	85.7288	3.196	26.82	0.0000	79.4648	91.9927
lnvkm	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
79663	-143292.6	-98876.9	25	197803.8	2.48	0.31

[1]AIC*n is the AIC reported by STATA 10

Table 5: Full Output from ZTP on Annual Data with Offset lnpop.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Year	-0.0439	0.001	-29.48	0.0000	-0.0468	-0.0409
25 to 34	-0.0360	0.008	-4.73	0.0000	-0.0509	-0.0211
35 to 44	-0.3279	0.009	-38.12	0.0000	-0.3447	-0.3110
45 to 54	-0.6573	0.010	-63.11	0.0000	-0.6777	-0.6369
55 to 64	-1.0649	0.014	-76.35	0.0000	-1.0923	-1.0376
65 Plus	-0.8410	0.013	-66.52	0.0000	-0.8658	-0.8162
Female	-0.8344	0.008	-108.36	0.0000	-0.8495	-0.8194
speed limit 40	-1.4719	0.014	-107.23	0.0000	-1.4988	-1.4450
speed limit 50	-2.6463	0.048	-54.85	0.0000	-2.7408	-2.5517
speed limit 60	-0.1981	0.006	-30.51	0.0000	-0.2108	-0.1854
speed limit 70	-1.3099	0.014	-94.77	0.0000	-1.3370	-1.2828
HGV_LGV	-1.5269	0.015	-103.27	0.0000	-1.5558	-1.4979
Motorcycle	-1.0075	0.010	-104.80	0.0000	-1.0263	-0.9886
Other	-1.8873	0.020	-93.71	0.0000	-1.9267	-1.8478
Junction	0.0567	0.006	9.65	0.0000	0.0452	0.0682
Roundabout	-2.1736	0.094	-23.12	0.0000	-2.3579	-1.9894
Slippy	-2.4806	0.047	-52.31	0.0000	-2.5736	-2.3877
Snow	-4.4606	0.352	-12.69	0.0000	-5.1497	-3.7714
Wet	-0.5302	0.006	-82.35	0.0000	-0.5428	-0.5175
dark	-0.4626	0.006	-71.69	0.0000	-0.4752	-0.4499
Mean Index of Multiple Deprivation	0.0473	0.004	12.89	0.0000	0.0401	0.0545
Percentage Motorway	-0.0287	0.003	-8.22	0.0000	-0.0356	-0.0219
Prosecutions	0.0034	0.004	0.95	0.3400	-0.0036	0.0104
FPN	-0.0720	0.004	-19.98	0.0000	-0.0791	-0.0649
VDRN	-0.0206	0.003	-6.45	0.0000	-0.0269	-0.0144
WW	-0.0265	0.004	-6.96	0.0000	-0.0339	-0.0190
Constant	79.1260	2.980	26.55	0.0000	73.2857	84.9663
lnpop	(offset)					
	Model Information Criteria					
Number Obs	ll(null)	ll(model)	df	AIC*n[1]	AIC	Pseudo R^2
91504	-165143	-114962	28	229980	2.51	0.30

[1]AIC*n is the AIC reported by STATA 10

Table 6: Full Output from ZTP on Annual Data with Offset lnvkm.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Year	-0.0599	0.001	-40.66	0.0000	-0.0628	-0.0570
25 to 34	-0.0363	0.008	-4.77	0.0000	-0.0512	-0.0214
35 to 44	-0.3275	0.009	-38.08	0.0000	-0.3443	-0.3106
45 to 54	-0.6573	0.010	-63.11	0.0000	-0.6777	-0.6369
55 to 64	-1.0650	0.014	-76.35	0.0000	-1.0923	-1.0376
65 Plus	-0.8391	0.013	-66.37	0.0000	-0.8639	-0.8144
Female	-0.8334	0.008	-108.21	0.0000	-0.8485	-0.8183
speed limit 40	-1.4699	0.014	-107.07	0.0000	-1.4968	-1.4430
speed limit 50	-2.6490	0.048	-54.90	0.0000	-2.7436	-2.5544
speed limit 60	-0.2046	0.006	-31.52	0.0000	-0.2173	-0.1919
speed limit 70	-1.3140	0.014	-95.04	0.0000	-1.3411	-1.2869
HGV_LGV	-1.5278	0.015	-103.31	0.0000	-1.5568	-1.4989
Motorcycle	-1.0049	0.010	-104.51	0.0000	-1.0237	-0.9860
Other	-1.8855	0.020	-93.61	0.0000	-1.9249	-1.8460
Junction	0.0564	0.006	9.60	0.0000	0.0449	0.0679
Roundabout	-2.1713	0.094	-23.09	0.0000	-2.3556	-1.9870
Slippy	-2.4850	0.047	-52.39	0.0000	-2.5779	-2.3920
Snow	-4.4755	0.352	-12.73	0.0000	-5.1647	-3.7863
Wet	-0.5304	0.006	-82.38	0.0000	-0.5430	-0.5177
dark	-0.4609	0.006	-71.43	0.0000	-0.4735	-0.4482
Geographic Area sqkm	-0.0409	0.003	-11.91	0.0000	-0.0477	-0.0342
Mean Index of Multiple Deprivation	0.1758	0.004	46.73	0.0000	0.1685	0.1832
Percentage Motorway	-0.1031	0.004	-29.45	0.0000	-0.1100	-0.0963
Prosecutions	0.0321	0.004	9.07	0.0000	0.0252	0.0391
FPN	-0.0418	0.004	-11.79	0.0000	-0.0487	-0.0348
VDRN	-0.0219	0.003	-6.94	0.0000	-0.0281	-0.0157
WW	-0.0423	0.004	-11.03	0.0000	-0.0498	-0.0348
Constant	113.5627	2.949	38.50	0.0000	107.7821	119.3400
lnvkm	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
91504	-168158	-114884	28	229824	2.51	0.32

[1]AIC*n is the AIC reported by STATA 10

Table 7: Full Output from ZTP on Annual Lagged Data with Offset lnpop.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Year	-0.0447	0.002	-24.05	0.0000	-0.0484	-0.0411
25 to 34	-0.0482	0.008	-5.81	0.0000	-0.0645	-0.0320
35 to 44	-0.3093	0.009	-33.35	0.0000	-0.3275	-0.2912
45 to 54	-0.6449	0.011	-57.15	0.0000	-0.6670	-0.6228
55 to 64	-1.0569	0.015	-69.77	0.0000	-1.0866	-1.0272
65 Plus	-0.8272	0.014	-60.46	0.0000	-0.8541	-0.8004
Female	-0.8354	0.008	-99.49	0.0000	-0.8518	-0.8189
speed limit 40	-1.4517	0.015	-97.90	0.0000	-1.4808	-1.4227
speed limit 50	-2.6045	0.051	-51.04	0.0000	-2.7046	-2.5045
speed limit 60	-0.1902	0.007	-26.94	0.0000	-0.2041	-0.1764
speed limit 70	-1.2789	0.015	-86.08	0.0000	-1.3080	-1.2498
HGV_LGV	-1.5313	0.016	-93.95	0.0000	-1.5632	-1.4993
Motorcycle	-0.9705	0.010	-94.72	0.0000	-0.9906	-0.9504
Other	-1.8622	0.022	-85.29	0.0000	-1.9050	-1.8194
Junction	0.0504	0.006	7.90	0.0000	0.0379	0.0629
Roundabout	-2.1795	0.094	-23.17	0.0000	-2.3638	-1.9951
Slippy	-2.4237	0.049	-49.51	0.0000	-2.5197	-2.3278
Snow	-4.3118	0.351	-12.27	0.0000	-5.0006	-3.6230
Wet	-0.5326	0.007	-75.97	0.0000	-0.5463	-0.5188
dark	-0.4547	0.007	-64.88	0.0000	-0.4684	-0.4409
Mean Index of Multiple Deprivation	0.0457	0.004	11.45	0.0000	0.0379	0.0535
Percentage Motorway	-0.0303	0.004	-8.00	0.0000	-0.0377	-0.0229
Lag Prosecutions	0.0024	0.004	0.61	0.5410	-0.0053	0.0100
Lag FPN	-0.0641	0.004	-16.62	0.0000	-0.0716	-0.0565
Lag VDRN	-0.0268	0.003	-7.93	0.0000	-0.0335	-0.0202
Lag WW	-0.0301	0.004	-7.45	0.0000	-0.0380	-0.0222
Constant	80.8949	3.722	21.74	0.0000	73.6007	88.1892
lnpop	(offset)					
	Model Information Criteria					
Number Obs	ll(null)	ll(model)	df	AIC*n[1]	AIC	Pseudo R^2
79663	-140826	-98773	28	197601	2.48	0.30

[1]AIC*n is the AIC reported by STATA 10

Table 8: Full Output from ZTP on Annual Lagged Data with Offset Invkm.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Year	-0.0597	0.002	-32.52	0.0000	-0.0633	-0.0561
25 to 34	-0.0486	0.008	-5.85	0.0000	-0.0648	-0.0323
35 to 44	-0.3092	0.009	-33.34	0.0000	-0.3274	-0.2910
45 to 54	-0.6447	0.011	-57.13	0.0000	-0.6668	-0.6226
55 to 64	-1.0572	0.015	-69.79	0.0000	-1.0869	-1.0275
65 Plus	-0.8253	0.014	-60.32	0.0000	-0.8521	-0.7985
Female	-0.8341	0.008	-99.33	0.0000	-0.8505	-0.8176
speed limit 40	-1.4498	0.015	-97.75	0.0000	-1.4789	-1.4207
speed limit 50	-2.6087	0.051	-51.12	0.0000	-2.7087	-2.5087
speed limit 60	-0.1970	0.007	-27.91	0.0000	-0.2109	-0.1832
speed limit 70	-1.2830	0.015	-86.33	0.0000	-1.3121	-1.2539
HGV_LGV	-1.5316	0.016	-93.95	0.0000	-1.5635	-1.4996
Motorcycle	-0.9681	0.010	-94.48	0.0000	-0.9882	-0.9480
Other	-1.8603	0.022	-85.20	0.0000	-1.9031	-1.8175
Junction	0.0501	0.006	7.84	0.0000	0.0376	0.0626
Roundabout	-2.1832	0.094	-23.20	0.0000	-2.3677	-1.9988
Slippy	-2.4255	0.049	-49.54	0.0000	-2.5214	-2.3295
Snow	-4.3239	0.351	-12.30	0.0000	-5.0127	-3.6350
Wet	-0.5328	0.007	-76.01	0.0000	-0.5465	-0.5190
dark	-0.4526	0.007	-64.59	0.0000	-0.4664	-0.4389
Geographic Area sqkm	-0.0429	0.004	-11.52	0.0000	-0.0502	-0.0356
Mean Index of Multiple Deprivation	0.1756	0.004	42.98	0.0000	0.1676	0.1836
Percentage Motorway	-0.1053	0.004	-27.74	0.0000	-0.1127	-0.0978
Lag Prosecutions	0.0287	0.004	7.44	0.0000	0.0211	0.0363
Lag FPN	-0.0332	0.004	-8.77	0.0000	-0.0406	-0.0258
Lag VDRN	-0.0262	0.003	-7.85	0.0000	-0.0328	-0.0197
Lag WW	-0.0449	0.004	-11.02	0.0000	-0.0529	-0.0369
Constant	113.2790	3.676	30.81	0.0000	106.0737	120.4843
Invkm	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
79663	-143293	-98741	28	197538	2.48	0.31

[1]AIC*n is the AIC reported by STATA 10

Table 9: Full Output from ZTP on Annual Data with Speeding Related FPN's (FPN_G16) and Offset Inpop.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Year	-0.0306	0.002	-18.95	0.0000	-0.0337	-0.0274
25 to 34	-0.0361	0.008	-4.74	0.0000	-0.0510	-0.0212
35 to 44	-0.3282	0.009	-38.16	0.0000	-0.3451	-0.3114
45 to 54	-0.6585	0.010	-63.22	0.0000	-0.6789	-0.6381
55 to 64	-1.0662	0.014	-76.44	0.0000	-1.0935	-1.0389
65 Plus	-0.8427	0.013	-66.65	0.0000	-0.8675	-0.8179
Female	-0.8352	0.008	-108.45	0.0000	-0.8503	-0.8201
speed limit 40	-1.4750	0.014	-107.48	0.0000	-1.5019	-1.4481
speed limit 50	-2.6485	0.048	-54.90	0.0000	-2.7430	-2.5540
speed limit 60	-0.1966	0.006	-30.28	0.0000	-0.2093	-0.1839
speed limit 70	-1.3114	0.014	-94.90	0.0000	-1.3385	-1.2843
HGV_LGV	-1.5283	0.015	-103.39	0.0000	-1.5573	-1.4994
Motorcycle	-1.0089	0.010	-104.95	0.0000	-1.0277	-0.9901
Other	-1.8901	0.020	-93.87	0.0000	-1.9295	-1.8506
Junction	0.0569	0.006	9.69	0.0000	0.0454	0.0684
Roundabout	-2.1827	0.094	-23.21	0.0000	-2.3670	-1.9985
Slippy	-2.4807	0.047	-52.32	0.0000	-2.5736	-2.3877
Snow	-4.4613	0.352	-12.69	0.0000	-5.1504	-3.7722
Wet	-0.5309	0.006	-82.45	0.0000	-0.5435	-0.5183
dark	-0.4628	0.006	-71.72	0.0000	-0.4754	-0.4501
Mean Index of Multiple Deprivation	0.0456	0.004	12.32	0.0000	0.0383	0.0529
Percentage Motorway	-0.0207	0.004	-5.84	0.0000	-0.0276	-0.0137
Prosecutions	-0.0246	0.003	-8.03	0.0000	-0.0306	-0.0186
FPN G16	-0.0556	0.003	-16.26	0.0000	-0.0623	-0.0489
VDRN	-0.0183	0.003	-5.75	0.0000	-0.0245	-0.0121
WW	-0.0356	0.004	-9.31	0.0000	-0.0431	-0.0281
Constant	52.5122	3.229	16.26	0.0000	46.1842	58.8402
lnpop	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
91504	-165143	-115027	28	230110	2.51	0.30

[1]AIC*n is the AIC reported by STATA 10

Table 10: Full Output from ZTP on Annual Data with Speeding Related FPN's (FPN_G16) and Offset lnvkm.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Year	-0.0502	0.002	-31.40	0.0000	-0.0534	-0.0471
25 to 34	-0.0364	0.008	-4.78	0.0000	-0.0513	-0.0215
35 to 44	-0.3276	0.009	-38.09	0.0000	-0.3445	-0.3108
45 to 54	-0.6579	0.010	-63.17	0.0000	-0.6783	-0.6375
55 to 64	-1.0657	0.014	-76.40	0.0000	-1.0930	-1.0384
65 Plus	-0.8401	0.013	-66.44	0.0000	-0.8649	-0.8153
Female	-0.8337	0.008	-108.25	0.0000	-0.8488	-0.8186
speed limit 40	-1.4715	0.014	-107.20	0.0000	-1.4984	-1.4446
speed limit 50	-2.6487	0.048	-54.90	0.0000	-2.7433	-2.5541
speed limit 60	-0.2036	0.006	-31.36	0.0000	-0.2163	-0.1909
speed limit 70	-1.3141	0.014	-95.05	0.0000	-1.3412	-1.2870
HGV_LGV	-1.5285	0.015	-103.37	0.0000	-1.5575	-1.4995
Motorcycle	-1.0054	0.010	-104.57	0.0000	-1.0243	-0.9866
Other	-1.8868	0.020	-93.69	0.0000	-1.9262	-1.8473
Junction	0.0566	0.006	9.64	0.0000	0.0451	0.0681
Roundabout	-2.1755	0.094	-23.13	0.0000	-2.3598	-1.9912
Slippy	-2.4845	0.047	-52.38	0.0000	-2.5775	-2.3916
Snow	-4.4765	0.352	-12.73	0.0000	-5.1656	-3.7873
Wet	-0.5307	0.006	-82.44	0.0000	-0.5434	-0.5181
dark	-0.4609	0.006	-71.43	0.0000	-0.4736	-0.4483
Geographic Area sqkm	-0.0396	0.003	-11.54	0.0000	-0.0463	-0.0329
Mean Index of Multiple Deprivation	0.1736	0.004	45.92	0.0000	0.1662	0.1810
Percentage Motorway	-0.0963	0.004	-27.15	0.0000	-0.1033	-0.0894
Prosecutions	0.0182	0.003	6.04	0.0000	0.0123	0.0242
FPN G16	-0.0428	0.003	-12.70	0.0000	-0.0495	-0.0362
VDRN	-0.0209	0.003	-6.62	0.0000	-0.0271	-0.0147
WW	-0.0466	0.004	-12.17	0.0000	-0.0542	-0.0391
Constant	94.2594	3.203	29.43	0.0000	87.9815	100.5373
lnvkm	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
91504	-168158	-114871	28	229798	2.51	0.31

[1]AIC*n is the AIC reported by STATA 10

Table 11: Full Output from ZTP on Annual Lagged Data with Speeding Related FPN's (FPN_G16) and Offset lnpop.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Year	-0.0312	0.002	-15.89	0.0000	-0.0350	-0.0273
25 to 34	-0.0485	0.008	-5.84	0.0000	-0.0648	-0.0322
35 to 44	-0.3098	0.009	-33.40	0.0000	-0.3280	-0.2916
45 to 54	-0.6459	0.011	-57.23	0.0000	-0.6680	-0.6238
55 to 64	-1.0581	0.015	-69.85	0.0000	-1.0878	-1.0284
65 Plus	-0.8284	0.014	-60.54	0.0000	-0.8552	-0.8016
Female	-0.8360	0.008	-99.57	0.0000	-0.8525	-0.8196
speed limit 40	-1.4548	0.015	-98.12	0.0000	-1.4838	-1.4257
speed limit 50	-2.6067	0.051	-51.09	0.0000	-2.7067	-2.5067
speed limit 60	-0.1889	0.007	-26.74	0.0000	-0.2027	-0.1750
speed limit 70	-1.2810	0.015	-86.24	0.0000	-1.3101	-1.2519
HGV_LGV	-1.5326	0.016	-94.05	0.0000	-1.5645	-1.5007
Motorcycle	-0.9718	0.010	-94.85	0.0000	-0.9919	-0.9517
Other	-1.8648	0.022	-85.43	0.0000	-1.9076	-1.8220
Junction	0.0504	0.006	7.90	0.0000	0.0379	0.0629
Roundabout	-2.1736	0.094	-23.10	0.0000	-2.3581	-1.9892
Slippy	-2.4251	0.049	-49.55	0.0000	-2.5210	-2.3291
Snow	-4.3113	0.351	-12.27	0.0000	-5.0001	-3.6225
Wet	-0.5333	0.007	-76.07	0.0000	-0.5470	-0.5196
dark	-0.4546	0.007	-64.87	0.0000	-0.4684	-0.4409
Mean Index of Multiple Deprivation	0.0442	0.004	10.98	0.0000	0.0363	0.0521
Percentage Motorway	-0.0230	0.004	-5.95	0.0000	-0.0305	-0.0154
Lag Prosecutions	-0.0239	0.003	-7.20	0.0000	-0.0304	-0.0174
Lag FPN 16	-0.0492	0.004	-13.46	0.0000	-0.0564	-0.0420
Lag VDRN	-0.0242	0.003	-7.21	0.0000	-0.0308	-0.0177
Lag WW	-0.0373	0.004	-9.16	0.0000	-0.0453	-0.0293
Constant	53.8009	3.927	13.70	0.0000	46.1037	61.4981
lnpop	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
79663	-140826	-98819	28	197693	2.48	0.30

