THE SEARCH FOR A ROBUST MEASURE OF ROAD SAFETY ADVERTISING EFFECTIVENESS

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ABSTRACT

Loss of life resulting from road accidents incurs an immeasurable social and financial cost on society every year. Fortunately, the number of road injuries and fatalities has been reducing in most industralised countries for the past three decades due to the ongoing improvement of the engineering of roadways, the safety of vehicles and the changing attitudes and behaviour of drivers. Governments are constantly developing innovative tactics to further reduce the number of road accidents.

One such initiative has been the adoption of marketing theory and specifically, advertising, by transport agencies in Australia and New Zealand into their road safety strategies. The Governments of both countries have proclaimed the campaigns to have been a success. However, the two road safety advertising campaigns have been studied by a number of researchers with conflicting results and conclusions about their efficacy. The studies have varied in form, estimation, outcomes, and data, making the comparison of their claims often very difficult. Policymakers and the public rely on the research of road safety experts when deciding on the best actions to undertake. However, the experts have each in turn argued that their approach was the most appropriate and that other researchers had done something wrong to reach their conclusions.

The objective of this research was to identify a robust measure of road safety advertising effectiveness to take the confusion out of the ongoing debate.

Using a single set of data and a range of advertising forms and road safety outcomes, previous evaluations of the New Zealand campaign were replicated and extended to discover which approach provided the best explanation of the value of road safety advertising. A further refinement was then made that addressed a potential problem with the original methods. Therefore, the research exhausted all the appropriate single and multiple equation approaches to the econometric evaluation of the effectiveness on road safety advertising using non-experimental data.

The research shows that using one data source and a range of road safety outcomes, a robust and consistent measure of advertising effectiveness could not be identified among the approaches investigated. Furthermore, there is no objective way of knowing which of the models tested best reflects the actual situation. Therefore, it is claimed that a viable solution to this dilemma is to implement an experimental approach to identify the true effect of road safety advertising on driver behaviour.

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CHAPTER 1. INTRODUCTION

Accidents resulting from road crashes have long been a significant cause of death and injury worldwide, prompting authorities to implement a range of measures designed to improve the safety of vehicles, improve the engineering of roadways, and improve the behaviour of drivers. In spite of these measures, road fatality rates are still high and remain a concern in many countries, including New Zealand.

In recent years, efforts to reduce road accidents have shifted away from engineering solutions, onto an emphasis on human factors. Modifying driver attitudes and behaviour has become the focus, and the adoption of marketing and advertising has become a key, if not the major, component of many road safety strategies. Two countries in particular, Australia and New Zealand, have adopted this approach with New Zealand adopting the Australian blueprint. The New Zealand road safety advertising campaign is the focus of this thesis.

Following the implementation of large budget mass media advertising, Government authorities in New Zealand have heralded the campaign to have been highly successful and cost effective in reducing road accidents, deaths and injuries. In the first three years of the road safety campaign, fatalities in New Zealand fell by 15%. Further to the noted reductions in certain road safety statistics, a series of econometric evaluations of the New Zealand campaign have been completed and some of these have formed the basis of the claims of success. However, there has been much argument over the form and variables used in the evaluations and the results have been sometimes conflicting. Clearly, conflicting findings make it challenging for policy makers to sustain a position on the campaign's true effectiveness and, in turn, potentially undermine the public's confidence in the investment in road safety.

Econometric evaluations of the campaign carried out by Cameron & Vulcan (1998) Tay (1999, 2001) and Guria and Leung (2004) found the New Zealand campaign to have been successful, whereas other evaluations completed by Macpherson and Lewis (1996, 1998) and White, Walker, Glonek & Burn's (2000A) found no evidence of any effect on driver behaviour. Unfortunately, a comparison of the evaluations of the New Zealand campaign is made difficult as they have each utilised quite distinct econometric models. The models of the New Zealand campaign have varied in terms of, levels of data (monthly, quarterly and yearly), estimation (ordinary least squares, autoregression generalised least squares) functional forms (double-log, log-linear, linear-log and linear), dependent variables (positive breath tests, serious crashes, high-alcohol hour serious crashes, fatalities) advertising measures (adstock, TARPs, categorical), and the configuration of other variables used to represent effects external to the campaign.

However, there is one characteristic shared by all the previous evaluations of the New Zealand campaign that may explain the failure of previous studies to find any agreement on the effect of the road safety advertising. All of the attempts, thus far, to evaluate the New Zealand campaign have utilised single-equation measures and it has been suggested by Macpherson and Lewis (1998) that a single equation measure may be inappropriate for modelling the road safety data. They noted that road safety advertising will tend to be scheduled at times when high levels of drink-driving or high numbers of road accidents are expected to occur. So, while road safety advertising will be related to changes in drink-driving, changes in the level of drink-driving will also be related to changes in advertising – representing a two-way relationship. Therefore, it is possible that two-way, endogenous, relationships may exist in the road safety data between advertising and other key explanatory variables and any road safety outcome utilised as the dependent variable in the models. For example, the level of advertising and enforcement will increase during the festive season, a season traditionally associated with higher levels of drinking and driving. The existence of such two-way relationships between explanatory variables and the dependent variable will result in biased estimates when using single-equation methods. Single-equation methods assume that the estimated relationships are all one-way. Unfortunately, when using non-experimental data there is no way of knowing whether the estimated relationships are one-way or two-way. However, if no consistency is identified in the key explanatory variables across any of the single-equation measures then it is possible that this is due to their endogenous nature.

This study proposes that there are two possible explanations for the contradictory findings in regards to the New Zealand road safety campaign's success. That is, the inconsistent results may be due to the many disparities in the evaluation models developed, or they may be a consequence of the inappropriate use of single-equation models to describe a multiple-equation environment.

The study reported in this thesis takes the econometric models that have been used to evaluate the New Zealand road safety advertising and applies them to a single time series that encompasses the first three years of the campaign. The original evaluation procedures are replicated and then extended by repeating the models using a series of road safety outcomes.

After demonstrating that the single-equation measures are unable to produce consistent advertising estimates a multiple equation approach, two stage least squares, is undertaken to address the possible endogeneity of some explanatory variables. Therefore, the current study will exhaust all the appropriate single and multiple equation methods for the post-campaign evaluation of the campaign's effectiveness across a range of road safety outcome variables. The objective is to attempt to draw a conclusion as to which econometric approach, if any, provides a robust measure of the effectiveness of road safety advertising.

In order for policy makers to have confidence in a method when evaluating the effectiveness of road safety advertising effectiveness, the approach used should be resistant or robust to any change in the outcome chosen for the model. If a measure is sensitive to a change in the road safety outcome, then it will be vulnerable to the argument that the resulting estimates are purely a function of the configuration of the model and method chosen by the researcher. To this end, a robust measure is defined in this thesis as an econometric method that produces consistent advertising estimates in terms of direction and statistical significance across road safety outcomes. In addition, as there are arguments for and against the type of variable used to represent the advertising exposure in evaluation models - Adstock versus TARPs, all road safety advertising themes versus drink-drive themes – different advertising variables will be used, where possible, in additional replications of the previous methods. Consistent advertising estimates are further defined as advertising estimates that are either all significant and negative in direction or significant and positive in direction.

At this stage it should be noted that it is acknowledged that there is also a considerable level of academic debate surrounding the overall subject of advertising effectiveness. The many ongoing academic arguments around the issue range from: the merits of pre-testing advertising, the most appropriate types of pre-testing methods, communication variables versus behavioural variables, the choice among the available communication variables to the much broader and overarching question of how advertising actually works. However, none of these issues are relevant to the research question addressed by this thesis. The focus of this thesis is the comparison of accepted econometric methods for the evaluation of road safety advertising and whether any consistency can be found in the conclusions derived from one of these models that would provide policy makers and the public with confidence in their application.

The thesis is organised as follows; Chapter 2 reviews the literature relating to road safety modelling and examines the series of evaluations of the New Zealand road safety advertising campaign. Chapter 3 reports the results of the replications and extensions of the single equation models previously used to examine the New Zealand road safety advertising campaign. Each approach will be tested across a range of road safety outcomes and, where possible, advertising variables to try and identify a robust measure of advertising effectiveness.

Chapter 4 describes how two stage least squares estimation can overcome the problem of endogeneity and explains why this particular method is the most appropriate multiple equation method for the modelling of road safety data if two way relationships exist. Chapter 5 reports the results of the multiple equation two stage least squares approach to the evaluation of the New Zealand campaign again using a range of advertising exposure variable and a series of road safety outcomes. Once again, the objective is to determine whether a consistent measure of road safety advertising effectiveness can be identified that can then be confidently used by policy makers to judge a campaign's effect on road safety.