[1]AIC*n is the AIC reported by STATA 10

Table 12: Full Output from ZTP on Annual Lagged Data with Speeding Related FPN's (FPN_G16) and Offset Invkm.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Year	-0.0504	0.002	-25.91	0.0000	-0.0542	-0.0466
25 to 34	-0.0488	0.008	-5.87	0.0000	-0.0650	-0.0325
35 to 44	-0.3094	0.009	-33.36	0.0000	-0.3276	-0.2912
45 to 54	-0.6451	0.011	-57.16	0.0000	-0.6672	-0.6229
55 to 64	-1.0578	0.015	-69.83	0.0000	-1.0875	-1.0281
65 Plus	-0.8258	0.014	-60.36	0.0000	-0.8527	-0.7990
Female	-0.8343	0.008	-99.35	0.0000	-0.8507	-0.8178
speed limit 40	-1.4512	0.015	-97.86	0.0000	-1.4803	-1.4221
speed limit 50	-2.6077	0.051	-51.10	0.0000	-2.7077	-2.5077
speed limit 60	-0.1962	0.007	-27.79	0.0000	-0.2100	-0.1824
speed limit 70	-1.2833	0.015	-86.36	0.0000	-1.3125	-1.2542
HGV_LGV	-1.5321	0.016	-93.99	0.0000	-1.5641	-1.5002
Motorcycle	-0.9684	0.010	-94.51	0.0000	-0.9885	-0.9483
Other	-1.8613	0.022	-85.25	0.0000	-1.9041	-1.8186
Junction	0.0501	0.006	7.85	0.0000	0.0376	0.0626
Roundabout	-2.1740	0.094	-23.10	0.0000	-2.3585	-1.9896
Slippy	-2.4258	0.049	-49.55	0.0000	-2.5218	-2.3298
Snow	-4.3241	0.351	-12.30	0.0000	-5.0129	-3.6353
Wet	-0.5331	0.007	-76.05	0.0000	-0.5468	-0.5193
dark	-0.4525	0.007	-64.57	0.0000	-0.4662	-0.4387
Geographic Area sqkm	-0.0406	0.004	-10.89	0.0000	-0.0479	-0.0333
Mean Index of Multiple Deprivation	0.1732	0.004	42.21	0.0000	0.1652	0.1812
Percentage Motorway	-0.0986	0.004	-25.56	0.0000	-0.1062	-0.0911
Lag Prosecutions	0.0178	0.003	5.46	0.0000	0.0114	0.0242
Lag FPN 16	-0.0379	0.004	-10.50	0.0000	-0.0450	-0.0308
Lag VDRN	-0.0255	0.003	-7.65	0.0000	-0.0320	-0.0190
Lag WW	-0.0476	0.004	-11.70	0.0000	-0.0556	-0.0397
Constant	94.6673	3.895	24.31	0.0000	87.0341	102.3004
Invkm	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n**[1]	**AIC**	**Pseudo R^2**
79663	-143293	-98723	28	197502	2.48	0.32

[1]AIC*n is the AIC reported by STATA 10

Output from Quarterly Data

Table 13: Full Output from ZTP on Quarterly Data with Offset lnpop.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Year	-0.0212	0.004	-4.97	0.0000	-0.0296	-0.0129
Quarter 2	0.2616	0.018	14.58	0.0000	0.2264	0.2968
Quarter 3	0.2801	0.017	16.24	0.0000	0.2463	0.3139
Quarter 4	0.1441	0.018	8.16	0.0000	0.1095	0.1787
25 to 34	-0.0358	0.014	-2.53	0.0110	-0.0635	-0.0081
35 to 44	-0.2632	0.016	-16.35	0.0000	-0.2948	-0.2316
45 to 54	-0.6169	0.021	-29.67	0.0000	-0.6576	-0.5761
55 to 64	-1.0336	0.030	-35.02	0.0000	-1.0915	-0.9758
65 Plus	-0.7408	0.025	-29.60	0.0000	-0.7898	-0.6917
Female	-0.8318	0.016	-51.96	0.0000	-0.8632	-0.8004
speed limit 40	-1.4969	0.032	-46.94	0.0000	-1.5594	-1.4343
speed limit 50	-2.5752	0.115	-22.30	0.0000	-2.8016	-2.3489
speed limit 60	-0.0271	0.013	-2.13	0.0330	-0.0519	-0.0022
speed limit 70	-1.1194	0.030	-37.66	0.0000	-1.1777	-1.0612
HGV_LGV	-1.5587	0.035	-44.21	0.0000	-1.6278	-1.4896
Motorcycle	-0.7267	0.018	-41.05	0.0000	-0.7614	-0.6920
Other	-1.8083	0.046	-39.23	0.0000	-1.8987	-1.7180
Junction	0.0458	0.011	4.01	0.0000	0.0234	0.0681
Roundabout	-2.1986	0.070	-31.21	0.0000	-2.3367	-2.0606
Slippy	-1.9243	0.086	-22.26	0.0000	-2.0937	-1.7549
Snow	-3.5711	0.575	-6.21	0.0000	-4.6990	-2.4432
Wet	-0.3872	0.013	-30.34	0.0000	-0.4123	-0.3622
dark	-0.2936	0.012	-23.61	0.0000	-0.3180	-0.2692
Geographic Area sqkm	0.0027	0.006	0.42	0.6730	-0.0099	0.0153
Mean Index of Multiple Deprivation	0.0777	0.006	12.33	0.0000	0.0654	0.0901
Percentage Motorway	-0.0417	0.007	-6.37	0.0000	-0.0545	-0.0288
All Penalties	-0.0423	0.006	-7.11	0.0000	-0.0539	-0.0306
Constant	33.1262	8.558	3.87	0.0000	16.3520	49.9004
lnpop	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
77868	-76967.3	-53372.8	28	106801.7	1.37	0.31

[1]AIC*n is the AIC reported by STATA 10

Table 14: Full Output from ZTP on Quarterly Lagged Data with Offset lnpop.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Year	-0.0239	0.004	-5.82	0.0000	-0.0319	-0.0158
Quarter 2	0.2852	0.017	16.46	0.0000	0.2512	0.3191
Quarter 3	0.3110	0.017	18.67	0.0000	0.2783	0.3436
Quarter 4	0.1618	0.017	9.52	0.0000	0.1285	0.1951
25 to 34	-0.0394	0.014	-2.83	0.0050	-0.0667	-0.0121
35 to 44	-0.2645	0.016	-16.67	0.0000	-0.2956	-0.2334
45 to 54	-0.6192	0.021	-30.18	0.0000	-0.6594	-0.5790
55 to 64	-1.0371	0.029	-35.64	0.0000	-1.0941	-0.9800
65 Plus	-0.7461	0.025	-30.20	0.0000	-0.7945	-0.6976
Female	-0.8340	0.016	-52.83	0.0000	-0.8649	-0.8031
speed limit 40	-1.4828	0.031	-47.53	0.0000	-1.5439	-1.4216
speed limit 50	-2.5715	0.114	-22.56	0.0000	-2.7949	-2.3481
speed limit 60	-0.0256	0.013	-2.04	0.0410	-0.0502	-0.0010
speed limit 70	-1.1228	0.029	-38.26	0.0000	-1.1804	-1.0653
HGV_LGV	-1.5557	0.035	-44.14	0.0000	-1.6248	-1.4867
Motorcycle	-0.7237	0.018	-40.95	0.0000	-0.7584	-0.6891
Other	-1.8041	0.046	-39.15	0.0000	-1.8944	-1.7137
Junction	0.0441	0.011	3.92	0.0000	0.0221	0.0662
Roundabout	-2.1862	0.069	-31.58	0.0000	-2.3219	-2.0505
Slippy	-1.8993	0.083	-22.95	0.0000	-2.0614	-1.7371
Snow	-3.0626	0.406	-7.54	0.0000	-3.8587	-2.2665
Wet	-0.3771	0.013	-30.14	0.0000	-0.4017	-0.3526
dark	-0.2775	0.012	-22.77	0.0000	-0.3014	-0.2536
Geographic Area sqkm	0.0013	0.006	0.20	0.8420	-0.0111	0.0137
Mean Index of Multiple Deprivation	0.0833	0.006	13.18	0.0000	0.0709	0.0957
Percentage Motorway	-0.0400	0.006	-6.18	0.0000	-0.0527	-0.0273
Lag1 All Penalties	-0.0275	0.007	-4.02	0.0000	-0.0409	-0.0141
Lag2 All Penalties	-0.0230	0.007	-3.47	0.0010	-0.0360	-0.0100
Constant	38.5272	8.205	4.70	0.0000	22.4463	54.6081
lnpop	(offset)					

	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
80584	-79432	-55112.4	29	110282.9	1.37	0.31

[1]AIC*n is the AIC reported by STATA 10

Table 15: Full Output from ZTP on Quarterly Data with Offset Invkm.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Year	-0.0360	0.004	-8.44	0.0000	-0.0443	-0.0276
Quarter 2	0.2654	0.018	14.78	0.0000	0.2302	0.3006
Quarter 3	0.2831	0.017	16.39	0.0000	0.2493	0.3170
Quarter 4	0.1500	0.018	8.48	0.0000	0.1153	0.1846
25 to 34	-0.0365	0.014	-2.58	0.0100	-0.0643	-0.0088
35 to 44	-0.2635	0.016	-16.35	0.0000	-0.2951	-0.2319
45 to 54	-0.6182	0.021	-29.71	0.0000	-0.6589	-0.5774
55 to 64	-1.0329	0.030	-34.98	0.0000	-1.0908	-0.9750
65 Plus	-0.7392	0.025	-29.52	0.0000	-0.7883	-0.6901
Female	-0.8305	0.016	-51.85	0.0000	-0.8619	-0.7991
speed limit 40	-1.4959	0.032	-46.88	0.0000	-1.5584	-1.4333
speed limit 50	-2.5930	0.116	-22.45	0.0000	-2.8194	-2.3666
speed limit 60	-0.0493	0.013	-3.89	0.0000	-0.0741	-0.0244
speed limit 70	-1.1312	0.030	-38.03	0.0000	-1.1895	-1.0729
HGV_LGV	-1.5583	0.035	-44.17	0.0000	-1.6275	-1.4892
Motorcycle	-0.7240	0.018	-40.87	0.0000	-0.7587	-0.6893
Other	-1.8029	0.046	-39.10	0.0000	-1.8933	-1.7125
Junction	0.0468	0.011	4.11	0.0000	0.0245	0.0692
Roundabout	-2.1944	0.070	-31.14	0.0000	-2.3326	-2.0563
Slippy	-1.9265	0.086	-22.28	0.0000	-2.0960	-1.7570
Snow	-3.5918	0.576	-6.24	0.0000	-4.7198	-2.4638
Wet	-0.3861	0.013	-30.22	0.0000	-0.4111	-0.3610
dark	-0.2922	0.012	-23.47	0.0000	-0.3166	-0.2678
Geographic Area sqkm	-0.0379	0.006	-5.86	0.0000	-0.0505	-0.0252
Mean Index of Multiple Deprivation	0.2221	0.006	34.80	0.0000	0.2096	0.2346
Percentage Motorway	-0.1016	0.006	-15.68	0.0000	-0.1143	-0.0889
All Penalties	-0.0162	0.006	-2.77	0.0060	-0.0277	-0.0048
Constant	65.0241	8.533	7.62	0.0000	48.2997	81.7485
Invkm	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
77868	-77958.8	-53300.5	28.00	106657.1	1.37	0.32

[1]AIC*n is the AIC reported by STATA 10

Table 16: Full Output from ZTP on Quarterly Lagged Data with Offset lnvkm.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Year	-0.0372	0.004	-9.10	0.0000	-0.0452	-0.0292
Quarter 2	0.2800	0.017	16.14	0.0000	0.2460	0.3140
Quarter 3	0.2985	0.017	17.90	0.0000	0.2658	0.3312
Quarter 4	0.1578	0.017	9.28	0.0000	0.1245	0.1912
25 to 34	-0.0402	0.014	-2.88	0.0040	-0.0675	-0.0128
35 to 44	-0.2649	0.016	-16.69	0.0000	-0.2960	-0.2338
45 to 54	-0.6204	0.021	-30.22	0.0000	-0.6607	-0.5802
55 to 64	-1.0363	0.029	-35.60	0.0000	-1.0933	-0.9792
65 Plus	-0.7444	0.025	-30.11	0.0000	-0.7929	-0.6960
Female	-0.8330	0.016	-52.73	0.0000	-0.8639	-0.8020
speed limit 40	-1.4821	0.031	-47.48	0.0000	-1.5433	-1.4209
speed limit 50	-2.5912	0.114	-22.73	0.0000	-2.8146	-2.3677
speed limit 60	-0.0473	0.013	-3.78	0.0000	-0.0718	-0.0228
speed limit 70	-1.1346	0.029	-38.63	0.0000	-1.1922	-1.0771
HGV_LGV	-1.5551	0.035	-44.10	0.0000	-1.6242	-1.4860
Motorcycle	-0.7212	0.018	-40.78	0.0000	-0.7558	-0.6865
Other	-1.7988	0.046	-39.02	0.0000	-1.8892	-1.7085
Junction	0.0452	0.011	4.02	0.0000	0.0232	0.0673
Roundabout	-2.1828	0.069	-31.52	0.0000	-2.3186	-2.0471
Slippy	-1.9004	0.083	-22.96	0.0000	-2.0627	-1.7382
Snow	-3.0780	0.406	-7.58	0.0000	-3.8741	-2.2818
Wet	-0.3764	0.013	-30.06	0.0000	-0.4010	-0.3519
dark	-0.2761	0.012	-22.64	0.0000	-0.3000	-0.2522
Geographic Area sqkm	-0.0398	0.006	-6.23	0.0000	-0.0523	-0.0273
Mean Index of Multiple Deprivation	0.2240	0.006	34.98	0.0000	0.2115	0.2365
Percentage Motorway	-0.1013	0.006	-15.81	0.0000	-0.1139	-0.0888
Lag1 All Penalties	-0.0129	0.007	-1.92	0.0550	-0.0260	0.0003
Lag2 All Penalties	-0.0047	0.007	-0.72	0.4700	-0.0175	0.0081
Constant	67.5469	8.171	8.27	0.0000	51.5318	83.5621
lnvkm	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n**[1]	**AIC**	**Pseudo R^2**
80584	-80467.3	-55042.1	29	110142.2	1.37	0.32

[1]AIC*n is the AIC reported by STATA 10

Table 17: Full Output from ZTP on Quarterly Data with Offset lnpop.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Year	-0.0372	0.004	-9.02	0.0000	-0.0453	-0.0291
Quarter 2	0.2599	0.016	16.15	0.0000	0.2284	0.2915
Quarter 3	0.2729	0.016	16.67	0.0000	0.2408	0.3050
Quarter 4	0.1428	0.017	8.56	0.0000	0.1101	0.1755
25 to 34	-0.0351	0.014	-2.48	0.0134	-0.0628	-0.0073
35 to 44	-0.2649	0.015	-17.26	0.0000	-0.2950	-0.2348
45 to 54	-0.6114	0.020	-31.06	0.0000	-0.6500	-0.5728
55 to 64	-1.0357	0.028	-36.88	0.0000	-1.0907	-0.9806
65 Plus	-0.7532	0.024	-31.45	0.0000	-0.8001	-0.7063
Female	-0.8182	0.015	-54.35	0.0000	-0.8477	-0.7887
speed limit 40	-1.5111	0.030	-49.77	0.0000	-1.5707	-1.4516
speed limit 50	-2.6390	0.114	-23.15	0.0000	-2.8624	-2.4156
speed limit 60	-0.0583	0.012	-4.83	0.0000	-0.0820	-0.0346
speed limit 70	-1.1390	0.028	-40.14	0.0000	-1.1946	-1.0834
HGV_LGV	-1.5426	0.033	-46.64	0.0000	-1.6074	-1.4778
Motorcycle	-0.7269	0.017	-42.99	0.0000	-0.7600	-0.6938
Other	-1.8116	0.044	-41.29	0.0000	-1.8976	-1.7256
Junction	0.0459	0.011	4.24	0.0000	0.0247	0.0671
Roundabout	-2.1765	0.066	-32.78	0.0000	-2.3066	-2.0464
Slippy	-1.8863	0.079	-23.74	0.0000	-2.0421	-1.7306
Snow	-3.6879	0.576	-6.41	0.0000	-4.8162	-2.5596
Wet	-0.3977	0.012	-32.74	0.0000	-0.4215	-0.3739
dark	-0.3058	0.012	-25.75	0.0000	-0.3291	-0.2826
Geographic Area sqkm	0.0137	0.006	2.15	0.0320	0.0012	0.0262
Mean Index of Multiple Deprivation	0.0925	0.006	14.77	0.0000	0.0803	0.1048
Percentage Motorway	-0.0376	0.006	-5.96	0.0000	-0.0500	-0.0252
Prosecutions	0.0268	0.006	4.83	0.0000	0.0159	0.0376
FPN	-0.0574	0.006	-9.73	0.0000	-0.0690	-0.0459
VDRN	-0.0239	0.007	-3.63	0.0000	-0.0368	-0.0110
WW	-0.0707	0.006	-11.14	0.0000	-0.0831	-0.0583
Constant	65.1188	8.262	7.88	0.0000	48.9258	81.3118
lnpop	(offset)					
	Model Information Criteria					
Number Obs	ll(null)	ll(model)	df	AIC*n[1]	AIC	Pseudo R^2
86371	-85370	-58997	31	118056	1.37	0.31

[1]AIC*n is the AIC reported by STATA 10

Table 18: Full Output from ZTP on Quarterly Data with Offset lnvkm.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Year	-0.0535	0.004	-13.03	0.0000	-0.0615	-0.0454
Quarter 2	0.2587	0.016	16.07	0.0000	0.2272	0.2903
Quarter 3	0.2710	0.016	16.54	0.0000	0.2389	0.3031
Quarter 4	0.1446	0.017	8.66	0.0000	0.1119	0.1773
25 to 34	-0.0357	0.014	-2.52	0.0120	-0.0634	-0.0079
35 to 44	-0.2653	0.015	-17.28	0.0000	-0.2954	-0.2352
45 to 54	-0.6126	0.020	-31.11	0.0000	-0.6512	-0.5740
55 to 64	-1.0347	0.028	-36.83	0.0000	-1.0898	-0.9797
65 Plus	-0.7514	0.024	-31.37	0.0000	-0.7983	-0.7044
Female	-0.8173	0.015	-54.27	0.0000	-0.8468	-0.7878
speed limit 40	-1.5105	0.030	-49.73	0.0000	-1.5701	-1.4510
speed limit 50	-2.6559	0.114	-23.29	0.0000	-2.8793	-2.4324
speed limit 60	-0.0768	0.012	-6.37	0.0000	-0.1005	-0.0532
speed limit 70	-1.1499	0.028	-40.50	0.0000	-1.2055	-1.0942
HGV_LGV	-1.5428	0.033	-46.63	0.0000	-1.6077	-1.4780
Motorcycle	-0.7247	0.017	-42.85	0.0000	-0.7579	-0.6916
Other	-1.8082	0.044	-41.20	0.0000	-1.8943	-1.7222
Junction	0.0464	0.011	4.29	0.0000	0.0252	0.0676
Roundabout	-2.1737	0.066	-32.73	0.0000	-2.3038	-2.0435
Slippy	-1.8886	0.079	-23.76	0.0000	-2.0444	-1.7328
Snow	-3.7064	0.576	-6.44	0.0000	-4.8348	-2.5780
Wet	-0.3973	0.012	-32.69	0.0000	-0.4211	-0.3735
dark	-0.3043	0.012	-25.60	0.0000	-0.3275	-0.2810
Geographic Area sqkm	-0.0361	0.006	-5.61	0.0000	-0.0486	-0.0235
Mean Index of Multiple Deprivation	0.2412	0.006	37.92	0.0000	0.2287	0.2536
Percentage Motorway	-0.1029	0.006	-16.41	0.0000	-0.1151	-0.0906
Prosecutions	0.0272	0.006	4.94	0.0000	0.0164	0.0380
FPN	-0.0201	0.006	-3.48	0.0000	-0.0314	-0.0088
VDRN	-0.0414	0.007	-6.26	0.0000	-0.0543	-0.0284
WW	-0.0646	0.006	-10.29	0.0000	-0.0769	-0.0523
Constant	99.9977	8.209	12.18	0.0000	83.9084	116.0870
lnvkm	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
86371	-86498	-58954	31	117969	1.37	0.32

[1]AIC*n is the AIC reported by STATA 10

Table 19: Full Output from ZTP on Quarterly Lagged Data with Offset lnpop.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Year	-0.0358	0.005	-7.84	0.0000	-0.0447	-0.0268
Quarter 2	0.2658	0.017	15.19	0.0000	0.2315	0.3001
Quarter 3	0.2784	0.018	15.76	0.0000	0.2438	0.3131
Quarter 4	0.1360	0.018	7.68	0.0000	0.1013	0.1707
25 to 34	-0.0383	0.014	-2.75	0.0060	-0.0656	-0.0110
35 to 44	-0.2632	0.016	-16.58	0.0000	-0.2943	-0.2321
45 to 54	-0.6165	0.021	-30.03	0.0000	-0.6567	-0.5763
55 to 64	-1.0372	0.029	-35.63	0.0000	-1.0942	-0.9801
65 Plus	-0.7471	0.025	-30.22	0.0000	-0.7955	-0.6986
Female	-0.8331	0.016	-52.74	0.0000	-0.8640	-0.8021
speed limit 40	-1.4862	0.031	-47.63	0.0000	-1.5474	-1.4251
speed limit 50	-2.5758	0.114	-22.60	0.0000	-2.7991	-2.3524
speed limit 60	-0.0414	0.013	-3.29	0.0010	-0.0660	-0.0167
speed limit 70	-1.1262	0.029	-38.35	0.0000	-1.1837	-1.0686
HGV_LGV	-1.5585	0.035	-44.20	0.0000	-1.6276	-1.4894
Motorcycle	-0.7226	0.018	-40.86	0.0000	-0.7573	-0.6880
Other	-1.7993	0.046	-39.03	0.0000	-1.8897	-1.7090
Junction	0.0426	0.011	3.79	0.0000	0.0206	0.0647
Roundabout	-2.1806	0.069	-31.49	0.0000	-2.3164	-2.0449
Slippy	-1.8949	0.083	-22.89	0.0000	-2.0571	-1.7327
Snow	-3.0581	0.406	-7.53	0.0000	-3.8542	-2.2620
Wet	-0.3758	0.013	-30.02	0.0000	-0.4004	-0.3513
dark	-0.2790	0.012	-22.89	0.0000	-0.3029	-0.2551
Geographic Area sqkm	0.0172	0.007	2.62	0.0090	0.0043	0.0300
Mean Index of Multiple Deprivation	0.0862	0.007	12.91	0.0000	0.0731	0.0993
Percentage Motorway	-0.0370	0.007	-5.61	0.0000	-0.0499	-0.0241
Lag 1 Prosecutions	0.0159	0.006	2.88	0.0040	0.0051	0.0267
Lag 1 FPN	-0.0083	0.014	-0.61	0.5420	-0.0350	0.0184
Lag 1 VDRN	-0.0675	0.018	-3.85	0.0000	-0.1019	-0.0331
Lag 1 WW	0.0042	0.018	0.23	0.8200	-0.0318	0.0402
Lag 2 Prosecutions	0.0260	0.005	4.75	0.0000	0.0153	0.0367
Lag 2 FPN	-0.0544	0.014	-3.99	0.0000	-0.0811	-0.0277
Lag 2 VDRN	-0.0072	0.017	-0.43	0.6680	-0.0398	0.0255
Lag 2 WW	-0.0130	0.018	-0.74	0.4590	-0.0473	0.0214
Constant	62.4085	9.138	6.83	0.0000	44.4986	80.3183
lnpop	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
80584	-79432	-54955	35	109980	1.36	0.31

[1]AIC*n is the AIC reported by STATA 10

Table 20: Full Output from ZTP on Quarterly Lagged Data with Offset lnvkm.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Year	-0.0536	0.005	-11.82	0.0000	-0.0624	-0.0447
Quarter 2	0.2662	0.018	15.20	0.0000	0.2319	0.3005
Quarter 3	0.2724	0.018	15.43	0.0000	0.2378	0.3070
Quarter 4	0.1311	0.018	7.40	0.0000	0.0963	0.1658
25 to 34	-0.0390	0.014	-2.80	0.0050	-0.0663	-0.0116
35 to 44	-0.2637	0.016	-16.61	0.0000	-0.2948	-0.2326
45 to 54	-0.6183	0.021	-30.11	0.0000	-0.6585	-0.5780
55 to 64	-1.0367	0.029	-35.60	0.0000	-1.0938	-0.9797
65 Plus	-0.7458	0.025	-30.15	0.0000	-0.7942	-0.6973
Female	-0.8327	0.016	-52.70	0.0000	-0.8637	-0.8017
speed limit 40	-1.4863	0.031	-47.61	0.0000	-1.5474	-1.4251
speed limit 50	-2.5936	0.114	-22.75	0.0000	-2.8170	-2.3701
speed limit 60	-0.0596	0.013	-4.75	0.0000	-0.0842	-0.0350
speed limit 70	-1.1367	0.029	-38.69	0.0000	-1.1943	-1.0792
HGV_LGV	-1.5590	0.035	-44.20	0.0000	-1.6282	-1.4899
Motorcycle	-0.7206	0.018	-40.73	0.0000	-0.7552	-0.6859
Other	-1.7961	0.046	-38.95	0.0000	-1.8865	-1.7057
Junction	0.0434	0.011	3.86	0.0000	0.0213	0.0655
Roundabout	-2.1789	0.069	-31.46	0.0000	-2.3147	-2.0432
Slippy	-1.8983	0.083	-22.93	0.0000	-2.0606	-1.7360
Snow	-3.0701	0.406	-7.56	0.0000	-3.8663	-2.2739
Wet	-0.3758	0.013	-30.00	0.0000	-0.4004	-0.3513
dark	-0.2776	0.012	-22.76	0.0000	-0.3015	-0.2537
Geographic Area sqkm	-0.0327	0.007	-4.94	0.0000	-0.0457	-0.0197
Mean Index of Multiple Deprivation	0.2348	0.007	34.63	0.0000	0.2215	0.2480
Percentage Motorway	-0.1039	0.007	-15.87	0.0000	-0.1167	-0.0910
Lag 1 Prosecutions	0.0150	0.005	2.74	0.0060	0.0043	0.0257
Lag 1 FPN	0.0018	0.014	0.13	0.8960	-0.0248	0.0283
Lag 1 VDRN	-0.0646	0.017	-3.77	0.0000	-0.0981	-0.0310
Lag 1 WW	-0.0036	0.019	-0.19	0.8460	-0.0400	0.0328
Lag 2 Prosecutions	0.0260	0.005	4.77	0.0000	0.0153	0.0366
Lag 2 FPN	-0.0256	0.014	-1.89	0.0580	-0.0522	0.0009
Lag 2 VDRN	-0.0045	0.016	-0.28	0.7810	-0.0365	0.0274
Lag 2 WW	-0.0282	0.018	-1.60	0.1090	-0.0628	0.0063
Constant	100.3602	9.068	11.07	0.0000	82.5881	118.1323
lnvkm	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
80584	-80467	-54918	35	109906	1.36	0.32

[1]AIC*n is the AIC reported by STATA 10

Table 21: Full Output from ZTP on Quarterly Data with Speeding Related FPN's (FPN_G16) and Offset lnpop.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Year	-0.0286	0.004	-6.42	0.0000	-0.0373	-0.0198
Quarter 2	0.2628	0.016	16.31	0.0000	0.2312	0.2944
Quarter 3	0.2775	0.016	16.90	0.0000	0.2453	0.3097
Quarter 4	0.1476	0.017	8.83	0.0000	0.1148	0.1803
25 to 34	-0.0350	0.0141	-2.47	0.0130	-0.0627	-0.0072
35 to 44	-0.2652	0.015	-17.28	0.0000	-0.2952	-0.2351
45 to 54	-0.6116	0.020	-31.08	0.0000	-0.6502	-0.5730
55 to 64	-1.0363	0.028	-36.92	0.0000	-1.0913	-0.9813
65 Plus	-0.7538	0.024	-31.49	0.0000	-0.8007	-0.7069
Female	-0.8189	0.015	-54.42	0.0000	-0.8484	-0.7894
speed limit 40	-1.5125	0.030	-49.83	0.0000	-1.5720	-1.4530
speed limit 50	-2.6368	0.114	-23.13	0.0000	-2.8602	-2.4134
speed limit 60	-0.0517	0.012	-4.29	0.0000	-0.0753	-0.0281
speed limit 70	-1.1368	0.028	-40.07	0.0000	-1.1924	-1.0812
HGV_LGV	-1.5437	0.033	-46.69	0.0000	-1.6085	-1.4789
Motorcycle	-0.7276	0.017	-43.05	0.0000	-0.7608	-0.6945
Other	-1.8137	0.044	-41.35	0.0000	-1.8997	-1.7277
Junction	0.0463	0.011	4.28	0.0000	0.0251	0.0675
Roundabout	-2.1786	0.066	-32.82	0.0000	-2.3087	-2.0485
Slippy	-1.8858	0.079	-23.74	0.0000	-2.0415	-1.7301
Snow	-3.6838	0.576	-6.40	0.0000	-4.8120	-2.5555
Wet	-0.3986	0.012	-32.83	0.0000	-0.4224	-0.3748
dark	-0.3056	0.012	-25.74	0.0000	-0.3289	-0.2823
Geographic Area sqkm	0.0096	0.006	1.52	0.1290	-0.0028	0.0219
Mean Index of Multiple Deprivation	0.0821	0.006	12.99	0.0000	0.0698	0.0945
Percentage Motorway	-0.0359	0.006	-5.56	0.0000	-0.0485	-0.0232
Prosecutions	0.0244	0.006	4.40	0.0000	0.0135	0.0353
FPN G16	-0.0492	0.006	-7.85	0.0000	-0.0615	-0.0369
VDRN	-0.0775	0.006	-12.32	0.0000	-0.0898	-0.0652
WW	-0.0301	0.007	-4.54	0.0000	-0.0431	-0.0171
Constant	47.7658	8.907	5.36	0.0000	30.3076	65.2240
lnpop	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
86371	-85370	-59013	31	118088	1.37	0.31

[1]AIC*n is the AIC reported by STATA 10

Table 22: Full Output from ZTP on Quarterly Data with Speeding Related FPN's (FPN_G16) and Offset Invkm.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Year	-0.0462	0.004	-10.44	0.0000	-0.0548	-0.0375
Quarter 2	0.2623	0.016	16.27	0.0000	0.2307	0.2939
Quarter 3	0.2772	0.016	16.85	0.0000	0.2450	0.3094
Quarter 4	0.1494	0.017	8.93	0.0000	0.1166	0.1822
25 to 34	-0.0357	0.0142	-2.52	0.0120	-0.0634	-0.0079
35 to 44	-0.2651	0.015	-17.27	0.0000	-0.2952	-0.2350
45 to 54	-0.6127	0.020	-31.11	0.0000	-0.6513	-0.5741
55 to 64	-1.0352	0.028	-36.85	0.0000	-1.0902	-0.9801
65 Plus	-0.7518	0.024	-31.39	0.0000	-0.7988	-0.7049
Female	-0.8175	0.015	-54.29	0.0000	-0.8471	-0.7880
speed limit 40	-1.5113	0.030	-49.76	0.0000	-1.5709	-1.4518
speed limit 50	-2.6535	0.114	-23.27	0.0000	-2.8769	-2.4300
speed limit 60	-0.0749	0.012	-6.22	0.0000	-0.0985	-0.0513
speed limit 70	-1.1488	0.028	-40.47	0.0000	-1.2044	-1.0931
HGV_LGV	-1.5433	0.033	-46.65	0.0000	-1.6082	-1.4785
Motorcycle	-0.7249	0.017	-42.86	0.0000	-0.7580	-0.6917
Other	-1.8088	0.044	-41.22	0.0000	-1.8948	-1.7228
Junction	0.0468	0.011	4.33	0.0000	0.0256	0.0680
Roundabout	-2.1737	0.066	-32.73	0.0000	-2.3039	-2.0436
Slippy	-1.8874	0.079	-23.75	0.0000	-2.0432	-1.7316
Snow	-3.7051	0.576	-6.44	0.0000	-4.8335	-2.5767
Wet	-0.3976	0.012	-32.71	0.0000	-0.4214	-0.3738
dark	-0.3040	0.012	-25.58	0.0000	-0.3273	-0.2807
Geographic Area sqkm	-0.0342	0.006	-5.37	0.0000	-0.0467	-0.0217
Mean Index of Multiple Deprivation	0.2357	0.006	36.87	0.0000	0.2232	0.2482
Percentage Motorway	-0.0980	0.006	-15.36	0.0000	-0.1105	-0.0855
Prosecutions	0.0276	0.006	5.01	0.0000	0.0168	0.0384
FPN G16	-0.0323	0.006	-5.24	0.0000	-0.0444	-0.0202
VDRN	-0.0647	0.006	-10.44	0.0000	-0.0768	-0.0525
WW	-0.0432	0.007	-6.54	0.0000	-0.0562	-0.0302
Constant	85.3777	8.848	9.65	0.0000	68.0357	102.7198
Invkm	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
86371	-86498	-58946	31	117954	1.37	0.32

[1]AIC*n is the AIC reported by STATA 10

Table 23: Full Output from ZTP on Quarterly Lagged Data with Speeding Related FPN's (FPN_G16) and Offset lnpop.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Year	-0.0273	0.005	-5.57	0.0000	-0.0369	-0.0177
Quarter 2	0.2728	0.018	15.57	0.0000	0.2385	0.3072
Quarter 3	0.2899	0.018	16.27	0.0000	0.2550	0.3249
Quarter 4	0.1472	0.018	8.22	0.0000	0.1121	0.1823
25 to 34	-0.0384	0.014	-2.76	0.0060	-0.0657	-0.0111
35 to 44	-0.2634	0.016	-16.60	0.0000	-0.2945	-0.2323
45 to 54	-0.6166	0.021	-30.05	0.0000	-0.6568	-0.5764
55 to 64	-1.0377	0.029	-35.66	0.0000	-1.0947	-0.9807
65 Plus	-0.7474	0.025	-30.24	0.0000	-0.7959	-0.6990
Female	-0.8334	0.016	-52.78	0.0000	-0.8644	-0.8025
speed limit 40	-1.4877	0.031	-47.69	0.0000	-1.5489	-1.4266
speed limit 50	-2.5733	0.114	-22.58	0.0000	-2.7967	-2.3499
speed limit 60	-0.0331	0.013	-2.64	0.0080	-0.0576	-0.0085
speed limit 70	-1.1235	0.029	-38.27	0.0000	-1.1810	-1.0659
HGV_LGV	-1.5597	0.035	-44.25	0.0000	-1.6288	-1.4906
Motorcycle	-0.7233	0.018	-40.92	0.0000	-0.7580	-0.6887
Other	-1.8014	0.046	-39.09	0.0000	-1.8917	-1.7111
Junction	0.0428	0.011	3.81	0.0000	0.0208	0.0649
Roundabout	-2.1838	0.069	-31.54	0.0000	-2.3196	-2.0481
Slippy	-1.8940	0.083	-22.89	0.0000	-2.0562	-1.7318
Snow	-3.0517	0.406	-7.51	0.0000	-3.8478	-2.2557
Wet	-0.3769	0.013	-30.12	0.0000	-0.4014	-0.3524
dark	-0.2787	0.012	-22.88	0.0000	-0.3026	-0.2549
Geographic Area sqkm	0.0119	0.007	1.83	0.0680	-0.0009	0.0246
Mean Index of Multiple Deprivation	0.0757	0.007	11.16	0.0000	0.0624	0.0890
Percentage Motorway	-0.0371	0.007	-5.48	0.0000	-0.0503	-0.0238
Lag 1 Prosecutions	0.0155	0.006	2.80	0.0050	0.0046	0.0263
Lag 1 FPN G16	-0.0245	0.012	-2.06	0.0390	-0.0478	-0.0012
Lag 1 VDRN	-0.0656	0.018	-3.73	0.0000	-0.1001	-0.0311
Lag 1 WW	-0.0003	0.019	-0.02	0.9870	-0.0368	0.0362
Lag 2 Prosecutions	0.0239	0.005	4.34	0.0000	0.0131	0.0346
Lag 2 FPN G16	-0.0189	0.012	-1.56	0.1180	-0.0426	0.0048
Lag 2 VDRN	-0.0180	0.017	-1.08	0.2820	-0.0507	0.0148
Lag 2 WW	-0.0185	0.018	-1.04	0.2980	-0.0533	0.0163
Constant	45.4120	9.816	4.63	0.0000	26.1733	64.6506
lnpop	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
80584	-79432	-54986	35	110043	1.37	0.31

[1]AIC*n is the AIC reported by STATA 10

Table 24: Full Output from ZTP on Quarterly Lagged Data with Speeding Related FPN's (FPN_G16) and Offset Invkm.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Year	-0.0472	0.005	-9.70	0.0000	-0.0568	-0.0377
Quarter 2	0.2696	0.018	15.36	0.0000	0.2352	0.3040
Quarter 3	0.2791	0.018	15.67	0.0000	0.2442	0.3140
Quarter 4	0.1393	0.018	7.78	0.0000	0.1042	0.1744
25 to 34	-0.0391	0.014	-2.80	0.0050	-0.0664	-0.0117
35 to 44	-0.2637	0.016	-16.61	0.0000	-0.2949	-0.2326
45 to 54	-0.6183	0.021	-30.11	0.0000	-0.6585	-0.5780
55 to 64	-1.0372	0.029	-35.62	0.0000	-1.0942	-0.9801
65 Plus	-0.7462	0.025	-30.17	0.0000	-0.7946	-0.6977
Female	-0.8328	0.016	-52.71	0.0000	-0.8638	-0.8018
speed limit 40	-1.4870	0.031	-47.64	0.0000	-1.5482	-1.4258
speed limit 50	-2.5914	0.114	-22.73	0.0000	-2.8148	-2.3679
speed limit 60	-0.0566	0.013	-4.52	0.0000	-0.0812	-0.0321
speed limit 70	-1.1354	0.029	-38.65	0.0000	-1.1930	-1.0779
HGV_LGV	-1.5598	0.035	-44.22	0.0000	-1.6289	-1.4906
Motorcycle	-0.7207	0.018	-40.75	0.0000	-0.7554	-0.6860
Other	-1.7967	0.046	-38.97	0.0000	-1.8871	-1.7063
Junction	0.0437	0.011	3.88	0.0000	0.0216	0.0657
Roundabout	-2.1796	0.069	-31.47	0.0000	-2.3153	-2.0438
Slippy	-1.8971	0.083	-22.91	0.0000	-2.0594	-1.7349
Snow	-3.0688	0.406	-7.55	0.0000	-3.8649	-2.2726
Wet	-0.3762	0.013	-30.03	0.0000	-0.4008	-0.3517
dark	-0.2774	0.012	-22.74	0.0000	-0.3013	-0.2535
Geographic Area sqkm	-0.0324	0.007	-4.94	0.0000	-0.0453	-0.0195
Mean Index of Multiple Deprivation	0.2293	0.007	33.46	0.0000	0.2159	0.2428
Percentage Motorway	-0.1010	0.007	-15.11	0.0000	-0.1141	-0.0879
Lag 1 Prosecutions	0.0156	0.005	2.84	0.0050	0.0048	0.0264
Lag 1 FPN G16	-0.0177	0.012	-1.50	0.1320	-0.0408	0.0054
Lag 1 VDRN	-0.0619	0.017	-3.61	0.0000	-0.0955	-0.0283
Lag 1 WW	-0.0056	0.019	-0.30	0.7650	-0.0421	0.0310
Lag 2 Prosecutions	0.0257	0.005	4.72	0.0000	0.0150	0.0364
Lag 2 FPN G16	-0.0081	0.012	-0.67	0.5000	-0.0316	0.0154
Lag 2 VDRN	-0.0091	0.016	-0.56	0.5770	-0.0409	0.0228
Lag 2 WW	-0.0296	0.018	-1.67	0.0940	-0.0643	0.0051
Constant	87.6767	9.736	9.01	0.0000	68.5936	106.7597
Invkm	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
80584	-80467	-54917	35	109904	1.36	0.32