Chapter 6 will then draw together the key findings to attempt to identify a robust explanation of the effectiveness of the road safety advertising campaign.

In summary, the current study will:

- Attempt to identify a robust measure of the effectiveness of road safety advertising, by:
    - Replicating the existing evaluation models using a single time series,
    - Incorporating a range of road safety outcomes into the existing single equation models,
    - Utilising a multiple equation approach that solves a potential problem with the endogeneity of key explanatory variables.

CHAPTER 2. LITERATURE REVIEW

2.1 Background

Accidents resulting from road crashes are a significant cause of death and injury in many developed and developing countries and extract a huge toll on the respective communities (Decker, Graitcher, & Schaffner, 1998; Kenkel, 1993; Murray & Lopez, 1996; Sweedler, 1995). To provide some scope of the scale of human tragedy, in 2003, 40,000 people died and more than one million were injured in the Member states of the European Union with an estimated cost of 160 billion Euros. Furthermore, in 2000, there were 41,821 road fatalities and 5.3 million injuries from road crashes in the United States of America, resulting in an estimated annual social cost of over US$230 billion (IRTAD, 2005).

Understandably, Governments in many industralised countries have sought to reduce the social and economic impact of road accidents (Oppe, 1991). Transport authorities in these countries have implemented a range of countermeasures to improve the safety of vehicles, the engineering of roadways, and the behaviour of drivers. Road accident and fatality rates have trended progressively downwards in these countries over the last three decades (Beenstock & Gafni, 2000). For example, the median number of road fatalities per 100,000 of population in OECD countries has reduced from 18.5 in 1975 to 9.3 in 2003. Likewise, the median number of road deaths per 10,000 vehicles in the OECD has reduced from 7.2 in 1975 to 1.7 in 2003 (IRTAD, 2005). However, Beenstock and Gafni (2000) claim much of the reduction in road accident statistics of industralised countries can be largely attributed to incremental improvements in the safety of vehicles and road infrastructure.

Since the early 1990's the focus of transport authorities worldwide has slowly shifted to the human behaviours of speeding and drink-driving as they endeavour to reduce road tolls even further. One such approach has seen the use of large budget mass media road safety advertising campaigns in a number of industralised countries (Cameron, Haworth, Oxley, Newstead, & Le, 1993; Hakim, Shefer, Hakkert, & Hocherman, 1991; Tay, 2004).

Following the implementation of intensive campaigns of road safety advertising, Governments in both Australia and New Zealand have claimed that the measure has been highly successful in reducing road accidents, deaths and injuries (Falconer, 1996; Gregg, 1996). A number of critics have claimed that the downward trend in road accident statistics began well before the start of the campaigns and question whether the road safety advertising has had any effect at all (Beenstock & Gafni, 2000; Macpherson & Lewis, 1998; White, Walker, Glonek, & Burns, 2000a). Consequently, a series of evaluations of both the Victorian and the New Zealand campaigns have been undertaken in an attempt to estimate the effectiveness of the road safety advertising. However, the results have been mixed and contentious with one study after another claiming to have produced a better estimate of the actual advertising effect. The claims have ranged from arguments over the form and function of the evaluation models, to the specification and estimation of the advertising effects (Guria & Leung, 2004; Tay, 2001; White, 2000, 2003).

Both the Australian and New Zealand advertising campaigns will now be described along with the background to these campaigns. Following each campaign description, there will be an in-depth examination of the studies that have either formed the basis of the Government claims or represent counterclaims that the advertising has not been proven to be effective. The research into the evaluation of the road safety advertising will be reviewed in chronological order.

The modelling of road safety data involves the use of a number of technical terms. Many of these terms will be introduced in Chapter 2 along with a short explanation. However, a full explanation of technical terms used throughout the thesis will also be found in the Glossary of Terms on page 146.

2.2 The Victorian Experience

2.2.1 The Transport Accident Commission Campaign

In 1989, the Victorian Transport Accident Commission (TAC) in Australia approached Grey Advertising to develop a campaign to make road safety a top-of-mind social issue for the state's motorists. The Victorian advertising campaign represented one of the largest Government investments into the marketing of road safety worldwide. The campaign eventually formed the basis of a blueprint that a number of other countries have since adopted in their own attempts to curb the road toll.

The monthly number of road crashes and fatalities had steadily increased in Victoria from 1983 to 1988 and the TAC in Victoria, Australia was seeking a solution to the worsening situation (Delaney, Lough, Whelan, & Cameron, 2004). The objective of the advertising campaign was to change driver attitudes and behaviour and to launch and communicate two new Police enforcement initiatives. These new Police initiatives consisted of the random breath testing using Booze Buses and the use of hidden speed cameras. The advertising campaign was predominantly television advertising with 70% of the budget allocated to this medium alone. From 1989 to 1992, AUS$23 million was spent on the TAC campaign with another AUS$2.5 million on creating the advertisements (Cameron et al., 1993). This level of expenditure for a public health mass media advertising campaign was unheralded anywhere in the world at the time (Donovan, Jalleh, & Henley, 1999).

From mid-1989 road crash numbers in Victoria fell sharply and this trend continued for the next two years with fatalities reducing from 796 in 1989 to 396 in 1992. TAC and Victorian Government officials quickly claimed that these reductions were due to the TAC enforcement and publicity campaign and that the combination had contributed to a 25% reduction in serious casualty crashes per year (Bliss, Guria, Vulcan, & Cameron, 1998). Taking these claims one step further, it was calculated that the TAC campaign had saved AUS$1 billion in reduced payouts and that the net benefit to society as a whole was in excess of AUS$2.9 billion for the period from 1989 to 1996 (TAC, 2000). In addition, the television advertisements themselves won many plaudits in terms of execution (Donovan et al., 1999) and a number of prestigious advertising awards and accolades (Donovan et al., 1999; Harper, 1992; Harper & Forsyth, 1994; Harper & L'Hullier, 1990). Grey Advertising has continued to act as the TAC's advertising agency and television continues to be the key component in the TAC's media budget (Delaney et al., 2004).

Many of the claims regarding the benefits and effectiveness of the campaign have emerged from a TAC-funded series of evaluations conducted by the Monash University Accident Research Centre (MUARC). As a result of the MUARC program a vast range of reports, publications and conference papers have been produced (e.g. Cameron, Cavallo, & Sullivan, 1992a, 1992b; Cameron & Harrison, 1998; Cameron et al., 1993; Cameron & Newstead, 1993a, 1993b; Cameron & Newstead, 1996, 2000; Cameron, Newstead, & Gantzer, 1995a, 1995b; Cameron, Newstead, & Vulcan, 1994; Cameron & Vulcan, 1998; Cavallo & Cameron, 1992; Diamantopoulou, Cameron, & Shtifelman, 1998; Drummond, Sullivan, & Cavallo, 1992; Gantzer, Newstead, & Cameron, 1995; Narayan, Newstead, & Cameron, 1998; Newstead, Cameron, Gantzer, & Vulcan, 1995a, 1995b; Newstead, Cameron, & Narayan, 1998; Newstead, Mullan, & Cameron, 1995; Rogerson, Newstead, & Cameron, 1994; Shtifelman, Diamond, & Cameron, 1999; Thoresen, Fry, Heiman, & Cameron, 1992; Vulcan, 1993, 1998; Vulcan, Cameron, & Newstead, 1995). A number of other researchers have also provided some support for the claims made by the TAC (Bliss et al., 1998; Elliot, 1993; Forsyth & Ogden, 1993; RTA, 2002; Tay, 2003b, 2004, 2005b).

The research report that is central to many of the claimed benefits was the result of research carried out by a MUARC research team in 1993 (Cameron et al.). The MUARC research report is characterised by the development of multiple linear regression models and the estimation of a relationship between the TAC road safety advertising and the level of road accidents in Victoria.

The study that forms the basis of the Cameron et al (1993) report will now be described along with the claims of success that have been drawn from the report and the series of criticisms that have been directed at the research.

2.2.2 The MUARC Evaluation of the TAC Television Advertising

Following on from the introduction of the television campaign in Victoria, Australia, the TAC funded an evaluation focussed specifically on the effects of the advertising by MUARC (Cameron et al., 1993). The research consisted of an evaluation of the TAC advertising in the period of 1989 to 1992 and included the analysis of a large database of road safety variables from 1983 to 1992. The effectiveness of the road safety advertising was measured against serious casualty crashes. The variables used in the models were as follows (all monthly level):

- Dependent Variable
    - Serious casualty crashes in high and low alcohol hours
- Advertising measures
    - Drink-driving TARPs[1]
    - TARPs for all themes
    - Adstock[2] of drink-driving TARPs
    - Adstock of the TARPs for all themes
- Enforcement measure
    - Random breath tests
- Other external factors
    - Unemployment rate
    - Victorian alcohol sales
    - Linear trend component
    - Seasonal monthly dummy variables.

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[1] Target Audience Rating Points is a measure of audience reach. It is a summation of the Rating Points (the percentage of persons in the viewing area estimated to be watching the specific television channel at the time the advertisement is shown) for the particular Target Audience of the advertisement. Please refer to the Glossary and Appendix 1 for more details on these measures of advertising.

[2] Adstock is a Koyck decay function of the accumulation of Target Audience Rating Points (TARPs) in the current week along with the decayed effects (applying a specific retention factor) of TARPs placed in the previous week or weeks. Therefore, Adstock is cumulative decayed ratings and represents the amount of advertising current at the time.

The method of analysis used in the evaluation was double-log ordinary least squares (OLS) regression.

The research claimed links between levels of TAC publicity supporting the speed and alcohol enforcement programs and reductions in casualty crashes when other major factors are held constant. The study also estimated benefits, in terms of reduced TAC payments, were respectively 3.9 and 7.9 times the costs of advertising supporting the speed and alcohol enforcement programs. It was also concluded that drink-drive advertisements contributed from 6.7 to 7.5 percent, and speed advertisements contributed from 6.2 to 8.7 percent to the reduction in all serious casualty crashes from 1990 to 1992.

Estimates from the analysis were also used to create a cost-benefit function of the relationship between the advertising and serious crashes. From this function it was claimed that high levels of advertising – up to 800 TARPs per month on average for drink-drive advertising and 540 TARPs per month for speed advertising – were economically justified.

Despite the large body of research supporting the TAC claim that the road safety advertising was highly effective, a number of studies have since raised concerns about the validity of MUARC's research and their subsequent conclusions.

2.2.3 Some Criticisms of the MUARC Evaluation of the TAC Television Advertising Campaign

A series of criticisms of the Cameron et al (1993) evaluation have been raised by other road safety researchers in regards to the claims that have been subsequently made about the campaign's effectiveness. These criticisms will now be reviewed beginning with claims that Cameron et al model fails to take into account the effect of the local Victorian economy on the number of road crashes.

2.2.3.1 The Effect of the Economy on Victorian Crash Statistics

A number of researchers have demonstrated that major fluctuations in crash statistics can be entirely explained by changes in economic conditions. Partyka (1984) demonstrated that cycles in annual US road crash statistics were entirely accounted for by annual labour force statistics. Likewise, falling crash statistics in British Columbia, Canada, in 1982 were found to be entirely attributable to the declining economy (Cooper, 1986). Furthermore, the progress in economic conditions in East Germany following reunification was shown to be responsible for a four-fold increase in road fatalities (Winston, Rineer, Menon, & Baker, 1999).

The boom Victorian economy of the eighties mirrored that of Australia and the rest of the world and likewise, was affected by the stock market crash of 1987. As mentioned previously, crash numbers in Victoria fell sharply from mid 1989, approximately six months prior to the introduction of the TAC campaign. The steady rise and subsequent sharp fall in road crash and fatality numbers in Victoria between 1983 and 1992 and the implementation of the TAC campaign appeared to mirror the boom and bust cycle of the local economy (Thoresen et al., 1992). White, Walker, Glonek, & Burns (2000b) have argued that changes to the Victorian economy are largely responsible for the reduction in road accident statistics – not the TAC advertising campaign.

Harry (1997) reviewed the literature on the relationship between the economy and road crash statistics and concluded that as the level of the economy rises, the number of crashes will also rise. He attributed this relationship to the effect of changes in the economy on the quantity and quality of travel. As discretionary income increases with an improving economy, so too does the quantity of kilometres driven by society. Similarly, an upturn in the economy may result in a change in the quality of travel. With an improving economy there will be a corresponding increase in the number of young drivers able to afford discretionary social travel and higher alcohol consumption. Consequently, there will be an increase in young drivers' level of exposure to road crashes.

While the regression models developed by Cameron et al. (1993) included Unemployment as an indicator of the economy, White et al. (2000b) claim, following a re-analysis of the MUARC data, that the strong effects reported by Cameron et al (1993) were largely a result of their choice of economic indicator. White et al (2000) demonstrated that following the introduction of a smooth leading index as an alternative economic measure, the campaign estimates were found to be non-significant.

2.2.3.2 Potential Confounding Effect of Underlying Global Trend

White et al (2000) also noted that the reduction in Victorian road crashes preceded the introduction of the TAC campaign by six months and therefore, can not be solely attributed to the later change. Beenstock and Gafni (2000) also claim that the fall in the Victorian accident rate that corresponded to the period included in Cameron et al's (1993) evaluation may have simply been the renewal of a global downward trend in accident rates. For the 29 year period of 1970 to 1999 there has been a strong overall downward trend in Victorian monthly fatalities. As discussed previously, such a downward trend is consistent with crash trends across developed countries since about 1970 (Beenstock & Gafni, 2000; Broughton, 1991; Henderson, 1997) and that these long term trends are mainly due to social learning, the incremental effects of safer vehicles and improvements towards a safer road infrastructure.

Cameron et al (1993) accounted for trending effects in their models of Victorian serious crashes by including a trend variable. However, White et al (2000b) demonstrate that the monthly road fatalities for Victoria possessed a strong upward deviation from the long term global trend for the first six to seven years of the analysis period (from 1983 to 1992). They argue that this upward deviation is clearly not due to the implementation of TAC countermeasures as they precede these initiatives and if the reasons for the changes are not explicitly accounted for in the crash models the estimates of the countermeasures effects will be unreliable. None of the variables in the Cameron et al (1993) models accounts for this pattern in the Victorian crash data. This could, in turn, explain why the regression coefficients estimated in Cameron et al's models were in the opposite direction to what would be expected – the trend estimates were all positive.

2.2.3.3 Collinearity of Advertising and Enforcement

Estimates derived from regression models are susceptible to high levels of collinearity among explanatory variables (Hair, Anderson, Tatham, & Black, 1998). When explanatory variables are highly correlated (r <0.80) and are included in the same regression model, their effects can not be accurately separated. As discussed previously, one of the central objectives of the TAC advertising was to announce and reinforce police enforcement initiatives (Cameron et al., 1993). The end result of this co-ordination between countermeasures is a very high correlation of (r =0.95) between drink-drive advertising and drink-drive enforcement. However, this issue has been ignored by the MUARC researchers even though they were clearly aware of it. The issue of high collinearity between countermeasure variables was previously highlighted by MUARC (Drummond et al., 1992) where it was concluded "The effect of publicity cannot be partialled out from the effect of RBT operations" (p.59). In more recent research MUARC have further acknowledged the problem of collinearity between drink-drive advertising and enforcement variables and that the issue means that the separate effects of the countermeasures can not be estimated and that a combined measure is required (Narayan et al., 1998). Moreover, in their stated assumptions, Cameron et al (1993) recognise the potential for problems with high levels of collinearity between explanatory variables and claim that it is unlikely to affect the estimates. White at al (2002) concludes that the modelling of separate effects for the advertising component in the Cameron et al (1993) evaluation was invalid and based on the false assumption of no issues of collinearity. As a result, the claims of the advertising effects, the estimated advertising-response relationship, and the derived benefits, are also invalid.

2.2.3.4 The Quantitative Assumption

The use of monthly levels of advertising, either TARPs or Adstock, in the regression models developed by Cameron et al, assumes that the effect of the advertisements was quantitative, that is, the differences between the levels was important as opposed to the effect being simply categorical (no advertising vs. advertising). Cameron et al's use of a quantitative measure of advertising allowed them to calculate a dose-response relationship and to draw cost-benefit conclusions from the advertising estimates. White et al (2000b) claim to demonstrate that the use of a quantitative measure of advertising is inappropriate, since there was no TAC advertising prior to the end of 1989 and a number of months during the campaign contained no advertising at all, a simple qualitative dummy variable could be used to represent the beginning of the TAC advertising campaign. In their reanalysis of the data, White et al simply included a qualitative measure of advertising with a dummy variable. The model containing the TAC campaign dummy variable then produced non-significant estimates for the advertising effects. However, Cameron and Newstead (2000) reject this criticism and object to the statistical arguments used by White. They argue that it was inappropriate to add the qualitative measure into the existing model as it was very highly correlated to the existing quantitative advertising variable and any conclusions drawn from the resulting estimates were, in turn, invalid. White and Walker (2002) sidestepped the intricacies of the collinearity issue by conducting an alternative test of the quantitative assumption that was suggested by Cameron at a meeting held in 1999. Following the alternative test White and Walker (2002) concluded that the quantitative assumption was indeed invalid and that all attempts to calculate cost-benefit claims were subsequently invalid.