[1]AIC*n is the AIC reported by STATA 10

Table 25: Full Output from ZTP on Annual Data with Metropolitan PFA and Offset lnpop.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Year	-0.0439	0.001	-32.43	0.0000	-0.0466	-0.0413
25 to 34	0.0322	0.007	4.85	0.0000	0.0192	0.0452
35 to 44	-0.2951	0.008	-38.99	0.0000	-0.3100	-0.2803
45 to 54	-0.6865	0.009	-73.19	0.0000	-0.7048	-0.6681
55 to 64	-1.1106	0.013	-88.31	0.0000	-1.1352	-1.0859
65 Plus	-0.9487	0.012	-79.17	0.0000	-0.9721	-0.9252
Female	-0.8335	0.007	-124.49	0.0000	-0.8466	-0.8204
speed limit 40	-1.6383	0.012	-136.29	0.0000	-1.6619	-1.6147
speed limit 50	-2.7092	0.035	-77.80	0.0000	-2.7774	-2.6409
speed limit 60	-0.3529	0.006	-57.14	0.0000	-0.3650	-0.3408
speed limit 70	-1.4844	0.013	-111.47	0.0000	-1.5105	-1.4583
HGV_LGV	-1.5863	0.014	-109.77	0.0000	-1.6147	-1.5580
Motorcycle	-0.9541	0.008	-118.36	0.0000	-0.9699	-0.9383
Other	-1.3060	0.011	-116.18	0.0000	-1.3281	-1.2840
Junction	0.1962	0.005	37.55	0.0000	0.1860	0.2065
Roundabout	-1.8147	0.031	-58.57	0.0000	-1.8754	-1.7539
Slippy	-2.4355	0.047	-51.53	0.0000	-2.5281	-2.3428
Snow	-4.4389	0.351	-12.63	0.0000	-5.1276	-3.7502
Wet	-0.4162	0.006	-71.91	0.0000	-0.4276	-0.4049
dark	-0.4833	0.006	-85.70	0.0000	-0.4943	-0.4722
Mean Index of Multiple Deprivation	0.0245	0.003	7.24	0.0000	0.0179	0.0312
Percentage Motorway	-0.0908	0.003	-29.98	0.0000	-0.0967	-0.0848
Prosecutions	0.0350	0.003	11.18	0.0000	0.0289	0.0412
FPN	-0.0128	0.003	-4.51	0.0000	-0.0184	-0.0072
VDRN	-0.0341	0.003	-12.96	0.0000	-0.0392	-0.0289
WW	-0.0079	0.003	-2.43	0.0150	-0.0142	-0.0015
Constant	79.3831	2.710	29.29	0.0000	74.0709	84.6953
lnpop	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
95868	-211786	-142748	28	285550	2.98	0.33

[1]AIC*n is the AIC reported by STATA 10

Table 26: Full Output from ZTP on Annual Data with Metropolitan PFA and Offset lnvkm.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
Year	-0.0595	0.001	-44.48	0.0000	-0.0621	-0.0568
25 to 34	0.0327	0.007	4.93	0.0000	0.0197	0.0457
35 to 44	-0.2947	0.008	-38.95	0.0000	-0.3095	-0.2799
45 to 54	-0.6868	0.009	-73.26	0.0000	-0.7051	-0.6684
55 to 64	-1.1091	0.013	-88.24	0.0000	-1.1337	-1.0844
65 Plus	-0.9484	0.012	-79.18	0.0000	-0.9719	-0.9249
Female	-0.8290	0.007	-123.83	0.0000	-0.8421	-0.8158
speed limit 40	-1.6334	0.012	-135.96	0.0000	-1.6570	-1.6099
speed limit 50	-2.6811	0.035	-76.88	0.0000	-2.7494	-2.6127
speed limit 60	-0.3614	0.006	-58.46	0.0000	-0.3735	-0.3493
speed limit 70	-1.4876	0.013	-111.77	0.0000	-1.5137	-1.4615
HGV_LGV	-1.6028	0.014	-110.96	0.0000	-1.6311	-1.5745
Motorcycle	-0.9406	0.008	-116.68	0.0000	-0.9564	-0.9248
Other	-1.2890	0.011	-114.74	0.0000	-1.3110	-1.2670
Junction	0.1948	0.005	37.29	0.0000	0.1845	0.2050
Roundabout	-1.7469	0.031	-56.36	0.0000	-1.8076	-1.6861
Slippy	-2.4456	0.047	-51.80	0.0000	-2.5381	-2.3530
Snow	-4.4637	0.351	-12.71	0.0000	-5.1522	-3.7752
Wet	-0.3596	0.006	-63.12	0.0000	-0.3708	-0.3484
dark	-0.4822	0.006	-85.53	0.0000	-0.4932	-0.4711
Geographic Area sqkm	-0.0907	0.003	-27.49	0.0000	-0.0972	-0.0842
Mean Index of Multiple Deprivation	0.1254	0.004	34.30	0.0000	0.1182	0.1325
Percentage Motorway	-0.2143	0.003	-68.50	0.0000	-0.2204	-0.2082
Prosecutions	0.0776	0.003	24.71	0.0000	0.0714	0.0838
FPN	0.0556	0.003	19.76	0.0000	0.0501	0.0611
VDRN	-0.0438	0.003	-16.45	0.0000	-0.0490	-0.0386
WW	-0.0201	0.003	-6.07	0.0000	-0.0266	-0.0136
Constant	112.8832	2.676	42.19	0.0000	107.6387	118.1277
lnvkm	(offset)					

	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
95868	-215984	-144355	28	288765	-3.01	0.33

[1]AIC*n is the AIC reported by STATA 10

Table 27: Full Output from ZTP on Annual Data with PFA as Categorical variable and Offset lnpop.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
YEAR	-0.0331	0.002	-20.11	0.0000	-0.0363	-0.0299
PFA 4	-0.2965	0.037	-8.03	0.0000	-0.3688	-0.2242
PFA 5	-0.3006	0.033	-9.00	0.0000	-0.3660	-0.2351
PFA 6	-0.5424	0.061	-8.86	0.0000	-0.6624	-0.4225
PFA 7	-0.3545	0.031	-11.31	0.0000	-0.4160	-0.2930
PFA 10	-0.7479	0.037	-20.00	0.0000	-0.8212	-0.6746
PFA 11	-0.7404	0.047	-15.91	0.0000	-0.8317	-0.6492
PFA 12	0.1149	0.030	3.82	0.0000	0.0560	0.1738
PFA 13	-0.4727	0.042	-11.22	0.0000	-0.5552	-0.3902
PFA 14	-0.5874	0.033	-17.60	0.0000	-0.6528	-0.5219
PFA 16	-0.2925	0.032	-9.13	0.0000	-0.3553	-0.2298
PFA 17	-0.5954	0.048	-12.31	0.0000	-0.6902	-0.5006
PFA 20	-0.3375	0.051	-6.61	0.0000	-0.4376	-0.2375
PFA 21	-0.8894	0.038	-23.47	0.0000	-0.9636	-0.8151
PFA 22	-0.3317	0.031	-10.70	0.0000	-0.3925	-0.2710
PFA 23	-0.0257	0.037	-0.69	0.4890	-0.0987	0.0472
PFA 30	-0.4231	0.034	-12.41	0.0000	-0.4899	-0.3563
PFA 31	-0.2548	0.031	-8.18	0.0000	-0.3159	-0.1938
PFA 32	-0.0612	0.033	-1.83	0.0670	-0.1267	0.0043
PFA 33	-0.7656	0.039	-19.70	0.0000	-0.8418	-0.6894
PFA 34	-0.1910	0.034	-5.60	0.0000	-0.2579	-0.1242
PFA 35	-0.2416	0.033	-7.26	0.0000	-0.3068	-0.1763
PFA 36	-0.3451	0.033	-10.39	0.0000	-0.4102	-0.2800
PFA 37	-0.5359	0.038	-13.94	0.0000	-0.6112	-0.4605
PFA 40	-0.6101	0.043	-14.04	0.0000	-0.6952	-0.5249
PFA 41	-0.4222	0.032	-13.17	0.0000	-0.4850	-0.3593
PFA 42	-0.4719	0.032	-14.60	0.0000	-0.5353	-0.4086
PFA 43	-0.6758	0.035	-19.18	0.0000	-0.7448	-0.6067
PFA 44	-0.6128	0.034	-18.14	0.0000	-0.6791	-0.5466
PFA 45	-0.7989	0.035	-22.80	0.0000	-0.8675	-0.7302
PFA 46	-0.6130	0.031	-19.98	0.0000	-0.6731	-0.5529
PFA 47	-0.4966	0.032	-15.38	0.0000	-0.5599	-0.4333
PFA 50	-0.6052	0.035	-17.49	0.0000	-0.6730	-0.5374
PFA 52	-0.7240	0.037	-19.76	0.0000	-0.7958	-0.6521
PFA 53	-0.5998	0.044	-13.66	0.0000	-0.6859	-0.5137
PFA 54	-0.0988	0.038	-2.57	0.0100	-0.1741	-0.0235
PFA 55	-0.4592	0.037	-12.46	0.0000	-0.5315	-0.3869
PFA 60	-0.5508	0.038	-14.45	0.0000	-0.6256	-0.4761
PFA 61	-0.4676	0.045	-10.34	0.0000	-0.5562	-0.3789
PFA 62	-0.9600	0.044	-21.77	0.0000	-1.0464	-0.8736
PFA 63	0.1641	0.034	4.83	0.0000	0.0975	0.2308
25 to 34	-0.0347	0.008	-4.56	0.0000	-0.0496	-0.0198
35 to 44	-0.3284	0.009	-38.16	0.0000	-0.3453	-0.3115
45 to 54	-0.6587	0.010	-63.21	0.0000	-0.6791	-0.6383
55 to 64	-1.0717	0.014	-76.79	0.0000	-1.0991	-1.0444

65 Plus	-0.8453	0.013	-66.81	0.0000	-0.8701	-0.8205
Female	-0.8410	0.008	-109.12	0.0000	-0.8561	-0.8258
speed limit 40	-1.4801	0.014	-107.68	0.0000	-1.5071	-1.4532
speed limit 50	-2.6434	0.048	-54.81	0.0000	-2.7379	-2.5489
speed limit 60	-0.2055	0.007	-31.49	0.0000	-0.2183	-0.1927
speed limit 70	-1.3104	0.014	-94.69	0.0000	-1.3375	-1.2833
HGV_LGV	-1.5505	0.015	-104.80	0.0000	-1.5795	-1.5215
Motorcycle	-1.0125	0.010	-105.20	0.0000	-1.0313	-0.9936
Other	-1.8985	0.020	-94.26	0.0000	-1.9379	-1.8590
Junction	0.0540	0.006	9.20	0.0000	0.0425	0.0656
Roundabout	-2.2024	0.094	-23.43	0.0000	-2.3866	-2.0182
Slippy	-2.5081	0.047	-52.88	0.0000	-2.6011	-2.4152
Snow	-4.4993	0.352	-12.80	0.0000	-5.1884	-3.8103
Wet	-0.5333	0.006	-82.78	0.0000	-0.5460	-0.5207
dark	-0.4637	0.006	-71.80	0.0000	-0.4764	-0.4511
Prosecutions	0.0035	0.011	0.33	0.7450	-0.0178	0.0249
FPN	-0.0063	0.005	-1.19	0.2350	-0.0168	0.0041
VDRN	0.0028	0.004	0.69	0.4870	-0.0050	0.0105
WW	0.0018	0.005	0.35	0.7240	-0.0081	0.0117
Constant	57.5495	3.296	17.46	0.0000	51.0895	64.0094
lnpop	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
91504	-165143.4	-112483.800	65	225097.6	2.46	0.32

[1]AIC*n is the AIC reported by STATA 10

Table 28: Full Output from ZTP on Annual Data with PFA as Categorical variable and Offset lnpop.

ZTP Model D.V. = KSI	Parameter Estimates	Std.Error	z	P>z	95% Confidence Interval	
YEAR	-0.0482	0.002	-29.31	0.0000	-0.0515	-0.0450
PFA 4	-0.0260	0.037	-0.70	0.4810	-0.0983	0.0463
PFA 5	0.3865	0.033	11.57	0.0000	0.3211	0.4520
PFA 6	-0.1121	0.061	-1.83	0.0670	-0.2321	0.0079
PFA 7	-0.4183	0.031	-13.34	0.0000	-0.4798	-0.3568
PFA 10	-0.3420	0.037	-9.15	0.0000	-0.4153	-0.2687
PFA 11	-0.3848	0.047	-8.26	0.0000	-0.4760	-0.2935
PFA 12	0.0898	0.030	2.99	0.0030	0.0309	0.1487
PFA 13	-0.0519	0.042	-1.23	0.2170	-0.1345	0.0306
PFA 14	-0.1942	0.033	-5.82	0.0000	-0.2596	-0.1288
PFA 16	0.0635	0.032	1.98	0.0470	0.0007	0.1263
PFA 17	-0.2743	0.048	-5.67	0.0000	-0.3691	-0.1795
PFA 20	0.1966	0.051	3.85	0.0000	0.0966	0.2967
PFA 21	-0.7287	0.038	-19.23	0.0000	-0.8029	-0.6544
PFA 22	-0.2908	0.031	-9.38	0.0000	-0.3515	-0.2301
PFA 23	-0.4083	0.037	-10.96	0.0000	-0.4813	-0.3352
PFA 30	-0.2318	0.034	-6.80	0.0000	-0.2985	-0.1650
PFA 31	0.1059	0.031	3.40	0.0010	0.0449	0.1670
PFA 32	0.2460	0.033	7.36	0.0000	0.1805	0.3115
PFA 33	-0.6218	0.039	-16.00	0.0000	-0.6980	-0.5456
PFA 34	-0.2931	0.034	-8.60	0.0000	-0.3600	-0.2263
PFA 35	-0.3151	0.033	-9.47	0.0000	-0.3804	-0.2499
PFA 36	-0.2049	0.033	-6.17	0.0000	-0.2700	-0.1398
PFA 37	-0.2845	0.038	-7.40	0.0000	-0.3598	-0.2091
PFA 40	-0.3211	0.043	-7.39	0.0000	-0.4063	-0.2359
PFA 41	-0.4020	0.032	-12.54	0.0000	-0.4649	-0.3392
PFA 42	-0.3172	0.032	-9.81	0.0000	-0.3805	-0.2538
PFA 43	-0.7355	0.035	-20.88	0.0000	-0.8045	-0.6664
PFA 44	-0.4940	0.034	-14.63	0.0000	-0.5602	-0.4278
PFA 45	-0.9735	0.035	-27.78	0.0000	-1.0422	-0.9048
PFA 46	-0.4644	0.031	-15.14	0.0000	-0.5245	-0.4043
PFA 47	-0.2565	0.032	-7.94	0.0000	-0.3198	-0.1932
PFA 50	-0.4232	0.035	-12.23	0.0000	-0.4910	-0.3553
PFA 52	-0.5841	0.037	-15.94	0.0000	-0.6560	-0.5123
PFA 53	-0.5020	0.044	-11.43	0.0000	-0.5881	-0.4159
PFA 54	-0.4443	0.038	-11.57	0.0000	-0.5196	-0.3690
PFA 55	0.3071	0.037	8.33	0.0000	0.2348	0.3793
PFA 60	-0.3065	0.038	-8.04	0.0000	-0.3812	-0.2317
PFA 61	-0.3254	0.045	-7.19	0.0000	-0.4140	-0.2367
PFA 62	-0.6825	0.044	-15.48	0.0000	-0.7689	-0.5961
PFA 63	0.3027	0.034	8.90	0.0000	0.2360	0.3693
25 to 34	-0.0347	0.008	-4.56	0.0000	-0.0496	-0.0198
35 to 44	-0.3284	0.009	-38.16	0.0000	-0.3453	-0.3115
45 to 54	-0.6587	0.010	-63.21	0.0000	-0.6791	-0.6383
55 to 64	-1.0717	0.014	-76.79	0.0000	-1.0991	-1.0444
65 Plus	-0.8453	0.013	-66.81	0.0000	-0.8701	-0.8205

Female	-0.8410	0.008	-109.12	0.0000	-0.8561	-0.8258
speed limit 40	-1.4801	0.014	-107.67	0.0000	-1.5070	-1.4531
speed limit 50	-2.6433	0.048	-54.81	0.0000	-2.7378	-2.5487
speed limit 60	-0.2057	0.007	-31.52	0.0000	-0.2185	-0.1929
speed limit 70	-1.3105	0.014	-94.70	0.0000	-1.3376	-1.2833
HGV_LGV	-1.5507	0.015	-104.81	0.0000	-1.5797	-1.5217
Motorcycle	-1.0125	0.010	-105.20	0.0000	-1.0313	-0.9936
Other	-1.8985	0.020	-94.26	0.0000	-1.9380	-1.8590
Junction	0.0540	0.006	9.19	0.0000	0.0425	0.0655
Roundabout	-2.2016	0.094	-23.42	0.0000	-2.3858	-2.0174
Slippy	-2.5080	0.047	-52.87	0.0000	-2.6009	-2.4150
Snow	-4.4978	0.352	-12.79	0.0000	-5.1869	-3.8088
Wet	-0.5333	0.006	-82.77	0.0000	-0.5459	-0.5207
dark	-0.4637	0.006	-71.80	0.0000	-0.4764	-0.4511
Prosecutions	0.0051	0.011	0.47	0.6380	-0.0163	0.0265
FPN	-0.0056	0.005	-1.04	0.2980	-0.0160	0.0049
VDRN	0.0011	0.004	0.29	0.7740	-0.0066	0.0089
WW	0.0006	0.005	0.12	0.9080	-0.0093	0.0105
Constant	90.2152	3.294	27.39	0.0000	83.7592	96.6712
Invkm	(offset)					
	Model Information Criteria					
Number Obs	**ll(null)**	**ll(model)**	**df**	**AIC*n[1]**	**AIC**	**Pseudo R^2**
91504	-168158.1	-112472.400	65	225074.8	2.50	0.33