2.2.3.5 Redefinition of the Dependent Variable

MUARC evaluations of the effects of the TAC campaign (including Cameron et al, 1993) made regular use of the number of Victorian serious crashes; however injury severity was radically redefined during the period covered by their analyses. In January 1989 Victoria Police made major changes to the definition of injury severity that had the effect, if left unadjusted, of reducing serious crash numbers by approximately one-third. Attempts were made to correct this problem and thereby conserve the reliability of the data. Nonetheless, White (2002) claims that the attempt was not entirely successful. Furthermore, the redefinition of the data coincided with the peak in Victorian crash numbers, the peak in economic conditions, and the implementation of the TAC road safety campaign. The overall effect of the redefinition is effectively a "17% free-kick" (pg. 22) that closely mirrors the level of the campaign effects claimed by MUARC. No reference to potential problems with the crash data or any note of its redefinition is contained within the MUARC report.

Despite these criticisms, the Victorian campaign and its corresponding research has been used to form a series of recommendations for the use of very high and sustained levels of television advertising using fear appeals combined with extremely visible enforcement in a number of locations. These include other Australian states (Cameron & Harrison, 1998; Cameron et al., 1997; Vulcan, Cameron, Mullan, & Dyte, 1996); New Zealand (Bliss et al., 1998); and South Africa (Gray & Myers, 1999; KwaZulu-Natal, 1996).

The blueprint from the TAC Victorian campaign was adopted by the Land Transport Safety Authority (LTSA) in New Zealand in 1995 and following a similar reduction in crash numbers, it was also claimed to be highly successful. The focus of the literature review will now shift to the New Zealand LTSA campaign and the subsequent evaluations of its effectiveness.

2.3 The New Zealand Adoption of the Victorian Blueprint.

2.3.1 The Supplementary Road Safety Package (SRSP)

Since the first fatal crash in 1908, a total of 34,000 people have lost their lives on New Zealand roads. Furthermore, while the number of road deaths has declined by 37% since 1990, the last decade has still seen 5004 die and 135,000 people injured as a result of traffic accidents – road accidents clearly represent a significant contribution to deaths in New Zealand (LTSA, 2004). The 1995 New Zealand road toll of 580 fatalities and 17,000 injuries was calculated to represent a conservative estimate of NZ$3.3 billion (Chapple, 1996; LTSA, 1996). The social cost of traffic accidents includes the loss of productivity, emergency and hospital costs, direct pain and suffering, and property damage. However, the real social cost is expected to be far greater than the estimated value.

In New Zealand, the Land Transport Authority (LTSA) is one of a number of Government agencies charged with the responsibility of reducing the loss of lives on New Zealand roads. In 1993, the LTSA oversaw the introduction of the compulsory breath testing (CBT) of NZ drivers along with a lowering of the maximum blood alcohol limit allowable for driving from 30 mg/100 ml to 20mg/100 ml as a new initiative designed to affect driver behaviour. In 1994, the LTSA approached the researchers at MUARC for extensive advice on implementing a blueprint of the successful Victorian road safety campaign (Cameron, Vulcan, Haworth, &

Kent., 1994). The Supplementary Road Safety Package (SRSP) was implemented in October 1995. The SRSP represented a large investment in road safety by the New Zealand Government. The sum of NZ$50.6 million was allocated over 4 years (21.2 million to N.Z. Police and 28.7 million to the LTSA). The Police time spent on breath screening tests increased dramatically over the first two years of the programme with 1.77 million tests in the second year of the campaign. This equated to testing 70% of all licensed drivers (Graham, 1998). Furthermore, the Police oversaw the introduction of speed cameras to reduce the contribution of speed to road accidents. However, as evidenced by the relative proportion of funding, a sustained road safety advertising campaign was a major and prominent component of the SRSP.

Following the guidelines of the MUARC researchers, the campaign was designed to change driver attitudes and behaviour and to support enforcement initiatives. The advertising was aimed to emulate the Victorian strategy in terms of style, content, intensity, media mix and timing. The following quote from Graham (1998) illustrates this point (p. 3).

"The blueprint specifies the tone and manner of the communication: realistic, non judgemental; convincing, not apologetic; emotional, not focused on injury to the offender; personal; shock but not overplaying the blood and guts or twisted metal; hitting core fears; leaving people to think 'I don't want to do this to someone'. The communication doesn't lecture, threaten, overdo statistics, nor suggest people can't have a drink."

While a wide range of advertising media was utilised, television advertising at a high level of intensity made up at least 70% of the advertising mix. The level of advertising increased in intensity twelve-fold with NZ$7.1 million spent in 1995, and increased to NZ$8.4 and NZ$9.8 million for 1996, and 1997 respectively, with a stated target of 800 TARPs per month (Bliss et al., 1998).

Graham (1998) outlines that the effectiveness of the campaign was to be judged in terms of advertising output and awareness, attitudinal measures, intermediate outcomes such as accidents involving alcohol or speed, and overall outcomes such as road fatalities. The stated objective of the SRSP was to save 80 lives, prevent 450 serious injuries, and prevent 1,600 minor injuries over the initial four year period.

2.3.2 The Outcomes

Following the introduction of the SRSP campaign the number of road fatalities dropped initially and the LTSA was quick to claim the success was largely due to the advertising campaign (Falconer, 1996; Gregg, 1996). This opinion appeared to be based solely on the reduction in fatalities. Furthermore, the advertising campaign was subsequently awarded the overall Golden Pinnacle award in 1998 for advertising effectiveness (Howard & Taylor, 1998). However, the campaign attracted a great deal of controversy and debate within New Zealand, much like it had done in Victoria, with a number of commentators questioning the advertising's involvement in the reduction in the road toll (Howard & Taylor, 1998; Jones, 1998; Kearns, 1996; O'Hanlon, 1998; Rotfeld, 1999; Turner, 1998). White (2000) pointed out that, there may have been some merit to these arguments as the New Zealand road toll had peaked in 1973 and had been trending steadily downward since mid 1987 (see Figure 1 below).

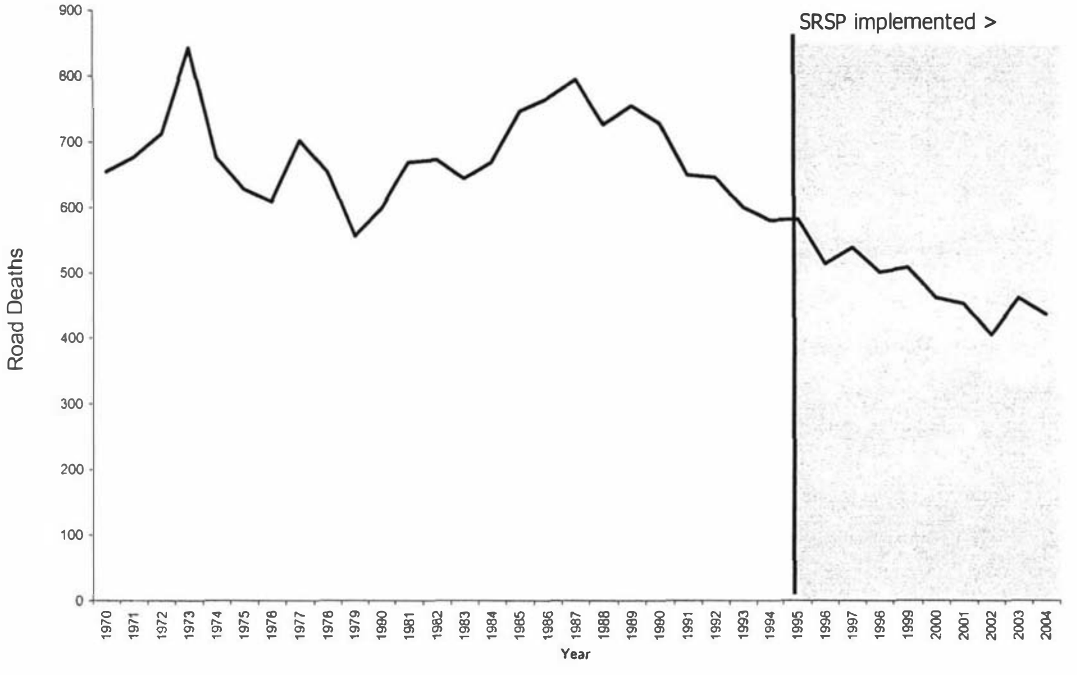


Figure 1. Annual Road Fatalities in New Zealand

2.3.3 Independent Evaluation

An additional aspect of the SRSP measures of effectiveness was that there must be a series of independent evaluations of the safety outcomes achieved (Graham, 1998). In their role as private consultants, MUARC researchers, Cameron and Vulcan were invited by the LTSA to conduct the independent review of the outcome of the first year of the SRSP (Bliss et al., 1998).