[1]AIC*n is the AIC reported by STATA 10

APPENDIX 5

Cluster Means Plots developed with KSI RATE by Population and FPN_1000's

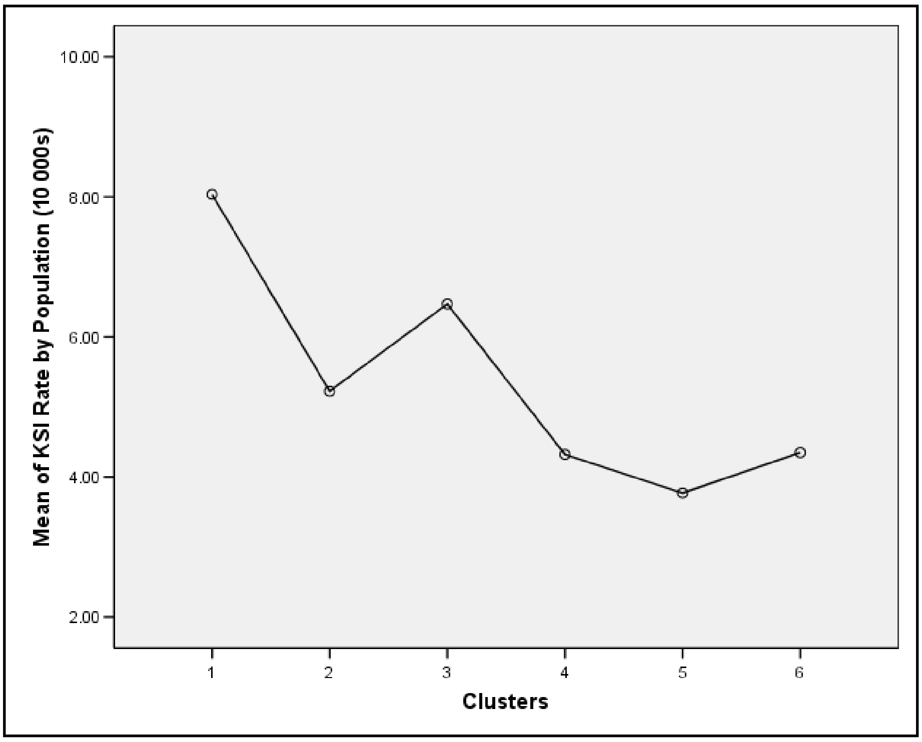


Figure 1: Cluster Means for KSI Rate by Population

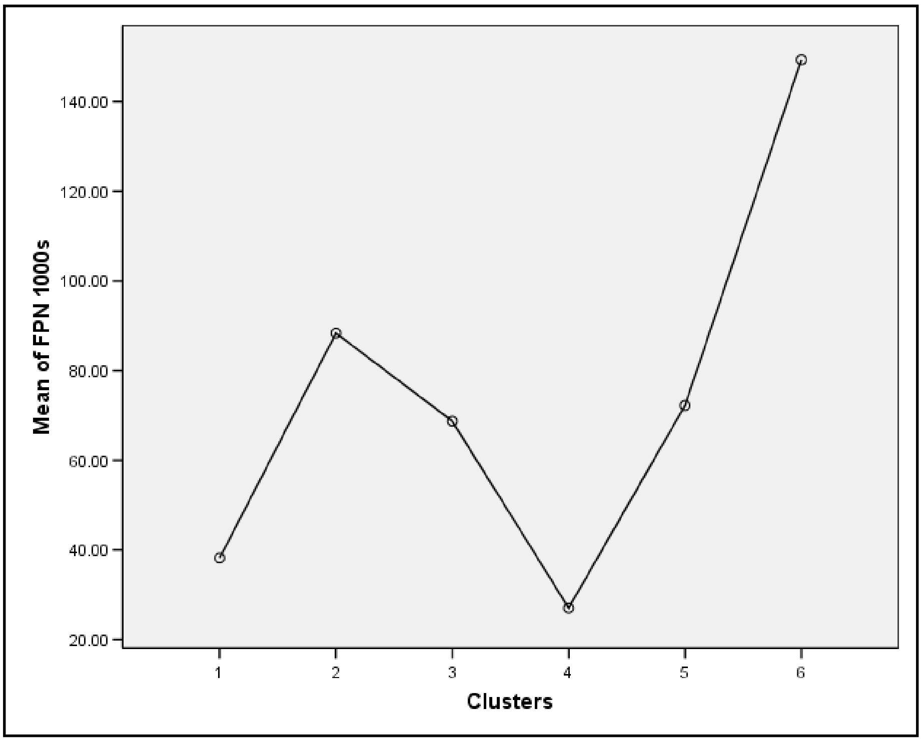


Figure 2: Cluster Means for FPN_1000's

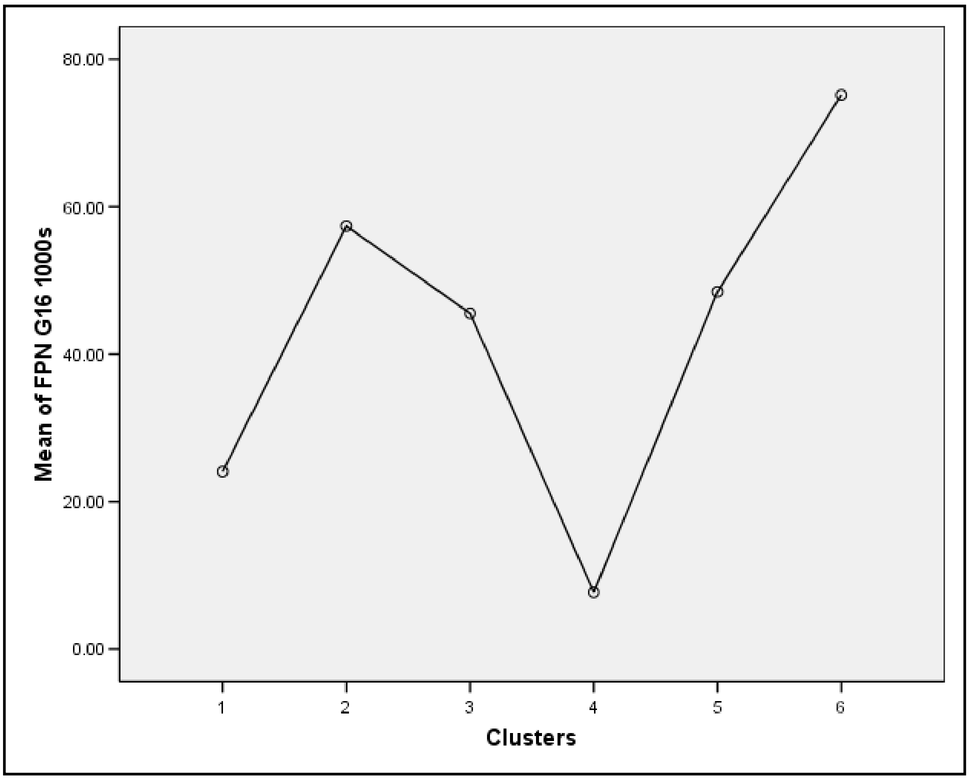


Figure 3: Cluster Means for FPN_G16_1000's

Cluster Means Plots developed with KSI RATE by Vkm and FPN_1000's

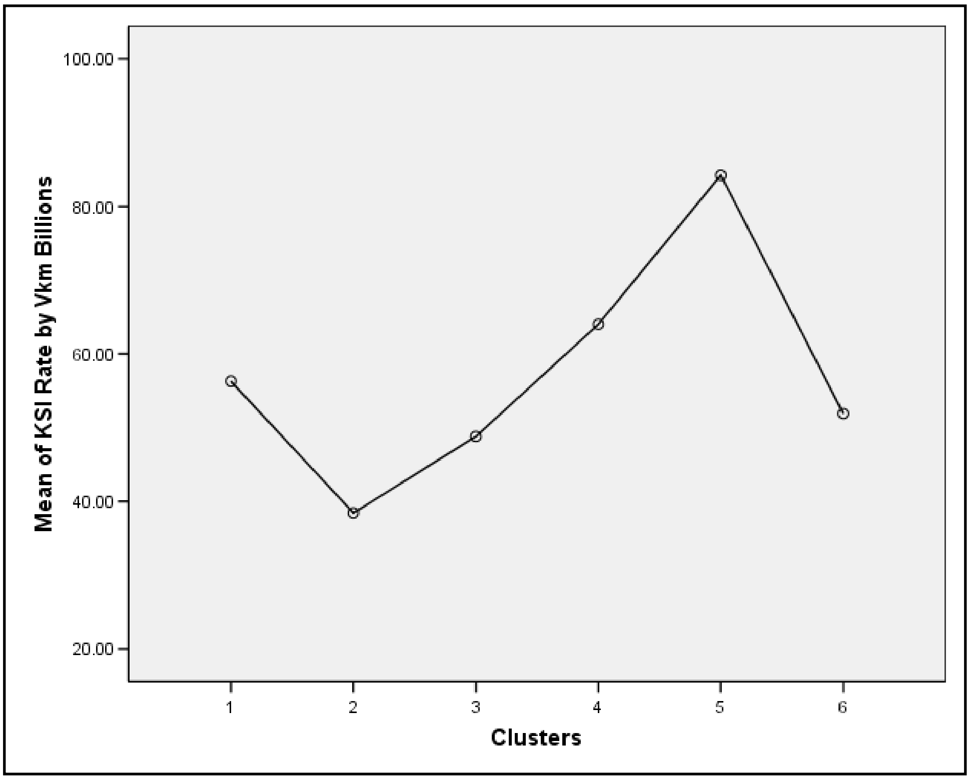


Figure 4: Cluster Means for KSI Rate by Vkm

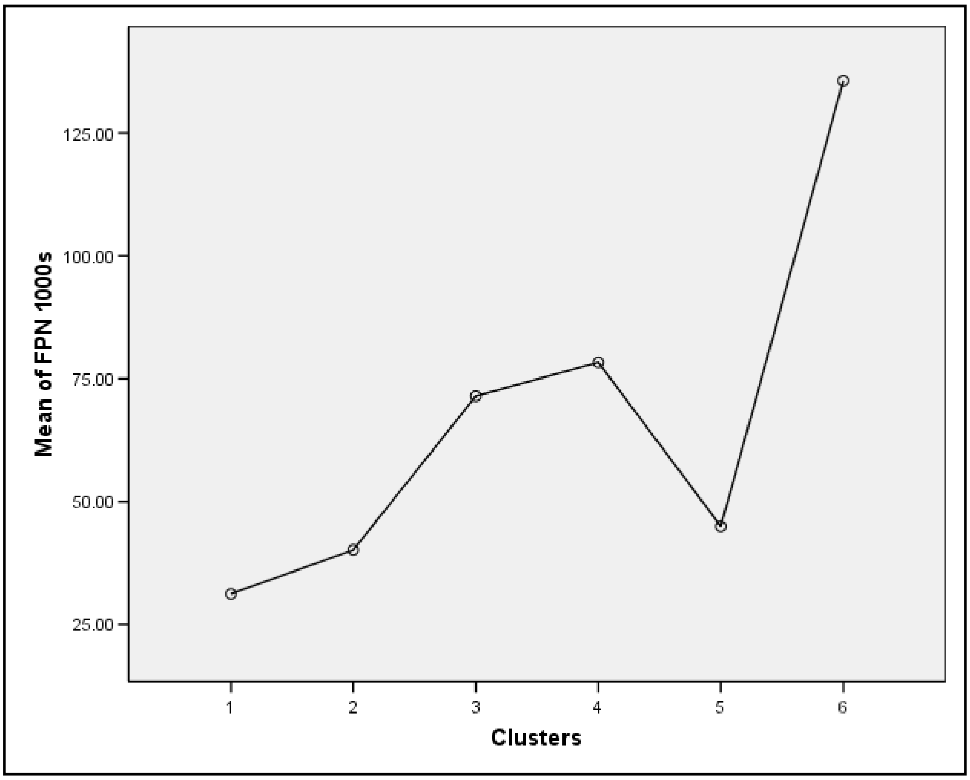


Figure 5: Cluster Means for FPN_1000's

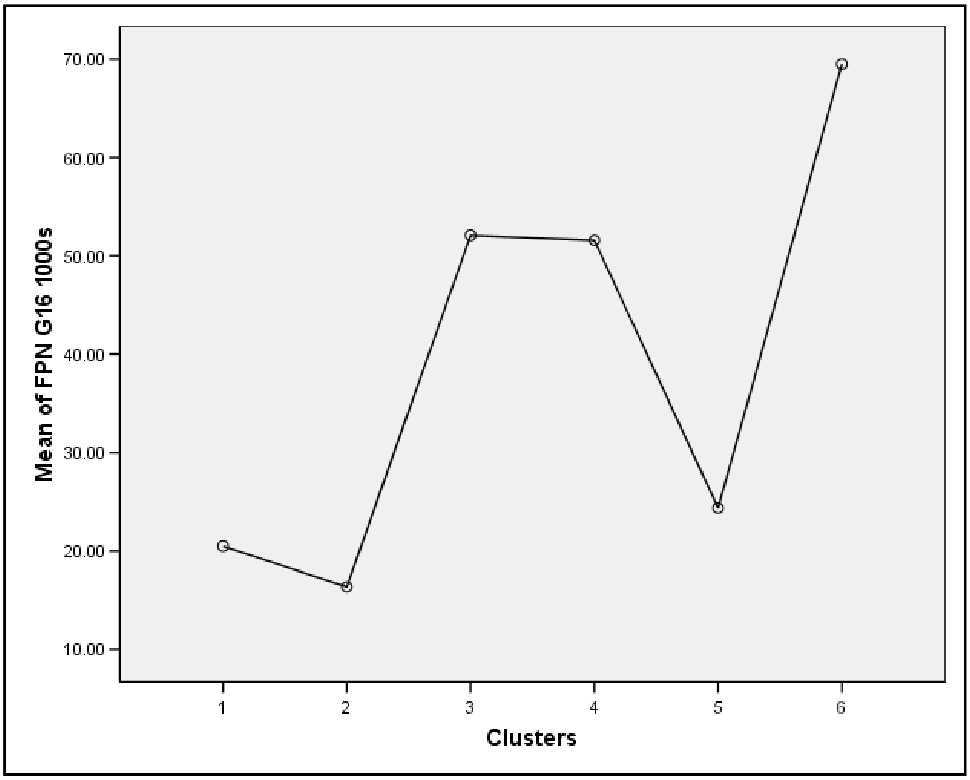


Figure 6: Cluster Means for FPN_G16_1000's

Appendix 6a

Quarter 3 Derived Cluster Model Parameters

Table 1: Multilevel Negative Binomial Models of Effect of ZFPN_G16_1000's on Derived Clusters in Quarter 3

Models Based on Derived Clusters	Null Model	Standard Error	p-value	Variance Components Model	Standard Error	p-value	NB Model ZFPN G16	Standard Error	p-value
Response	KSI			KSI			KSI		
Fixed Effect									
Constant	-1.830	0.040	0.000	-1.808	0.088	0.000	-1.868	0.079	0.000
Zfpn_G16_1000s							-0.178	0.070	0.005
Random Effect									
Level: CLUSTERS									
Constant				0.262	0.068	0.000	0.182	0.057	0.000
Zfpn_G16_1000s							0.028	0.030	0.088
Covariance							-0.042	0.032	0.190

Table 2: Multilevel Negative Binomial Models of Effect of ZLag1_FPN_G16_1000's and ZLag2_FPN_G16_1000's on Derived Clusters in Quarter 3

Models Based on Derived Clusters	Variance Components Model	Standard Error	p-value	NB Model ZFPN Lag1 G16	Standard Error	p-value	NB Model ZLag2 FPN G16	Standard Error	p-value
Response	KSI			KSI			KSI		
Fixed Effect									
Constant	-1.808	0.088	0.000	-1.869	0.079	0.000	-1.873	0.078	0.000
Zlag1_fpn_g16_1000s				-0.183	0.065	0.002			
Zlag2_fpn_g16_1000s							-0.256	0.081	0.001
Random Effect									
Level: CLUSTERS									
Constant	0.262	0.068	0.000	0.193	0.057	0.000	0.172	0.055	0.000
Zlag1_fpn_g16_1000s				0.020	0.024	0.202			
Covariance Lag1				-0.048	0.032	0.033			
Zlag2_fpn_g16_1000s							0.049	0.041	0.058
Covariance Lag2							-0.073	0.038	0.028

Quarter 4 Derived Cluster Model Parameters

Table 3: Multilevel Negative Binomial Models of Effect of ZLag1_FPN_1000's and ZLag2_FPN_1000's on Derived Clusters in Quarter 4

Models Based on Derived Clusters	Variance Components Model	Standard Error	p-value	NB Model ZLag1 FPN	Standard Error	p-value	NB Model ZLag2 FPN	Standard Error	p-value
Response	KSI			KSI			KSI		
Fixed Effect									
Constant	-1.850	0.089	0.000	-1.902	0.075	0.000	-1.914	0.077	0.000
Zlag1_FPN_1000s				-0.182	0.043	0.000			
Zlag2_FPN_1000s							-0.267	0.074	0.000
Random Effect									
Level: CLUSTERS									
Constant	0.270	0.070	0.000	0.197	0.054	0.000	0.163	0.057	0.001
Zlag1_FPN_1000s				0.004	0.016	0.201			
Covariance Lag1				-0.043	0.023	0.032			
Zlag2_FPN_1000s							0.038	0.039	0.083
Covariance Lag2							-0.043	0.030	0.076

Table 4: Multilevel Negative Binomial Models of Effect of ZFPN_G16_1000's on Derived Clusters in Quarter 4

Models Based on Derived Clusters	Null Model	Standard Error	p-value	Variance Components Model	Standard Error	p-value	NB Model ZFPN G16	Standard Error	p-value
Response	KSI			KSI			KSI		
Fixed Effect									
Constant	-1.866	0.040	0.000	-1.850	0.089	0.000	-1.904	0.078	0.000
ZFPN_G16_1000s							-0.200	0.057	0.000
Random Effect									
Level: CLUSTERS									
Constant				0.270	0.070	0.000	0.202	0.057	0.000
ZFPN_G16_1000s							0.008	0.020	0.172
Covariance							-0.039	0.026	0.066

Table 5: Multilevel Negative Binomial Models of Effect of ZLag1_FPN_G16_1000's and ZLag2_FPN_G16_1000's on Derived Clusters in Quarter 4

Models Based on Derived Clusters	Variance Components Model	Standard Error	p-value	NB Model ZLag1 FPN G16	Standard Error	p-value	NB Model ZLag2 FPN G16	Standard Error	p-value
Response	KSI			KSI			KSI		
Fixed Effect									
Constant	-1.850	0.089	0.000	-1.901	0.089	0.000	-1.891	0.082	0.000
Zlag1_FPN_G16_1000s				-0.139	0.033	0.000			
Zlag2_FPN_G16_1000s							-0.143	0.036	0.000
Random Effect									
Level: CLUSTERS									
Constant	0.270	0.070	0.000	0.230	0.069	0.000	0.244	0.059	0.000
Zlag1_FPN_G16_1000s				0.028	0.017	0.025			
Covariance Lag1				-0.083	0.032	0.004			
Zlag2_FPN_G16_1000s							0.023	0.016	0.037
Covariance Lag2							-0.074	0.028	0.004

Quarter 3 Regional Cluster Model Parameters

Table 6: Multilevel Negative Binomial Models of Effect of ZFPN_G16_1000's on Regional Clusters in Quarter 3

Models Based on Regional Clusters	Null Model	Standard Error	p-value	Variance Components Model	Standard Error	p-value	NB Model ZFPN G16	Standard Error	p-value
Response	KSI			KSI			KSI		
Fixed Effect									
Constant	-1.830	0.040	0.000	-1.813	0.114	0.000	-1.875	0.110	0.000
ZFPN_G16_1000s							-0.229	0.045	0.000
Random Effect									
Level: REGIONAL CLUSTER NAME									
Constant				0.103	0.055	0.015	0.107	0.051	0.009
ZFPN_G16_1000s							0.015	0.009	0.079
Covariance							-0.016	0.016	0.047

Table 7: Multilevel Negative Binomial Models of Effect of ZLag1_FPN_G16_1000's and ZLag2_FPN_G16_1000's on Regional Clusters in Quarter 3

Models Based on Regional Clusters	Variance Components Model	Standard Error	p-value	NB Model ZFPN Lag1 G16	Standard Error	p-value	NB Model ZLag2 FPN G16	Standard Error	p-value
Response	KSI			KSI			KSI		
Fixed Effect									
Constant	-1.813	0.114	0.000	-1.854	0.096	0.000	-1.855	0.098	0.000
Zlag1_FPN_G16_1000s				-0.204	0.046	0.000			
Zlag2_FPN_G16_1000s							-0.224	0.052	0.000
Random Effect									
Level: REGIONAL CLUSTER NAME									
Constant	0.103	0.055	0.015	0.071	0.039	0.017	0.075	0.041	0.016
Zlag1_FPN_G16_1000s				0.008	0.008	0.079			
Covariance Lag1				-0.024	0.015	0.055			
Zlag2_FPN_G16_1000s							0.008	0.009	0.094
Covariance Lag2							-0.018	0.016	0.130

Quarter 4 Regional Cluster Model Parameters

Table 8: Multilevel Negative Binomial Models of Effect of ZLag1_FPN_1000's and ZLag2_FPN_1000's on Regional Clusters in Quarter 4

Models Based on Regional Clusters	Variance Components Model	Standard Error	p-value	NB Model ZLag1 FPN	Standard Error	p-value	NB Model ZLag2 FPN	Standard Error	p-value
Response	KSI			KSI			KSI		
Fixed Effect									
Constant	-1.850	0.112	0.000	-1.881	0.109	0.000	-1.886	0.101	0.000
Zlag1_FPN_1000s				-0.293	0.065	0.000			
Zlag2_FPN_1000s							-0.273	0.081	0.000
Random Effect									
Level: REGIONAL CLUSTER NAME									
Constant	0.100	0.053	0.015	0.095	0.050	0.015	0.081	0.043	0.015
Zlag1_FPN_1000s				0.025	0.017	0.035			
Covariance Lag1				0.002	0.021	0.462			
Zlag2_FPN_1000s							0.042	0.027	0.030
Covariance Lag2							-0.012	0.025	0.316

Table 9: Multilevel Negative Binomial Models of Effect of ZFPN_G16_1000's on Regional Clusters in Quarter 4

Models Based on Regional Clusters	Null Model	Standard Error	p-value	Variance Components Model	Standard Error	p-value	NB Model ZFPN G16	Standard Error	p-value
Response	KSI			KSI			KSI		
Fixed Effect									
Constant	-1.866	0.040	0.000	-1.850	0.112	0.000	-1.891	0.108	0.000
ZFPN_G16_1000s							-0.264	0.073	0.000
Random Effect									
Level: REGIONAL CLUSTER NAME									
Constant				0.100	0.053	0.015	0.094	0.050	0.015
ZFPN_G16_1000s							0.032	0.022	0.150
Covariance							0.013	0.024	0.072