After a rather basic review of the advertising outcomes, the enforcement outcomes and the accident statistics for the first year of the campaign, Cameron and Vulcan (1996) concluded that some part of the reduction in road deaths could be attributed to components of the SRSP and that the reductions, though slight, were consistent with the findings from the Victorian campaign and therefore should be followed by much greater reductions in the following years.

One of the many recommendations within the Cameron and Vulcan (1996) report was the suggestion that further research should be undertaken to estimate the effects of the components within the SRSP. This was followed by the first in a series of quantitative evaluations of the SRSP and its components that was undertaken by Macpherson (1996) and Macpherson and Lewis (1996). In contrast to the original claims made by Cameron and Vulcan (1996), the findings of the first quantitative analysis failed to find any evidence of an advertising effect on the drink-drive behaviour of New Zealand drivers. The Macpherson (1996) study was followed by a succession of evaluations of the New Zealand SRSP that consisted of claims and counterclaims about the merits and weaknesses of competing analyses and the success, or lack of, of the road safety advertising utilised by the LTSA. All of the evaluations used models of historical road safety data to estimate the effect of the SRSP campaign. The studies were as follows:

- Macpherson (1996)
- Macpherson and Lewis (1996)
- Macpherson and Lewis (1998)
- Cameron and Vulcan (1998)
- Tay (1999)
- White et al (2000a)
- Tay (2001)
- Guria and Leung (2004)

Each of these studies will now be reviewed in chronological order. The model specification and findings of each evaluation will be described along with any criticisms of the approach taken that have been subsequently raised. These studies are examined here as they form the basis of a series of replications that will be undertaken in Chapter 3.

2.4 Macpherson (1996), Macpherson and Lewis (1996) and Macpherson and Lewis (1998)

Macpherson (1996), Macpherson and Lewis (1996) and Macpherson and Lewis (1998) all represent different aspects of the same body of research, here forth in this section all three studies will be simply referred to as M & L.

2.4.1 The M & L Models

In response to the largely unsubstantiated claims being made in the press by the LTSA (Falconer, 1996; Gregg, 1996), M & L made the first attempt at replicating the modelling approach used by Cameron et al (1993) in their highly lauded and proclaimed evaluation of the Victorian advertising campaign. While, Cameron et al (1993) created separate models of the speeding and drink-drive advertising to draw claims about the overall TAC campaign's effectiveness, M & L chose to focus on the specific effect of the New Zealand SRSP advertisements on drink-drive behaviour. The study sought to answer the question, 'Is exposure to the overall SRSP road safety advertising campaign or the specific SRSP drink-drive advertising translating into a shift in driver behaviour?'

The LTSA and the New Zealand media based their initial claims of the success of the SRSP campaign on reductions in the road toll that appeared to follow its introduction. However, M & L pointed out that crash numbers were falling in New Zealand well before the SRSP was implemented; and considered that crash data were insufficient to support a rigorous evaluation of the campaign's effectiveness. Furthermore, they claimed that fatalities are an overall measure and make no distinction between victims of drink-drive behaviour and any of the other factors involved in traffic accidents. This makes fatalities a rather blunt measure of the driving behaviour relative to other more explicit road safety outcomes that are available to researchers. Using the distinctions between SRSP outcomes proposed by Graham (1998), M & L chose to base their evaluation models on an intermediate outcome as opposed to the overall outcome of road fatalities that the LTSA claims were based upon. In an attempt to capture a finer perspective of the advertising effects on driving behaviour – M & L chose to use the number of positive evidential breath tests (EBTs) as the dependent variable in their models. They argued that one would reasonably expect that a measure more closely linked to the behaviour in question, drink-driving, would provide a more precise measurement of drink-drive advertisements than fatalities or other overall outcomes.

Following the basic model specifications from the Cameron et al (1993) evaluation, M & L used double-log OLS regression to estimate the relationship. The variables used in the models were:

- Dependent Variable
  - Positive evidential breath tests (EBTs)
- Independent variables
  - Advertising (used in separate models)
    - Adstock of drink-drive TARPs
    - Adstock of all-theme TARPs
  - Compulsory breath tests (CBTs)
  - Rate of unemployment
  - Trend
  - Seasonal effects (eleven dummy variables)

The models replicated the Cameron et al (1993) specifications for models of drink-drive advertising in that they contained a measure of the advertising intensity, a measure of the enforcement component, an economic indicator, and variables to represent underlying trend and seasonal effects.

Once again, consistent with the approach used by Cameron et al (1993), all data was at monthly level and the estimated models were expressed as multiplicative, as opposed to additive, by taking logs (to base e; where e = 2.7182818284) of both sides of the equation. The transformation allows a multiplicative equation to be converted to an additive version suitable for multiple regression analysis. The use of the double-log transformation is typical for the analysis of road safety data (Hakim et al., 1991) and was also utilised by Cameron et al (1993). The period covered by the study was October 1993 to September 1996, so the study encompassed the first year of the SRSP campaign.

After an initial analysis of the correlations between the variables, various models were developed to determine whether the SRSP advertising was having an effect on driving behaviour, as measured by positive EBTs. The EBT data was then adjusted for seasonal variation, trend, and the number of CBTs. The two forms of Adstock were then regressed against the adjusted EBTs. A distinction was made between the types of SRSP advertisements in an attempt to capture the specific effect of drink-drive advertising and the general (all-theme) effects of all of the road safety advertising (drink-drive, speed and seat belt) used in the campaign.

The estimates for the two types of adstock, the general all-theme and the specific drink-drive, were both in the expected direction (-.03 and -.01 respectively) that is, the models suggested that the advertising contributed to a fall in EBTs. However, neither coefficient was even close to being statistically significant at the 0.05 level.

A number of limitations within the study were identified by the authors: problems associated with analysing non-experimental data; the small number of observations used in the analysis; the accuracy and representativeness of the EBT data; and the assumption that the effect of the advertisements will be limited to only those people who would potentially drink and drive and would not affect other driving behaviours such as speeding.

In conclusion the authors acknowledged that the work represented a preliminary study and that the main findings were:

- The SRSP drink-drive advertising and drink-drive enforcement do not supplement one another to the same degree as was the case in Victoria and this lack of co-ordination may adversely affect the success of the advertising campaign – consistent with the finding in Cameron et al (1993).
- There is little evidence to suggest that the road safety or drink-drive television advertising is contributing to any shift in drink-driving behaviour, thereby indicating that the reduction in the New Zealand road toll is likely to be due to other factors.
- Just over half the variation in the number of positive evidential breath tests can be accounted for by seasonal variation, the number of compulsory breath tests, and the economic conditions.

M & L stated that it was important to note that the study was affected by limitations in the amount of data available which in turn lead to a smaller than optimal sample size. They suggested that clarification, validation and generalisation of the results identified in this study would only be obtained by conducting ongoing research in this area.

M & L also raised concerns that two-way relationships may exist between the SRSP advertising, enforcement, and road safety outcomes such as EBTs. Expected high levels of drink-driving are likely to lead to higher levels of advertising and enforcement. As a result of this two way relationship the dependent variable (EBTs or fatalities) is also an independent variable in the explanation of the levels of advertising and enforcement. M & L indicated that the presence of such a two-way relationship would make any estimates of the effect of the SRSP advertising biased and also affect the precision of the estimates.

2.4.2 Criticisms of the M & L Models

A number of researchers have criticised M & L's research in subsequent evaluations of the SRSP (Cameron & Vulcan, 1998; Guria, 1999; Guria, Jones, Leung, & Mara, 2003; Guria & Leung, 2004; Tay, 1999, 2001) and each of these criticisms will be addressed more thoroughly in the following sections. However, the key points raised in the criticisms by these researchers relate to: the use of EBTs as the outcome measure, the specification of the models, and the issue of autocorrelation in the time series data.