Appendix 6b

Q3 G16 Charts for Derived Cluster Models

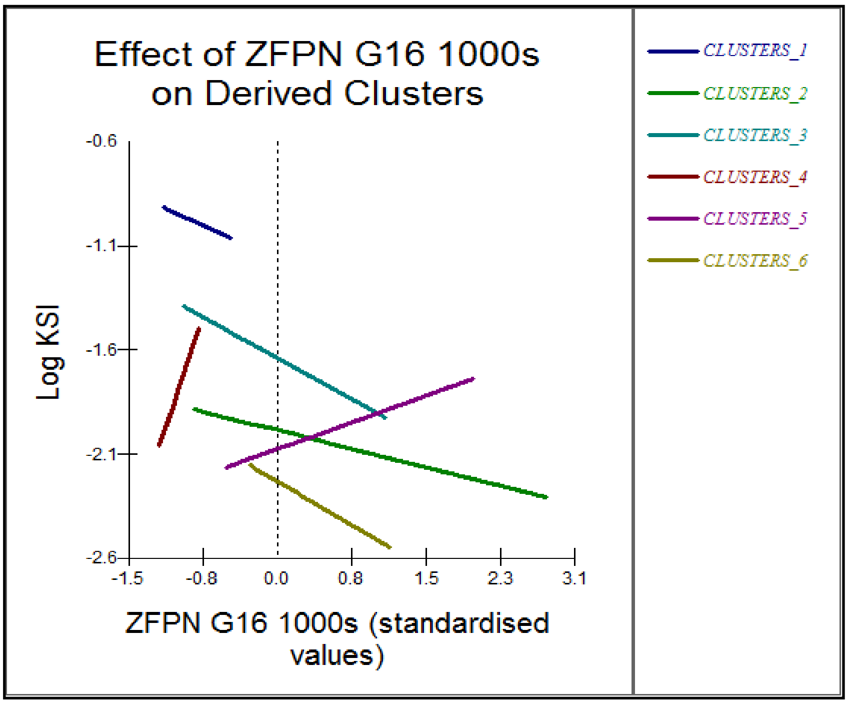


Figure 1: Effect of Enforcement, ZFPN_G16_1000's, on Derived Clusters in Quarter 3

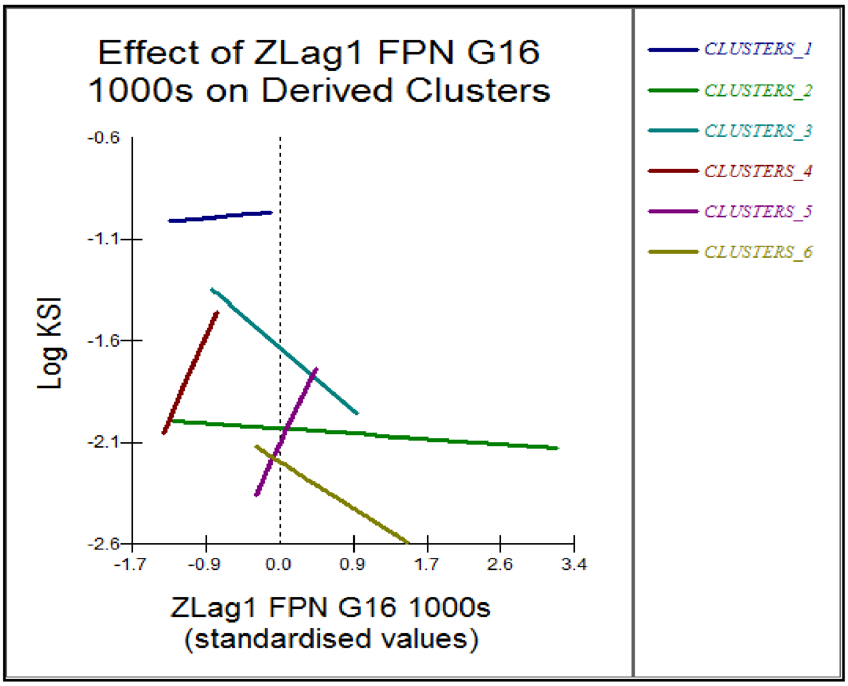


Figure 2: Effect of Enforcement, ZLag1_FPN_G16_1000's, on Derived Clusters in Quarter 3

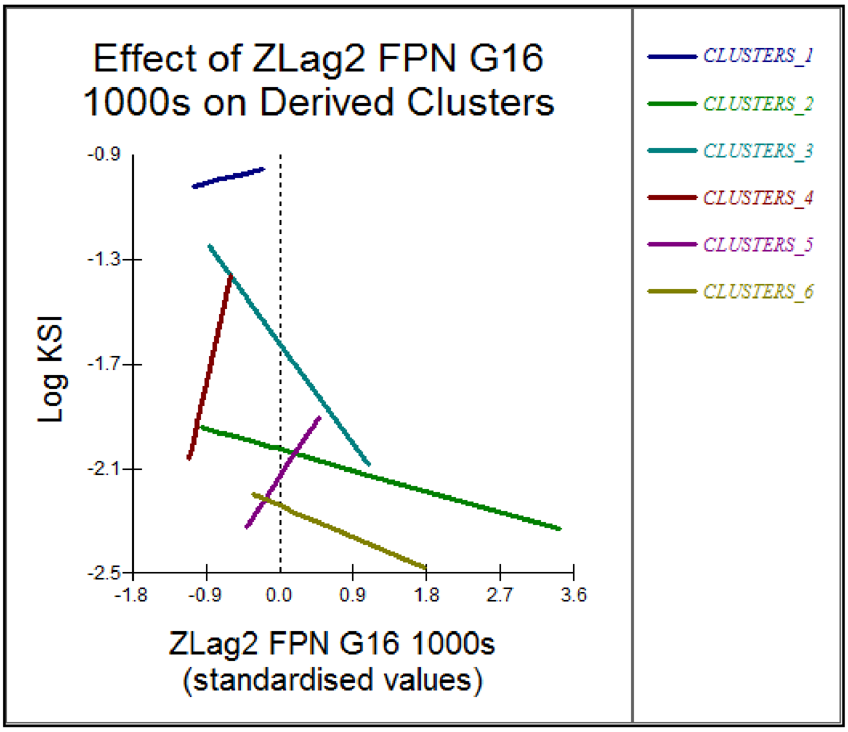


Figure 3: Effect of Enforcement, ZLag2_FPN_G16_1000's, on Derived Clusters in Quarter 3

Q4 Charts for Derived Cluster Models

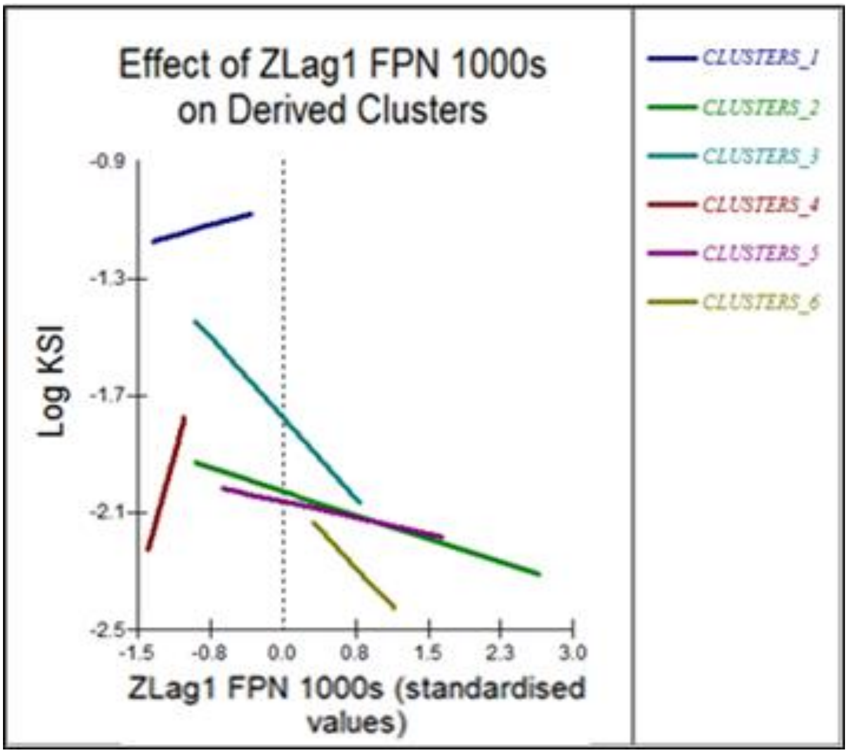


Figure 4: Effect of Enforcement, ZLag1_FPN _1000's, on Derived Clusters in Quarter 4

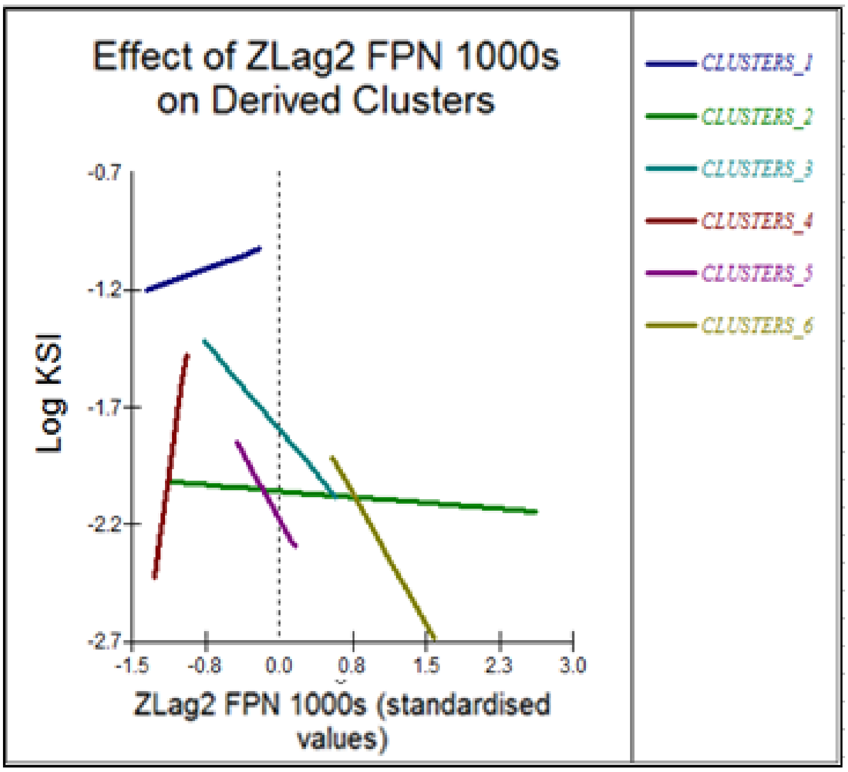


Figure 5: Effect of Enforcement, ZLag2_FPN _1000's, on Derived Clusters in Quarter 4

Q4 G16 Charts for Derived Cluster Models

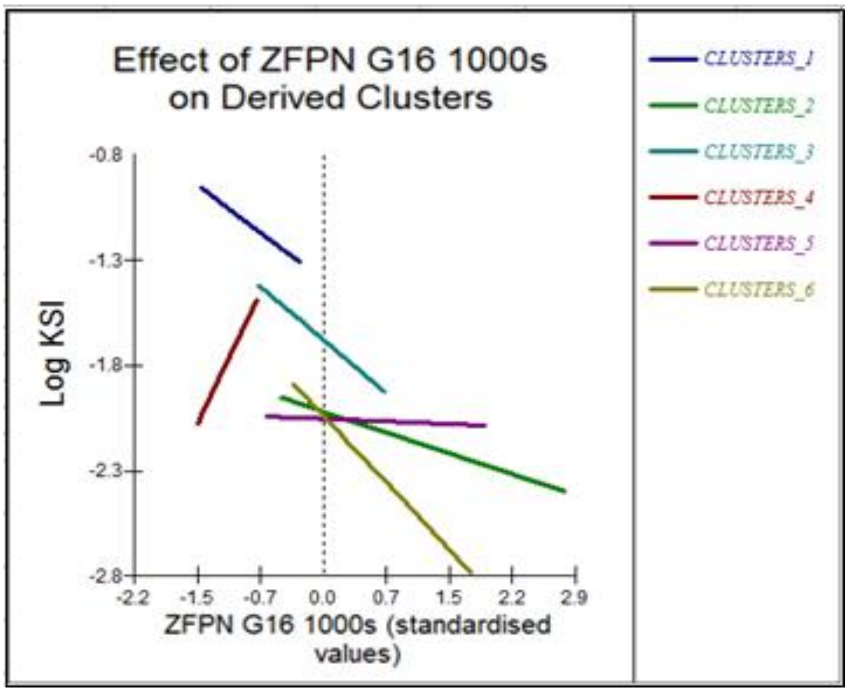


Figure 6: Effect of Enforcement, ZFPN_G16_1000's, on Derived Clusters in Quarter 4

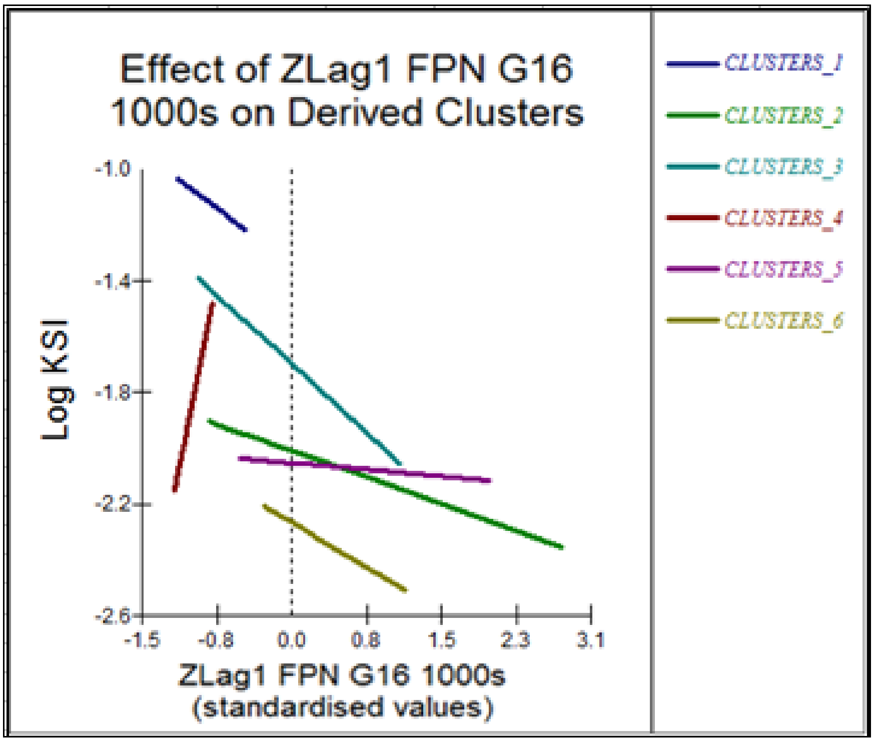


Figure 7: Effect of Enforcement, ZLag1_FPN_G16_1000's, on Derived Clusters in Quarter 4

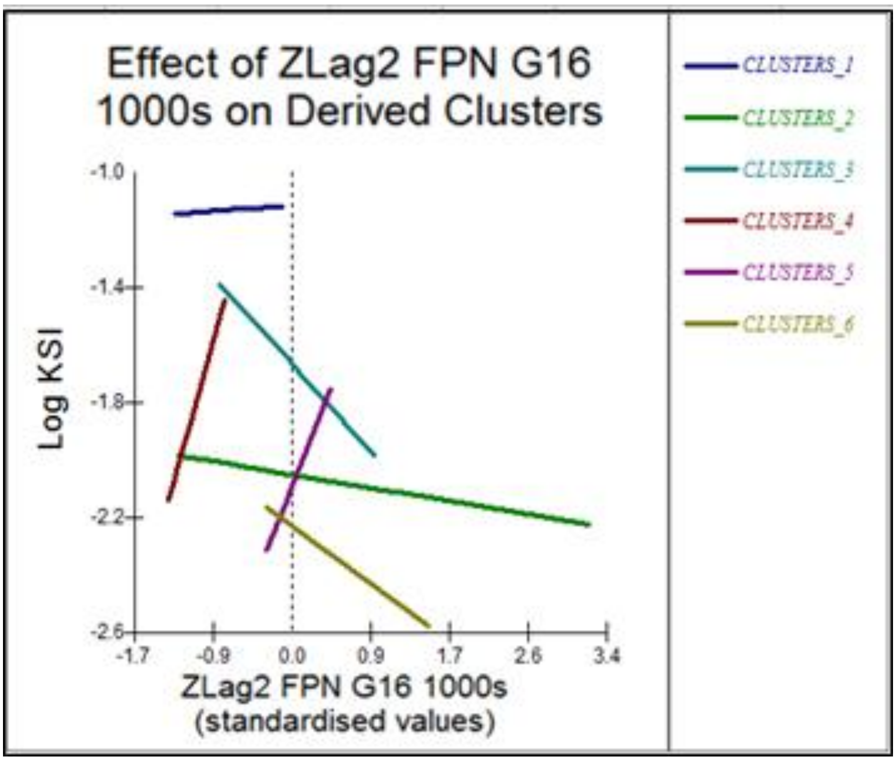


Figure 8: Effect of Enforcement, ZLag2_FPN_G16_1000's, on Derived Clusters in Quarter 4

Q3 Charts for Regional Cluster Models

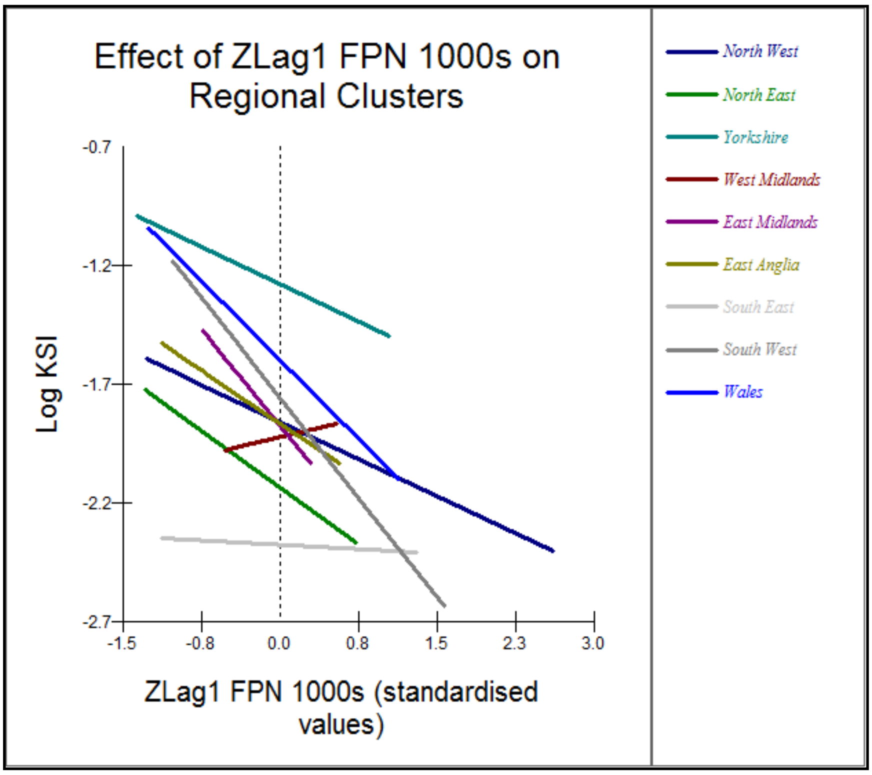


Figure 9: Effect of Enforcement, ZLag1_FPN _1000's, on Regional Clusters in Quarter 3

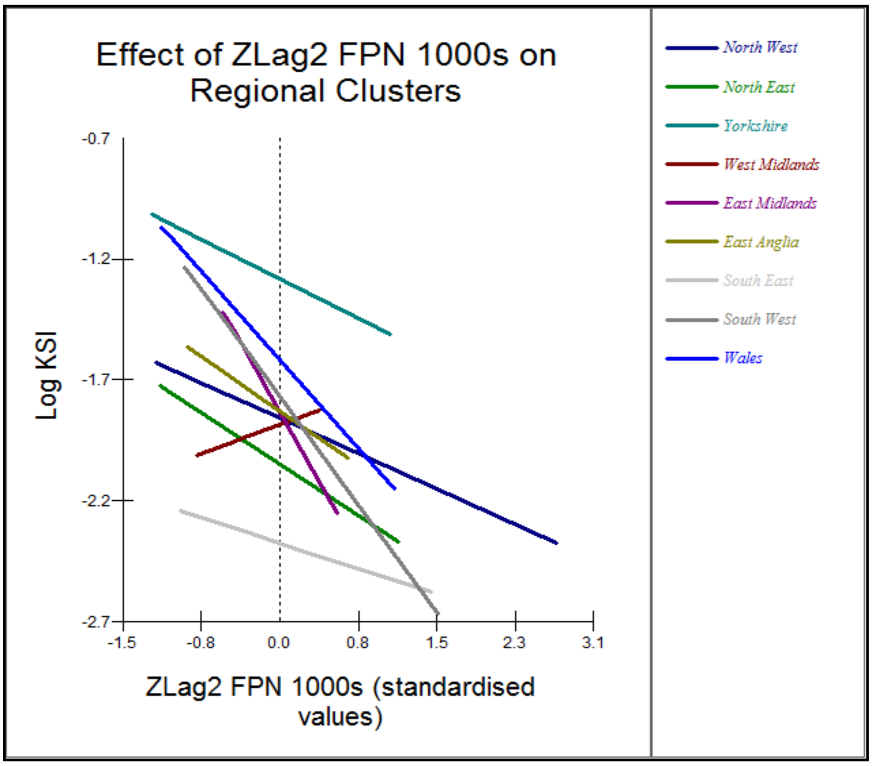


Figure 10: Effect of Enforcement, ZLag2_FPN _1000's, on Regional Clusters in Quarter 3

Q3 G16 Charts for Regional Cluster Models

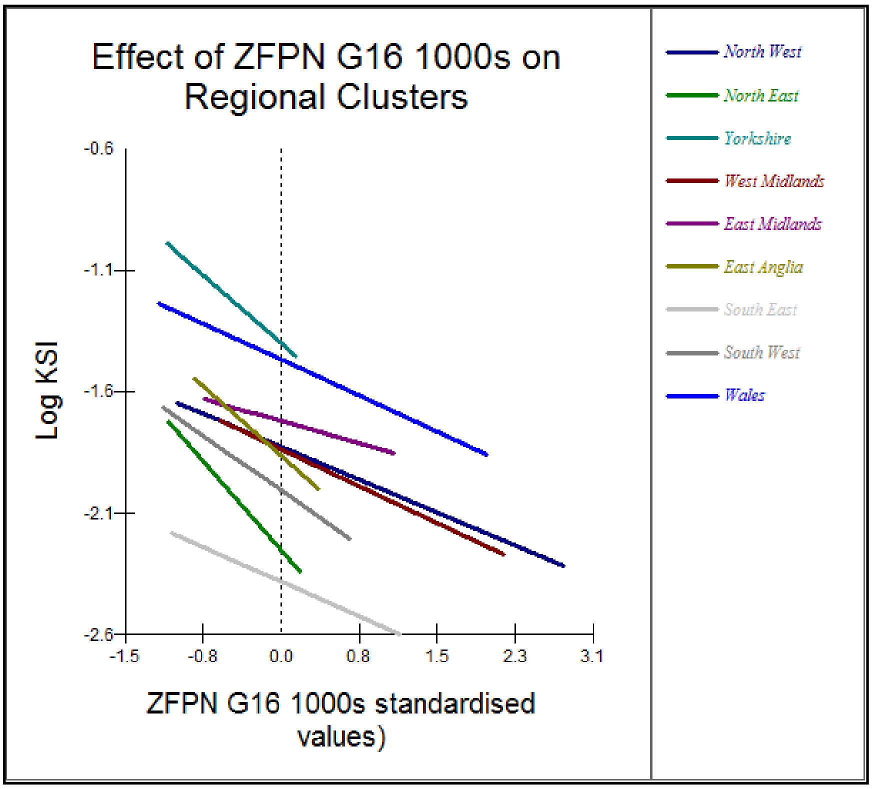


Figure 11: Effect of Enforcement, ZFPN _G16_1000's, on Regional Clusters in Quarter 3

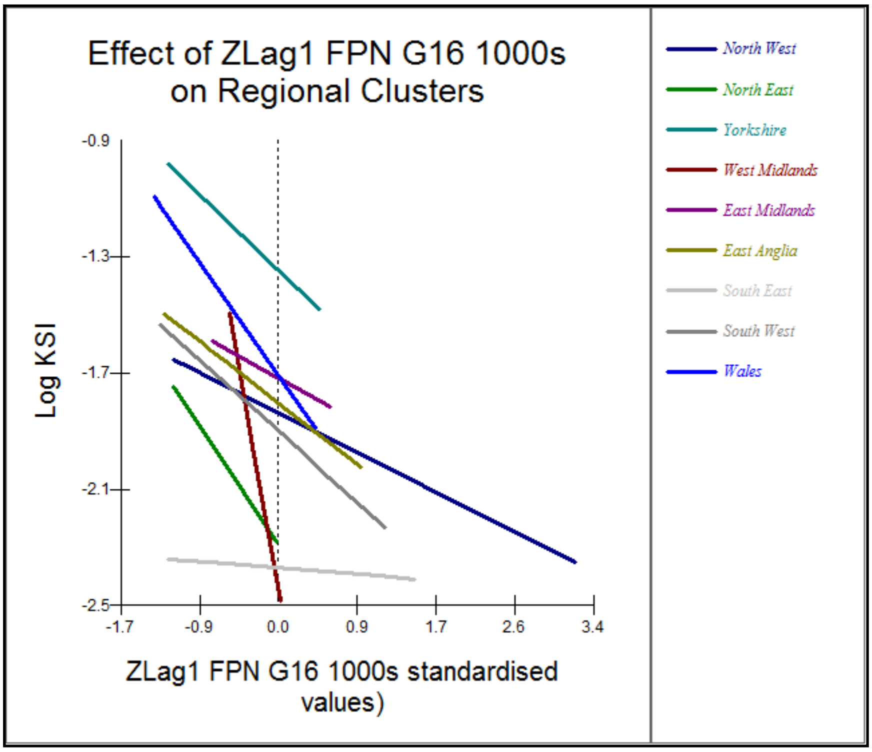


Figure 12: Effect of Enforcement, ZLag1_FPN _G16_1000's, on Regional Clusters in Quarter 3

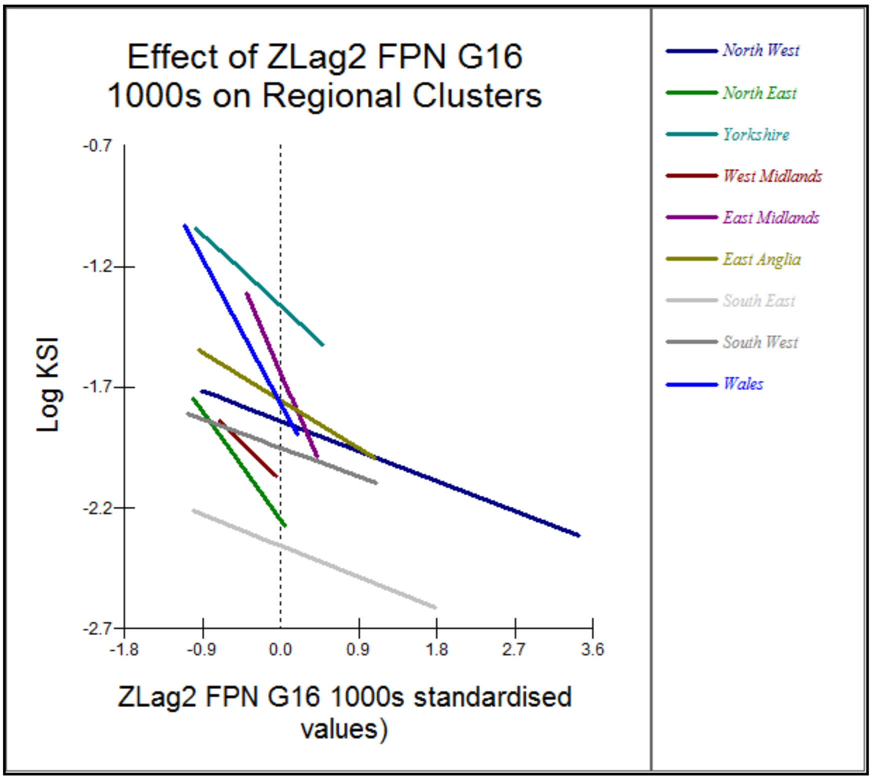


Figure 13: Effect of Enforcement, ZLag2_FPN _G16_1000's, on Regional Clusters in Quarter 3

Q4 Charts for Regional Cluster Models

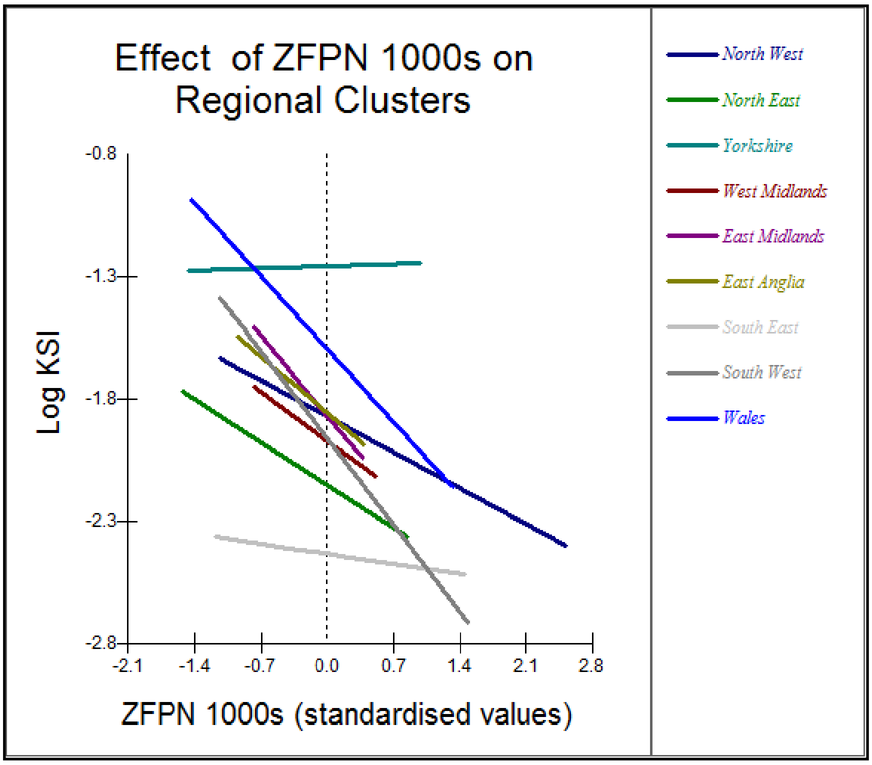


Figure 14: Effect of Enforcement, ZFPN _1000's, on Regional Clusters in Quarter 4

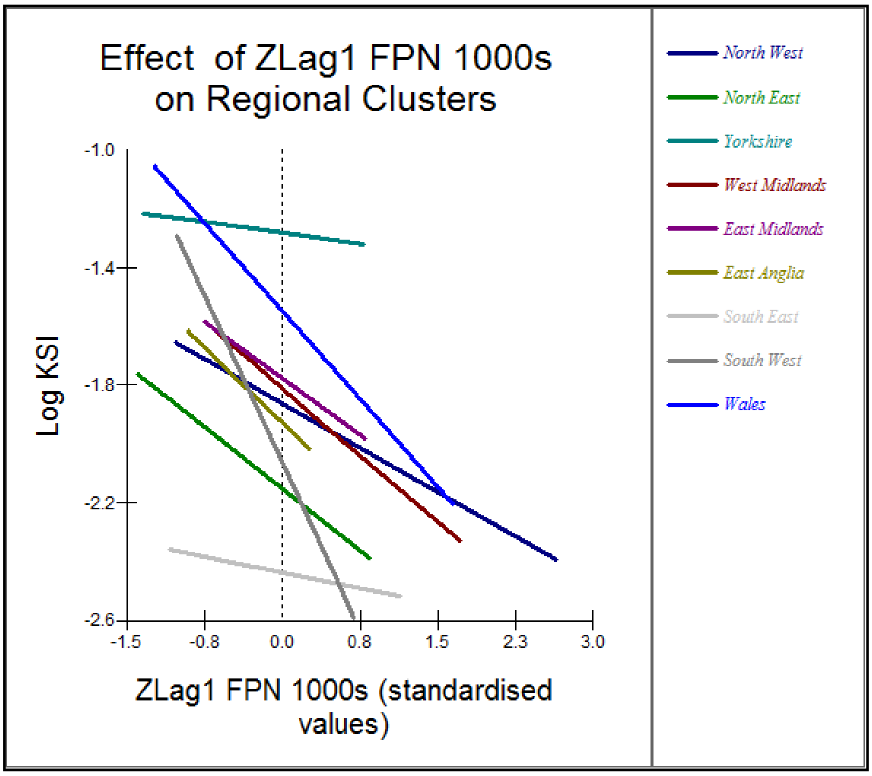


Figure 15: Effect of Enforcement, ZLag1_FPN _1000's, on Regional Clusters in Quarter 4

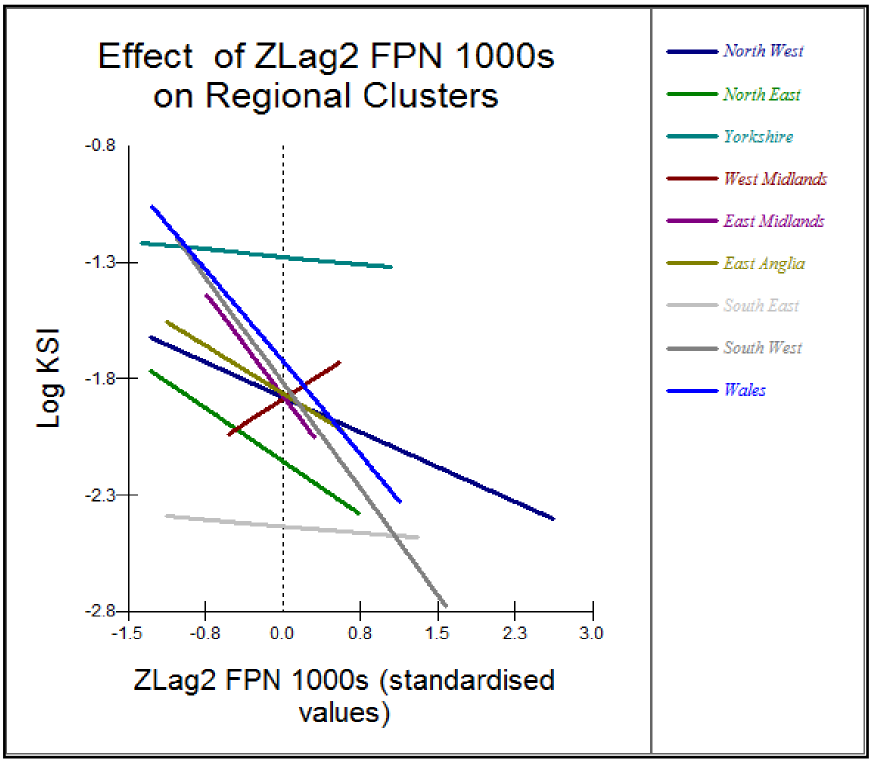


Figure 16: Effect of Enforcement, ZLag2_FPN _1000's, on Regional Clusters in Quarter 4

Q4 G16 Charts for Regional Cluster Models

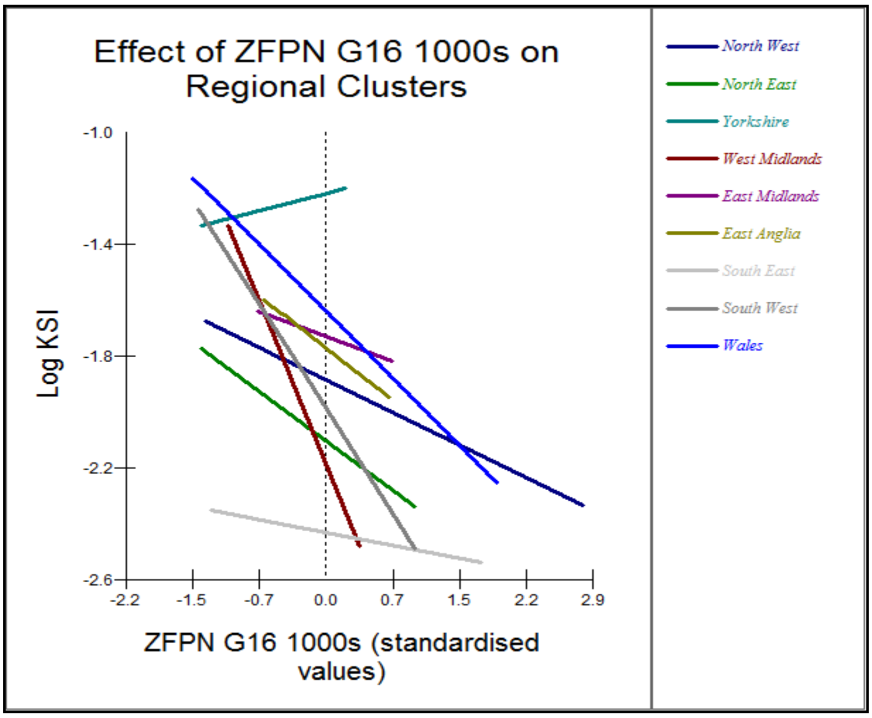


Figure 17: Effect of Enforcement, ZFPN _G16_1000's, on Regional Clusters in Quarter 4

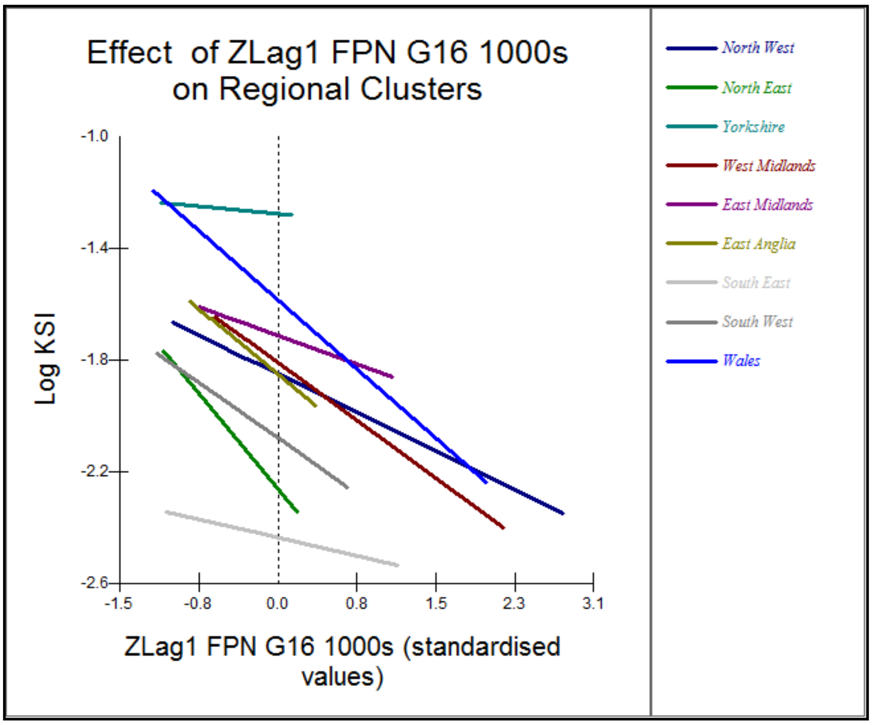


Figure 18: Effect of Enforcement, ZLag2_FPN _G16_1000's, on Regional Clusters in Quarter 4