2.4.2.1 Suitability of Positive Evidential Breath Tests (EBTs)

LTSA researchers Guria and Leung (1999; 2003; 2004) have argued that EBTs are not an appropriate measure of drink-drive behaviour, as there are too many factors affecting the number of EBTs. They argue that as enforcement becomes more targeted, the probability of being caught would increase. Therefore, the number of detected drink-driving offences could increase even if the violation rate has fallen. This would appear to be a compelling argument for not using EBTs as the outcome variable, but no evidence was provided by Guria et al to support the claim that there had been an increase in the targeting of enforcement. However, there is an argument against the claim that breath testing would become more efficient over time. The implementation of CBTs was funded by the LTSA purchasing a set number of tests from the New Zealand Police. It could therefore be argued that the use of this bulk-funding approach for the purchasing of CBTs would not necessarily imply greater levels of efficiency. Conversely, pre-purchasing of CBTs could encourage lower levels of efficiency as the Police endeavoured to complete quotas rather than focus solely on capturing offenders. This distraction may lead to the over testing of certain areas for the purposes of increasing the total number of tests undertaken rather than increasing the number of positive tests.

It would also be very difficult to find compelling evidence for gains or losses in efficiency for this large scale Police initiative that was spread over a long period of time. However, both these issues can be overcome by simply including a measure of enforcement into the model. The inclusion of CBTs into an advertising evaluation model, will account for changes in the level of enforcement activity (Macpherson, 2003). Including CBTs into the evaluation model has a similar effect to using a ratio of EBTs to CBTs as the dependent variable, while allowing the analysis to pick up any effect of a change in CBTs, such as might happen if an increased presence of enforcement made people change their behaviour – the deterrent effect of enforcement. However, simply using a ratio of EBTs to CBTs would assume the effect to be constant, whereas including CBTs as an explanatory variable allows it to take on any value (Macpherson, 2004). M & L, included a measure of enforcement in their models, CBTs, so the claims by Guria et al that EBTs would not take into account greater levels of targeting and would appear to be unfounded.

Tay (2003a) also suggests that EBTs are an inappropriate performance measure because the stated objective of the SRSP was to save 80 lives, 450 serious injuries, and 1,600 minor injuries over a four year period. Therefore, measures of road fatalities and injuries or the number of fatal and injury crashes would arguably be superior. While this perspective is clearly suitable if the aim was to simply evaluate the overall SRSP, it does not necessarily imply that overall outcomes are more suitable when evaluating the performance of individual components of the SRSP such as the road safety advertising.

Tay also argues (1999; 2001; 2003a) that EBTs will not necessarily capture all those who see the advertisements and then drink and drive and some people who are caught drinking and driving may not have seen the advertisements. However, this non-exclusivity argument can be equally applied to all measures of alcohol involvement in driving. Furthermore, alternative outcome measures, such as alcohol-related fatalities, are conditional on many other behaviours, decisions and events. The smaller the degree of separation between behaviours and outcomes we can obtain in analysing the effect on a particular behaviour of a campaign, the greater the likelihood of being able to pick up the effect. We could, in principle, obtain more precision in our analysis of the overall behaviours, by analysing separate behaviours, individually, than by analysing the overall behaviour with its prerequisite larger number of conditions.

The other criticism of EBTs was that it is vulnerable to extraneous factors. EBTs were chosen as an outcome measure by M & L specifically because it was considered less likely to be affected by 'other factors' compared to overall outcome measures such as crash fatalities. Once again, it would be extremely difficult to empirically prove what outcome measure would be less affected by other factors however, one would reasonably expect that a measure more closely linked to the behaviour in question, drink-driving, would provide a more precise measurement of drink-drive advertisements. EBTs by definition are a more suitable measure of drink-drive behaviour than overall road fatalities.

M & L also acknowledged that there were some potential limitations with the collection of EBT data. EBTs, as recorded, are subject to possible measurement error as the collection process is not fully documented and not all positive breath tests are necessarily an indication of drink-driving. M & L suggested that an alternative measure that could be more robust would be drink-drive convictions.

2.4.2.2 Model Specification Problems

It has also been alleged that the models developed by M & L could be subject to specification errors due to the omission of important variables (Cameron & Vulcan, 1998; Guria, 1999; Guria et al., 2003; Guria & Leung, 2004). Unfortunately, no indication has been provided by the researchers as to the identity of the important missing variables. Furthermore, as has been outlined in the preceding description of M & L, the model specifications they used closely mirrored that of the influential Cameron et al (1993) study that formed the basis of the implementation of the SRSP. If important information has been omitted from the M & L models, then the same criticism can be leveled at the MUARC models and the underlying basis of the SRSP advertising blueprint. The only variable that would 'appear' to be missing from the final M & L models would be unemployment, the economic indicator. M & L found that Unemployment was highly correlated to the Trend variable (r = .90) and subsequently removed it from the models. Unemployment had a slightly weaker relationship with EBTs than the trend so was chosen to be the omitted variable of the highly correlated pair. So, while an economic indicator is not represented explicitly in their models, it is represented implicitly by the presence of the trend. The M & L models still contain more components than competing alternatives, subsequently developed, that have been claimed by Guria et al (1999, 2003, and 2004) as more accurate representations of the effectiveness of the campaign. Each of these competing models will be discussed in more detail in following sections. The point to note, however, is that model specification arguments are often intractable; each model's composition consists of a researcher's perspective of a certain situation. This said, the criticisms against the specification of the M & L models would appear to be less than compelling.

2.4.2.3 Problems with Autocorrelation

Autocorrelation can be caused by the persistence from one period to the next of unobserved and unmeasurable factors that influence the dependent variable. Therefore, there might be a positive correlation between error terms in consequent periods – that is corr ($\varepsilon_t, \varepsilon_{t+1}$) > 0 (Lattin, Carroll, & Green, 2003). Autocorrelation can lead to an overestimation (positive autocorrelation) or underestimation (negative autocorrelation) of the precision of estimates which in turn may affect conclusions about statistical significance of those estimates.

Tay (1999) contended that the data used in M & L was likely to suffer from autocorrelation and that, as a result, first-order autoregressive modeling would be more appropriate. Other than simply plotting the residuals of the regression against time, autocorrelation may be detected by calculating the Durbin-Watson statistic. Although this is not an exact statistical test, there are tables that provide bounds to determine whether the evidence is conclusive or not (Lattin et al., 2003). Despite developing a series of auto-regressive models using the M & L data, Tay (1999) found that the Durbin-Watson tests for each model were in the inconclusive range and that there was no conclusive evidence that autocorrelation was a problem. The models created by Tay (1999) will be discussed in greater detail in section 3.4 beginning on page 76.

2.4.3 Conclusions and Implications of the M & L Models

M & L undertook the first quantitative evaluation of the New Zealand SRSP advertising campaign and chose to closely replicate the model specification and estimation procedures utilised by the highly lauded Cameron et al (1993). In an attempt to isolate the specific effects of the road safety advertising on driver behaviour M & L chose to use EBTs as their measure of effectiveness. After developing a series of models that took into account the various types of SRSP advertisements, M & L concluded that there was little to no evidence to support the previous LTSA claims that the campaign had been effective in altering driver behaviour.

Subsequently, a number of researchers have argued that the use of EBTs was inappropriate for evaluating the campaign's effectiveness while at the same time promoting their own model of the advertising. However, many of these criticisms appear to be unfounded given the specification of the M & L models.

2.5 Cameron and Vulcan (1998).

2.5.1 The First Two Years of the SRSP

In 1998, the LTSA commissioned another evaluation of the SRSP by Cameron and Vulcan that involved the development of an econometric estimation of the campaign's effectiveness (Bliss et al., 1998). This study has been put forward as being superior to the M & L model and so the focus of this review will now shift to this alternative perspective of the SRSP and its components.

Cameron and Vulcan were commissioned by the LTSA, in their role as independent researchers, to evaluate the overall effectiveness of the SRSP. The evaluation consisted of a series of regression models but the review here will focus on the two main models that form the basis of Cameron and Vulcan's key claims.

All the variables were measured at quarterly intervals over the period from the first quarter of 1990 to the second quarter of 1997, giving 30 quarterly values for each variable in the analysis. No explanation was provided for why the variables were measured at the quarterly level as opposed to the monthly level – all the information was readily available at the lower level and it would have noticeably increased the statistical power of the analysis as the observations would have increased to 120. No attempt was made to separate and estimate the effects of the individual components of the campaign other than separating the introduction of the CBT program introduced in 1993 and splitting the SRSP program into two variables (years), 1995/1996 and 1996/1997. By using a separate dummy variable for each year of the SRSP, Cameron and Vulcan were clearly anticipating that the effectiveness of the campaign was likely to change from year-to-year.

As with Cameron et al (1993) and the M & L study, all variables were subjected to a double-log transformation to the base 'e'. The variables were:

- Dependent variable
    - Serious Crashes
- Independent variables
    - Seasonal factors (dummy variables at the quarterly level, Q2, Q3, and Q4)
    - Compulsory breath tests (CBTs) - represented by a dummy variable
    - SRSP 95/96 - represented by a dummy variable
    - SRSP 96/97 - represented by a dummy variable
    - New car registrations
    - Unemployment rate

Two models were developed, the only distinction between them being the identity of the economic indicator. New car registrations were used in one model while the rate of unemployment was used in the second model. Somewhat surprisingly, neither of Cameron and Vulcan's models contained a trend independent variable. The decision to not include a measure of the trend will be discussed in the next section.

The results from the analysis are presented below with the exception of the estimates for the three seasonal dummy variables which were not considered by Cameron and Vulcan to be relevant to the conclusions.

Table 1. Cameron and Vulcan's Model using New Cars as the Economic Indicator

Independent variable	B	SE	t	p
CBT	-0.196	0.026	-7.534	.000
SRSP 95/96	-0.100	0.041	-2.438	.023
SRSP 96/97	-0.270	0.043	-6.255	.000
New Cars	0.290	0.061	4.768	.000

From Table 1 it can be seen that all four of the variables are statistically significant at the 0.05 level. The R-Square value for this model was 88%. From these results Cameron and Vulcan concluded the SRSP was responsible for a 9.5% reduction in serious casualty crashes in 1995/96 and a 23% reduction in 1996/97.

Table 2. Cameron and Vulcan's Model using Unemployment as the Economic Indicator

Independent variable	B	SE	t	p
CBT	-0.227	0.037	-6.210	.000
SRSP 95/96	-0.084	0.055	-1.542	.137
SRSP 96/97	-0.221	0.052	-4.245	.000
Unemployment	-0.278	0.110	-2.517	.020

From Table 2 it can be seen that the SRSP failed to make a significant contribution in 1995/96 (at the 0.05 level). The R-square for this model was slightly less than the first model at 81%. From these results Cameron and Vulcan concluded that the SRSP was responsible for a 8.2% reduction in 1995/96, despite the estimate's insignificance, and a 20.1% reduction in 1996/97. Overall, Cameron and Vulcan (1998, p.30) concluded that 'The results are consistent with a road safety initiative which is needed to develop during its first year and apparently became more effective during its second year". It was estimated that the first two years of the SRSP saved 109 lives and 1029 serious injuries. Subsequently, Graham (1998) estimated that the total savings amounted to a social benefit of at least NZ$611 million; a benefit-cost ratio of more than 28:1.

2.5.2 Criticisms of Cameron and Vulcan (1998)

The main criticism leveled at Cameron and Vulcan's (1998) evaluation of the SRSP is the noted absence of a trend variable in the models (Tay, 2001; White et al., 2000a). Their main argument for omitting a trend variable would appear to be (p.19):

"During the initial modeling, the trend function appeared to display a strong negative exponent. The analysis revealed that the negative trend apparent in the data may have been an artifact of reductions in road trauma levels due to the introduction of CBT and to the effects of the SRSP".

Cameron and Vulcan appear to be claiming that there were no significant incremental improvements in road safety from mid-1990 to mid-1997. Instead, they suggest that the effects of the introduction of the CBTs and the effects of the first two years of the SRSP are the only factors over that period that have improved road safety in New Zealand. A simple examination of Figure 1 (see Page 15) would suggest otherwise and Beenstock and Gafni (2000) found gradual improvements in road safety in most developing countries regardless of safety initiatives. It would appear that factors such as road and vehicle improvements, and possibly gradual improvements in driver behaviour were operating to enhance road safety in New Zealand during the 1990s. Fatalities fell sharply during 1990, 1991, and 1992, prior to the introduction of CBTs. One would then reasonably expect that the factors influencing these reductions would be operating independent of the CBT and SRSP programs. The inclusion of a trend variable would be critical in any evaluation model to account for the effect of such gradual improvements in road safety in New Zealand over that period.

This viewpoint is supported by Tay (2001, p.32) who claimed that:

> "If the model is fully specified, then there is no reason to include the trend variable. However, most applied researchers do not have the luxury of knowing, and having data on, all possible contributing factors that may affect the number of crashes".

Another argument put forward by Cameron and Vulcan (1998) for the omission of a trend variable is that the effect of the underlying trend was expected to be positive due to growth in road use. They claim that the resulting negative estimate for the trend indicates that incremental improvements in the road system are just offset by general increases in road use. This assertion implies that there are two equal and opposing forces at play in the underlying road safety of New Zealand roads that have effectively cancelled one another out. Gradual improvements in the road system were tending to decrease casualty numbers while the gradually improving economy was increasing road casualties – just slightly more so. White et al (2000a) argues that while this would be a good case for excluding both the economic indicator and the trend, it does not justify the exclusion of just the trend. Furthermore, White et al (2000a) argue that the data for the trend and economic indicators have very different shapes and there is little possibility that they would cancel one another out as proposed by Cameron and Vulcan.

Somewhat confusingly, Guria et al (2004), in defense of Cameron and Vulcan (1998), argue that the omission of a trend variable was appropriate and incorrectly suggest that the inclusion of a trend would have required the exclusion of the CBT and SRSP variables. Guria et al (2004) then go on to describe the development of a series of new models to evaluate the SRSP that explicitly include a trend variable. While the Guria et al (2004) models will be addressed in more detail in a following section, their own use of a trend variable to reanalyse the very same situation as Cameron and Vulcan, seriously undermines their defense of the earlier independent evaluation.

2.5.3. Conclusions and Implications of Cameron and Vulcan's Models

Cameron and Vulcan undertook the second quantitative evaluation of the New Zealand SRSP campaign. Cameron and Vulcan utilised quarterly level data based on serious crashes and separate models using either unemployment or new car registrations as the economic indicator to evaluate the first two years of the SRSP. From their analysis, Cameron and Vulcan concluded that the campaign was growing in effectiveness and indications where, following similar findings in Victoria, that this improvement would continue in subsequent years. While it is common practice to account for trending effects in road safety models by including a trend term (Hakim et al, 1991), Cameron and Vulcan argued that it was not required in their models. Conversely, re-analysis carried out by White et al, strongly suggests that Cameron and Vulcan's estimates and conclusions were highly sensitive to the decision to exclude a trend variable from the analysis.

The review will now examine the re-analysis of the SRSP campaign and the models developed by Cameron and Vulcan that was carried out by White et al (2000a).

2.6 White, Walker, Glonek, & Burn's (2000a) Re-Evaluation of the SRSP

2.6.1 The Inclusion of the Trend Variable

White et al (2000a) were the first people to question the omission of a trend variable in Cameron and Vulcan's (1998) evaluation of the SRSP. Following a reanalysis of the data, White et al concluded that by not including a trend term, Cameron and Vulcan (1998) have failed to take account of the underlying gradual improvements in road safety over the period of the study. Furthermore, White et al claimed that the estimates, models, and the subsequent claims were highly sensitive to the inclusion or exclusion of the trend variable. They illustrated that when the trend is included in the Cameron and Vulcan models, neither the CBT program nor the SRSP campaign make any significant contribution to the reduction in the number of New Zealand serious crashes.

White et al's re-evaluation began with the apparent contradiction in Cameron and Vulcan's assumption that the trend was not necessary. The first three years of the study period (1990 to 1993) contained a sharp fall in serious crash numbers in New Zealand and these reductions pointed to the presence of underlying incremental improvements in road safety. White et al then suggested that one argument for the downward trend over the first three years was that the pattern was the result of economic conditions. To test this possibility, White et al accounted for the effects of the economic indicators on casualty numbers and then plotted the residuals for each surrogate of the economy. The plot indicated strongly that road crash casualties were falling in the early 1990s even after accounting for the effects of the economic factors. It would seem that there was a genuine improvement in road safety at the time, and that the inclusion of a trend variable was the best way to account for these factors.

White et al then re-ran the Cameron and Vulcan models with the one change – the inclusion of a trend term. The results are presented in the tables below.