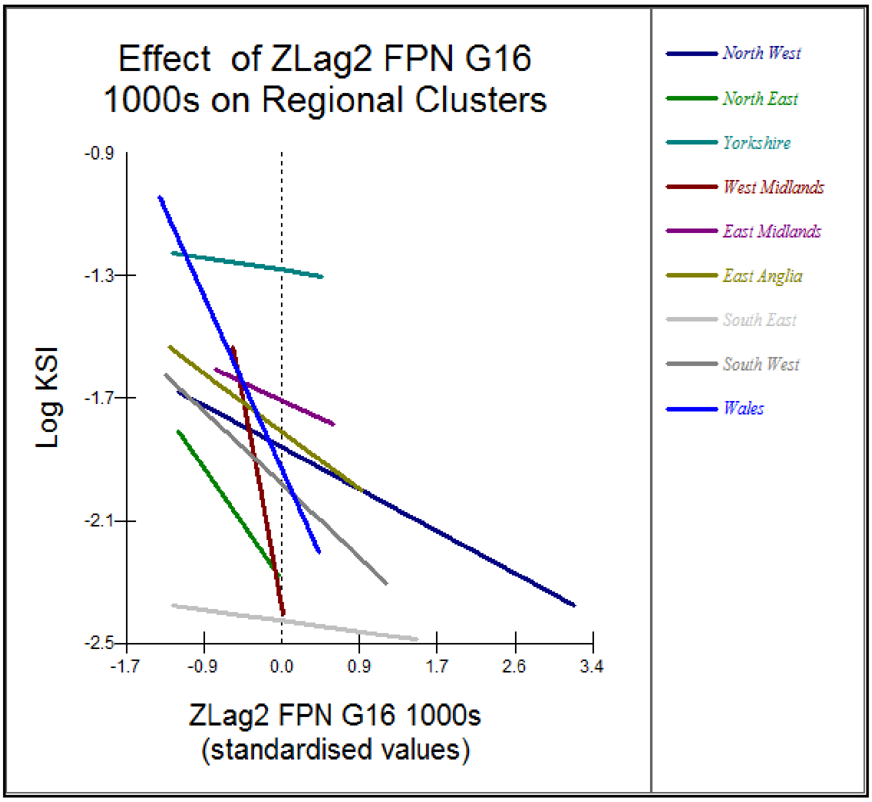


Figure 19: Effect of Enforcement, ZLag2_FPN _G16_1000's, on Regional Clusters in Quarter 4

Appendix 6c

Quarter 3 G16 Derived Cluster Data

Table 1: Parameter Estimates and p-values for Fixed Effects of ZFPN_G16_1000's on Derived Clusters in Quarter 3

Models based on Derived Clusters	Fixed Effect Parameter Estimate	Standard Error	Parameter Estimate / Standard Error	p-value
Cluster 3 with ZFPN_G16_1000's Effect	-0.254	0.119	-2.134	0.016
Cluster 5 with ZFPN_G16_1000's Effect	0.166	0.126	1.317	0.094
Cluster 2 with ZFPN_G16_1000's Effect	-0.114	0.094	-1.213	0.113
Cluster 4 with ZFPN_G16_1000's Effect	1.408	1.250	1.126	0.130
Cluster 6 with ZFPN_G16_1000's Effect	-0.267	0.292	-0.914	0.180
Cluster 1 with ZFPN_G16_1000's Effect	-0.206	0.573	-0.360	0.360

Table 2: Parameter Estimates and p-values for Fixed Effects of ZLag1_FPN_G16_1000's on Derived Clusters in Quarter 3

Models based on Derived Clusters	Fixed Effect Parameter Estimate	Standard Error	Parameter Estimate / Standard Error	p-value
Cluster 3 with ZLag1_FPN_G16_1000's Effect	-0.366	0.155	-2.361	0.009
Cluster 5 with ZLag1_FPN_G16_1000's Effect	0.902	0.694	1.300	0.097
Cluster 4 with ZLag1_FPN_G16_1000's Effect	0.980	0.831	1.179	0.119
Cluster 6 with ZLag1_FPN_G16_1000's Effect	-0.271	0.251	-1.080	0.140
Cluster 2 with ZLag1_FPN_G16_1000's Effect	-0.031	0.081	-0.383	0.351
Cluster 1 with ZLag1_FPN_G16_1000's Effect	0.034	0.396	0.086	0.466

Table 3: Parameter Estimates and p-values for Fixed Effects of ZLag2_FPN_G16_1000's on Derived Clusters in Quarter 3

Models based on Derived Clusters	Fixed Effect Parameter Estimate	Standard Error	Parameter Estimate / Standard Error	p-value
Cluster 3 with ZLag2_FPN_G16_1000's Effect	-0.432	0.197	-2.193	0.014
Cluster 4 with ZLag2_FPN_G16_1000's Effect	1.402	0.974	1.439	0.075
Cluster 5 with ZLag2_FPN_G16_1000's Effect	0.476	0.454	1.048	0.147
Cluster 2 with ZLag2_FPN_G16_1000's Effect	-0.089	0.089	-1.000	0.159
Cluster 6 with ZLag2_FPN_G16_1000's Effect	-0.135	0.205	-0.659	0.253
Cluster 1 with ZLag2_FPN_G16_1000's Effect	0.073	0.537	0.136	0.446

Quarter 4 Derived Cluster Data

Table 4: Parameter Estimates and p-values for Fixed Effects of ZLag1_FPN_1000's on Derived Clusters in Quarter 4

Models based on Derived Clusters	Fixed Effect Parameter Estimate	Standard Error	Parameter Estimate / Standard Error	p-value
Cluster 3 with ZLag1_FPN_1000's Effect	-0.370	0.140	-2.643	0.004
Cluster 2 with ZLag1_FPN_1000's Effect	-0.107	0.118	-0.907	0.182
Cluster 4 with ZLag1_FPN_1000's Effect	1.217	1.361	0.894	0.186
Cluster 6 with ZLag1_FPN_1000's Effect	-0.351	0.618	-0.568	0.290
Cluster 5 with ZLag1_FPN_1000's Effect	-0.073	0.133	-0.549	0.291
Cluster 1 with ZLag1_FPN_1000's Effect	0.093	0.547	0.170	0.433

Table 5: Parameter Estimates and p-values for Fixed Effects of ZLag2_FPN_1000's on Derived Clusters in Quarter 4

Models based on Derived Clusters	Fixed Effect Parameter Estimate	Standard Error	Parameter Estimate / Standard Error	p-value
Cluster 3 with ZLag2_FPN_1000's Effect	-0.498	0.191	-2.607	0.005
Cluster 4 with ZLag2_FPN_1000's Effect	2.873	1.393	2.062	0.020
Cluster 6 with ZLag2_FPN_1000's Effect	-0.750	0.449	-1.670	0.047
Cluster 5 with ZLag2_FPN_1000's Effect	-0.748	0.603	-1.240	0.110
Cluster 1 with ZLag2_FPN_1000's Effect	0.147	0.361	0.407	0.342
Cluster 2 with ZLag2_FPN_1000's Effect	-0.035	0.088	-0.398	0.345

Quarter 4 Derived Cluster G16 Data

Table 6: Parameter Estimates and p-values for Fixed Effects of ZFPN_G16_1000's on Derived Clusters in Quarter 4

Models based on Derived Clusters	Fixed Effect Parameter Estimate	Standard Error	Parameter Estimate / Standard Error	p-value
Cluster 3 with ZFPN_G16_1000's Effect	-0.347	0.150	-2.313	0.010
Cluster 6 with ZFPN_G16_1000's Effect	-0.442	0.257	-1.720	0.043
Cluster 4 with ZFPN_G16_1000's Effect	0.861	0.819	1.051	0.147
Cluster 2 with ZFPN_G16_1000's Effect	-0.135	0.135	-1.000	0.159
Cluster 1 with ZFPN_G16_1000's Effect	-0.311	0.383	-0.812	0.208
Cluster 5 with ZFPN_G16_1000's Effect	-0.016	0.126	-0.127	0.450

Table 7: Parameter Estimates and p-values for Fixed Effects of ZLag1_FPN_G16_1000's on Derived Clusters in Quarter 4

Models based on Derived Clusters	Fixed Effect Parameter Estimate	Standard Error	Parameter Estimate / Standard Error	p-value
Cluster 3 with ZLag1_FPN_G16_1000's Effect	-0.315	0.121	-2.603	0.005
Cluster 4 with ZLag1_FPN_G16_1000's Effect	1.668	1.446	1.154	0.124
Cluster 2 with ZLag1_FPN_1G16_000's Effect	-0.123	0.113	-1.088	0.138
Cluster 6 with ZLag1_FPN_G16_1000's Effect	-0.206	0.353	-0.584	0.280
Cluster 1 with ZLag1_FPN_G16_1000's Effect	-0.264	0.674	-0.392	0.348
Cluster 5 with ZLag1_FPN_G16_1000's Effect	-0.032	0.135	-0.237	0.406

Table 8: Parameter Estimates and p-values for Fixed Effects of ZLag2_FPN_G16_1000's on Derived Clusters in Quarter 4

Models based on Derived Clusters	Fixed Effect Parameter Estimate	Standard Error	Parameter Estimate / Standard Error	p-value
Cluster 3 with ZLag2_FPN_G16_1000's Effect	-0.357	0.165	-2.164	0.015
Cluster 4 with ZLag2_FPN_G16_1000's Effect	1.137	0.962	1.182	0.117
Cluster 5 with ZLag2_FPN_G16_1000's Effect	0.817	0.834	0.980	0.164
Cluster 6 with ZLag2_FPN_G16_1000's Effect	-0.235	0.302	-0.778	0.218
Cluster 2 with ZLag2_FPN_G16_1000's Effect	-0.054	0.094	-0.574	0.283
Cluster 1 with ZLag2_FPN_G16_1000's Effect	0.023	0.463	0.050	0.480

Quarter 3 Regional Cluster Data

Table 9: Parameter Estimates and p-values for Fixed Effects of ZLag1_FPN_1000's on Regional Clusters in Quarter 3

Models based on Regional Clusters	Fixed Effect Parameter Estimate	Standard Error	Parameter Estimate / Standard Error	p-value
North West with ZFPN_1000’s Effect	-0.207	0.057	-3.632	0.000
South West with ZFPN_1000’s Effect	-0.561	0.092	-6.098	0.000
Wales with ZFPN_1000’s Effect	-0.441	0.122	-3.615	0.000
North East with ZFPN_1000’S Effect	-0.318	0.130	-2.446	0.007
East Anglia with ZFPN_1000’s Effect	-0.298	0.127	-2.346	0.009
East Midlands with ZFPN_1000’s Effect	-0.545	0.263	-2.072	0.019
Yorkshire with ZFPN_1000’s Effect	-0.209	0.124	-1.685	0.046
West Midlands with ZFPN_1000’s Effect	0.105	0.236	0.445	0.328
South East with ZFPN_1000’s Effect	-0.025	0.077	-0.325	0.373

Table 10: Parameter Estimates and p-values for Fixed Effects of ZLag2_FPN_1000's on Regional Clusters in Quarter 3

Models based on Regional Clusters	Fixed Effect Parameter Estimate	Standard Error	Parameter Estimate / Standard Error	p-value
North West with ZFPN_1000’s Effect	-0.189	0.054	-3.500	0.000
East Midlands with ZFPN_1000’s Effect	-0.738	0.229	-3.223	0.000
South West with ZFPN_1000’s Effect	-0.577	0.092	-6.272	0.000
Wales with ZFPN_1000’s Effect	-0.470	0.129	-3.643	0.000
North East with ZFPN_1000’S Effect	-0.274	0.110	-2.491	0.006
East Anglia with ZFPN_1000’s Effect	-0.290	0.126	-2.302	0.010
South East with ZFPN_1000’s Effect	-0.136	0.081	-1.679	0.047
Yorkshire with ZFPN_1000’s Effect	-0.210	0.129	-1.628	0.052
West Midlands with ZFPN_1000’s Effect	0.152	0.212	0.717	0.237

Quarter 3 Regional Cluster G16 Data

Table 11: Parameter Estimates and p-values for Fixed Effects of ZFPN_G16_1000's on Regional Clusters in Quarter 3

Models based on Regional Clusters	Fixed Effect Parameter Estimate	Standard Error	Parameter Estimate / Standard Error	p-value
North West with ZFPN_G16_1000’s Effect	-0.175	0.060	-2.917	0.002
West Midlands with ZFPN_G16_1000’s Effect	-0.196	0.084	-2.333	0.010
North East with ZFPN_G16_1000’S Effect	-0.474	0.214	-2.215	0.013
East Anglia with ZFPN_G16_1000’s Effect	-0.370	0.170	-2.176	0.015
Wales with ZFPN_G16_1000’s Effect	-0.190	0.101	-1.881	0.030
South East with ZFPN_G16_1000’s Effect	-0.184	0.101	-1.822	0.034
South West with ZFPN_G16_1000’s Effect	-0.292	0.170	-1.718	0.043
Yorkshire with ZFPN_G16_1000’s Effect	-0.362	0.214	-1.692	0.045
East Midlands with ZFPN_G16_1000’s Effect	-0.118	0.141	-0.837	0.201

Table 12: Parameter Estimates and p-values for Fixed Effects of ZLag1_FPN_G16_G16_1000's on Regional Clusters in Quarter 3

Models based on Regional Clusters	Fixed Effect Parameter Estimate	Standard Error	Parameter Estimate / Standard Error	p-value
North West with ZFPN_G16_1000’s Effect	-0.161	0.050	-3.220	0.000
West Midlands with ZFPN_G16_1000’s Effect	-1.802	0.585	-3.080	0.001
Wales with ZFPN_G16_1000’s Effect	-0.460	0.168	-2.738	0.009
East Anglia with ZFPN_G16_1000’s Effect	-0.248	0.108	-2.296	0.011
South West with ZFPN_G16_1000’s Effect	-0.288	0.129	-2.233	0.013
North East with ZFPN_G16_1000’S Effect	-0.487	0.254	-1.917	0.028
Yorkshire with ZFPN_G16_1000’s Effect	-0.307	0.184	-1.668	0.048
East Midlands with ZFPN_G16_1000’s Effect	-0.176	0.227	-0.775	0.219
South East with ZFPN_G16_1000’s Effect	-0.025	0.074	-0.338	0.368

Table 13: Parameter Estimates and p-values for Fixed Effects of ZLag2_FPN_G16_1000's on Regional Clusters in Quarter 3

Models based on Regional Clusters	Fixed Effect Parameter Estimate	Standard Error	Parameter Estimate / Standard Error	p-value
Wales with ZFPN_G16_1000’s Effect	-0.669	0.218	-3.069	0.001
North West with ZFPN_G16_1000’s Effect	-0.137	0.049	-2.796	0.003
East Midlands with ZFPN_G16_1000’s Effect	-0.832	0.381	-2.184	0.014
East Anglia with ZFPN_G16_1000’s Effect	-0.222	0.108	-2.056	0.020
Yorkshire with ZFPN_G16_1000’s Effect	-0.330	0.221	-1.493	0.027
North East with ZFPN_G16_1000’S Effect	-0.500	0.277	-1.805	0.036
South East with ZFPN_G16_1000’s Effect	-0.142	0.080	-1.775	0.038
South West with ZFPN_G16_1000’s Effect	-0.131	0.145	-0.903	0.183
West Midlands with ZFPN_G16_1000’s Effect	-0.340	0.400	-0.850	0.198

Quarter 4 Regional Cluster Data

Table 14: Parameter Estimates and p-values for Fixed Effects of ZLag1_FPN_1000's on Regional Clusters in Quarter 4

Models based on Regional Clusters	Fixed Effect Parameter Estimate	Standard Error	Parameter Estimate / Standard Error	p-value
North West with ZFPN_1000’s Effect	-0.201	0.057	-3.526	0.000
South West with ZFPN_1000’s Effect	-0.761	0.128	-5.945	0.000
Wales with ZFPN_1000’s Effect	-0.400	0.095	-4.211	0.000
West Midlands with ZFPN_1000’s Effect	-0.301	0.099	-3.040	0.001
North East with ZFPN_1000’S Effect	-0.280	0.115	-2.435	0.007
East Anglia with ZFPN_1000’s Effect	-0.344	0.158	-2.177	0.015
East Midlands with ZFPN_1000’s Effect	-0.257	0.155	-1.658	0.049
South East with ZFPN_1000’s Effect	-0.072	0.096	-0.750	0.227
Yorkshire with ZFPN_1000’s Effect	-0.048	0.134	-0.358	0.360

Table 15: Parameter Estimates and p-values for Fixed Effects of ZLag2_FPN_1000's on Regional Clusters in Quarter 4

Models based on Regional Clusters	Fixed Effect Parameter Estimate	Standard Error	Parameter Estimate / Standard Error	p-value
North West with ZFPN_1000's Effect	-0.201	0.055	-3.655	0.000
South West with ZFPN_1000's Effect	-0.606	0.091	-6.659	0.000
Wales with ZFPN_1000's Effect	-0.527	0.120	-4.392	0.000
North East with ZFPN_1000'S Effect	-0.304	0.127	-2.394	0.008
East Midlands with ZFPN_1000's Effect	-0.592	0.255	-2.322	0.010
East Anglia with ZFPN_1000's Effect	-0.276	0.123	-2.244	0.012
South East with ZFPN_1000's Effect	-0.038	0.075	-0.507	0.306
Yorkshire with ZFPN_1000's Effect	-0.044	0.120	-0.367	0.357
West Midlands with ZFPN_1000's Effect	0.287	0.227	1.264	0.396

Quarter 4 Regional Cluster G16 Data

Table 16: Parameter Estimates and p-values for Fixed Effects of ZFPN_G16_1000's on Regional Clusters in Quarter 4

Models based on Regional Clusters	Fixed Effect Parameter Estimate	Standard Error	Parameter Estimate / Standard Error	p-value
West Midlands with ZFPN_G16_1000's Effect	-0.800	0.199	-4.020	0.000
South West with ZFPN_G16_1000's Effect	-0.517	0.108	-4.787	0.000
Wales with ZFPN_G16_1000's Effect	-0.329	0.096	-3.427	0.000
North West with ZFPN_G16_1000's Effect	-0.161	0.054	-2.981	0.001
North East with ZFPN_G16_1000'S Effect	-0.244	0.117	-2.085	0.019
East Anglia with ZFPN_G16_1000's Effect	-0.257	0.153	-1.680	0.046
South East with ZFPN_G16_1000's Effect	-0.063	0.074	-0.851	0.197
East Midlands with ZFPN_G16_1000's Effect	-0.122	0.170	-0.718	0.236
Yorkshire with ZFPN_G16_1000's Effect	0.086	0.180	0.478	0.316

Table 17: Parameter Estimates and p-values for Fixed Effects of ZLag1_FPN_G16_G16_1000's on Regional Clusters in Quarter 4

Models based on Regional Clusters	Fixed Effect Parameter Estimate	Standard Error	Parameter Estimate / Standard Error	p-value
West Midlands with ZFPN_G16_1000’s Effect	-0.268	0.083	-3.229	0.000
Wales with ZFPN_G16_1000’s Effect	-0.320	0.101	-3.168	0.000
North West with ZFPN_G16_1000’s Effect	-0.179	0.059	-3.034	0.001
North East with ZFPN_G16_1000’S Effect	-0.444	0.210	-2.114	0.017
East Anglia with ZFPN_G16_1000’s Effect	-0.302	0.166	-1.819	0.034
South West with ZFPN_G16_1000’s Effect	-0.257	0.167	-1.539	0.062
East Midlands with ZFPN_G16_1000’s Effect	-0.133	0.137	-0.971	0.166
South East with ZFPN_G16_1000’s Effect	-0.085	0.099	-0.859	0.196
Yorkshire with ZFPN_G16_1000’s Effect	-0.035	0.208	-0.168	0.433

Table 18: Parameter Estimates and p-values for Fixed Effects of ZLag2_FPN_G16_1000's on Regional Clusters in Quarter 4

Models based on Regional Clusters	Fixed Effect Parameter Estimate	Standard Error	Parameter Estimate / Standard Error	p-value
North West with ZFPN_G16_1000’s Effect	-0.161	0.050	-3.220	0.000
Wales with ZFPN_G16_1000’s Effect	-0.669	0.169	-3.959	0.000
West Midlands with ZFPN_G16_1000’s Effect	-1.581	0.576	-2.745	0.007
South West with ZFPN_G16_1000’s Effect	-0.280	0.129	-2.171	0.015
East Anglia with ZFPN_G16_1000’s Effect	-0.221	0.107	-2.065	0.019
North East with ZFPN_G16_1000’S Effect	-0.426	0.253	-1.684	0.046
East Midlands with ZFPN_G16_1000’s Effect	-0.139	0.224	-0.621	0.267
South East with ZFPN_G16_1000’s Effect	-0.042	0.074	-0.568	0.285
Yorkshire with ZFPN_G16_1000’s Effect	-0.048	0.182	-0.264	0.396

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