Table 3. White et al's Re-Evaluation of the SRSP with New Cars and the Trend

Independent variable	B	SE	t	p
CBT	-0.042	0.038	-1.102	.283
SRSP 95/96	0.017	0.039	0.436	.667
SRSP 96/97	-0.093	0.049	-1.874	.075
New Cars	0.205	0.048	4.306	.000
Trend	-0.014	0.003	-4.618	.000

Table 3 above shows that the CBT and SRSP variables fail to make a significant contribution (at the 0.05 level) to the reduction in casualty numbers with the trend included. However, the trend and new cars both make highly significant contributions. The proportion of variation in casualties has also increased to 91% compared to the 88% in Cameron and Vulcan's equivalent model.

The same conclusions can be made of the re-evaluation of the Cameron and Vulcan model using Unemployment as the economic indicator (see Table 4). Again the trend is highly significant, as is the economic indicator, and likewise the CBT and SRSP variables are clearly non-significant at the 0.05 level.

Table 4. White's Re-Evaluation of the SRSP with Unemployment and the Trend

Independent variable	B	SE	t	p
CBT	-0.029	0.047	-0.618	.543
SRSP 95/96	0.048	0.046	1.046	.307
SRSP 96/97	-.0.025	0.053	-0.471	.643
Unemployment	-0.198	0.077	-2.551	.019
Trend	-0.017	0.003	-5.049	.000

White et al checked the separate effects of the campaign variables (CBT, SRSP 95/96 and SRSP 96/97) by running the variables individually in the models while retaining the economic indicator and trend variables. One out of six models indicated a significant positive effect, (SRSP 96/97 using new cars and the trend) so the overall conclusion would still be that the campaigns made no difference to casualty numbers.

Cameron and Vulcan (1998) claimed that the exclusion of the trend variable did not lead to any substantial deterioration in the levels of the total amount of variance explained by the models. White et al argues that what they failed to make clear was that the exclusion of the trend variable radically changed the *pattern* of the results. White et al explains the predicament of the trend issue in the Cameron and Vulcan model:

"It would seem that the decision to exclude the trend variable from the New Zealand analyses while including it in the Victorian analyses, involved some subtlety of judgment. The consequences of those decisions were such that the estimated contributions of the countermeasure variables were much greater than if the opposite pattern of decisions had been made" (p.55).

2.6.2 Criticisms of White et al's (2000a) Re-Evaluation of the SRSP

Guria et al (2004), in their article describing another series of models to evaluate the SRSP, acknowledged the concerns White et al raised about Cameron and Vulcan's decision to not include a trend variable. However, they then incorrectly suggested that White had claimed that the inclusion of the trend would exclude any variables relating to the CBT or SRSP campaigns. Guria et al argued that such an approach would lead to biased results. It is difficult to see how they came to this conclusion as the models and subsequent estimates from White et al clearly include variables representing the road safety initiatives (for example see Table 3 and Table 4).

2.6.3. Conclusions and Implications of White et al's (2000a) Models

As part of a wider review of research undertaken by MUARC, White et al re-analysed Cameron and Vulcan's (1998) evaluation of the New Zealand SRSP campaign. White et al argued against Cameron and Vulcan's rationale for not using a trend term in their evaluation models and tested the proposition that the estimates and resulting conclusions would be sensitive to its exclusion. Using the same model specification as Cameron and Vulcan with the addition of a trend term, White et al confirmed the sensitivity of the model estimates, particularly the variables representing the SRSP campaign. In White et al's models, the new trend variable is significantly contributing to lower numbers of serious crashes and the SRSP estimates for the first two years of the campaign are non-significant. White et al concluded from their re-analysis that reductions in serious crashes in New Zealand were largely attributable to factors trending upwards over time. Criticisms raised against White et al's new models of the SRSP are not consistent with the actual model specifications and therefore do not challenge their findings.

In Guria et al (2004) a study by Tay (2001) is put forward as an example of a more thorough analysis of the SRSP and its components. While Tay (2001) does go on to offer an alternative model for the evaluation of the SRSP, this is only considered after a careful comparison of the models developed by Cameron and Vulcan (1998) and White (2000). It is in this thorough reconsideration of the two models, that Tay claims that the inclusion of a Trend variable was appropriate. It is difficult to follow why Guria et al would then claim that Tay (2001) provides further evidence of the validity of Cameron and Vulcan's model that excludes a trend. Tay (2001) will be discussed in detail in Section 2.8; however Tay (1999) conducted a much earlier evaluation of the M & L data and a review of this study will be the focus of the next section.

2.7 Tay's (1999) Evaluation of the SRSP Campaign

2.7.1 The Tay (1999) Approach

Tay re-analysed the data from Macpherson and Lewis (1998) with another estimation technique and different model specifications and came to the opposing conclusion that the SRSP advertising campaign had contributed significantly to a reduction in drink-drive behaviour.

The first point of difference of the M & L models and the Tay (1999) models is that seasonal dummy variables that were shown to be statistically non-significant were removed by Tay. Tay argues that there is no point to including all the seasonal variables but the reasoning for this is not provided. As the month of December features as a notable peak in the monthly EBT data, Tay chose it as the sole seasonal component in the analysis. Therefore, the initial models in Tay (1999) consisted of the following variables:

- Dependent variable
  - Positive evidential breath tests (EBTs)
- Independent variables
  - Trend
  - December dummy variable
  - Number of compulsory breath tests (CBTs)
  - All-theme Adstock

Tay refers to a previous study (Zlatoper, 1987) that found that the double-log models provided the poorest fit among several common functional forms. To test this proposition Tay ran the basic model above using four functional forms: double-log, linear-log, linear, and log-linear.

The Double-Log (or Log-Log) model:

$$\log(\text{EBT}_t) = \beta_0 + \beta_1\text{DEC}_t + \beta_2\text{Trend}_t + \beta_3\log(\text{CBT})_t + \beta_4\log(\text{Adstock})_t$$

Equation 1

The Linear-Log model:

$$\text{EBT}_t = \beta_0 + \beta_1\text{DEC}_t + \beta_2\text{Trend}_t + \beta_3\log(\text{CBT})_t + \beta_4\log(\text{Adstock})_t$$

Equation 2

The Log-Linear model:

$$\log(\text{EBT}_t) = \beta_0 + \beta_1\text{DEC}_t + \beta_2\text{Trend}_t + \beta_3\text{CBT}_t + \beta_4\text{Adstock}_t$$

Equation 3

The Linear model:

$$\text{EBT}_t = \beta_0 + \beta_1\text{DEC}_t + \beta_2\text{Trend}_t + \beta_3\text{CBT}_t + \beta_4\text{Adstock}_t$$

Equation 4

Source: (Tay, 1999)

Using the four functional forms, Tay found that the double-log function did indeed produce the poorest fit, along with the linear-log function (Adj. R^2 = .33 and .37 respectively) with the linear and log-linear providing the best fit to the EBT data (Adj. R^2 = .46 and .48 respectively). Unfortunately, no standard errors were provided by Tay so no conclusions can be made about the significance of the differences between the measures of fit.

Of the four independent variables included in the models, the Adstock and the December dummy variable were statistically significant at the 0.05 level across all the models. From these results Tay concluded that the advertising campaign had been a success in reducing the incidences of drink-drive behaviour and that there were clearly more incidences of drink-drive behaviour in the month of December because of the Christmas and holiday period. The non-significant contribution from CBTs was dismissed by Tay as a failure of the variable to truly represent enforcement rather than a reflection of the actual relationship between enforcement and drink-driving.

Tay calculated Durbin-Watson statistics for each of the basic models as he suspected autocorrelation may be a problem. However, only the linear model indicated a significant issue with autocorrelation, with the other three models being in the inconclusive range. Despite this, all the models were reformulated as first-order autoregressive models estimated using a Generalised Least Squares (GLS) procedure. The results from the first-order autoregressive models mirrored the basic model estimates in terms of statistical significance and fit. Tay concluded from these findings that the effect of the advertising campaign is not only significant, but consistent across the different functional forms and estimation procedures he used in his models.

One final change was made to the models at this point of the study. New variables were constructed to represent the introduction of the SRSP (DSRSP – a dummy variable indicating from the third quarter of 1995 onwards) and a variable to represent the interaction between DSRSP and Adstock (Sadstock). Sadstock was created to measure any structural change in the relationship between drink-driving behaviour and the advertising after the launch of the SRSP. Tay (1999) explains that a statistically significant and negative estimate for Sadstock, regardless of the estimate of DSRSP, would indicate that the fear-based SRSP advertising campaign has a larger impact in reducing drink-drive behaviour than the drink-drive advertising in general. A non-significant estimate for Sadstock and a significant and negative estimate for DSRSP would indicate the SRSP is effective in reducing the number of EBTs without changing the relationship between advertising and drink-drive behaviour. To summarise, the final first-order autoregressive models (using the four functional forms again) consisted of the following independent variables:

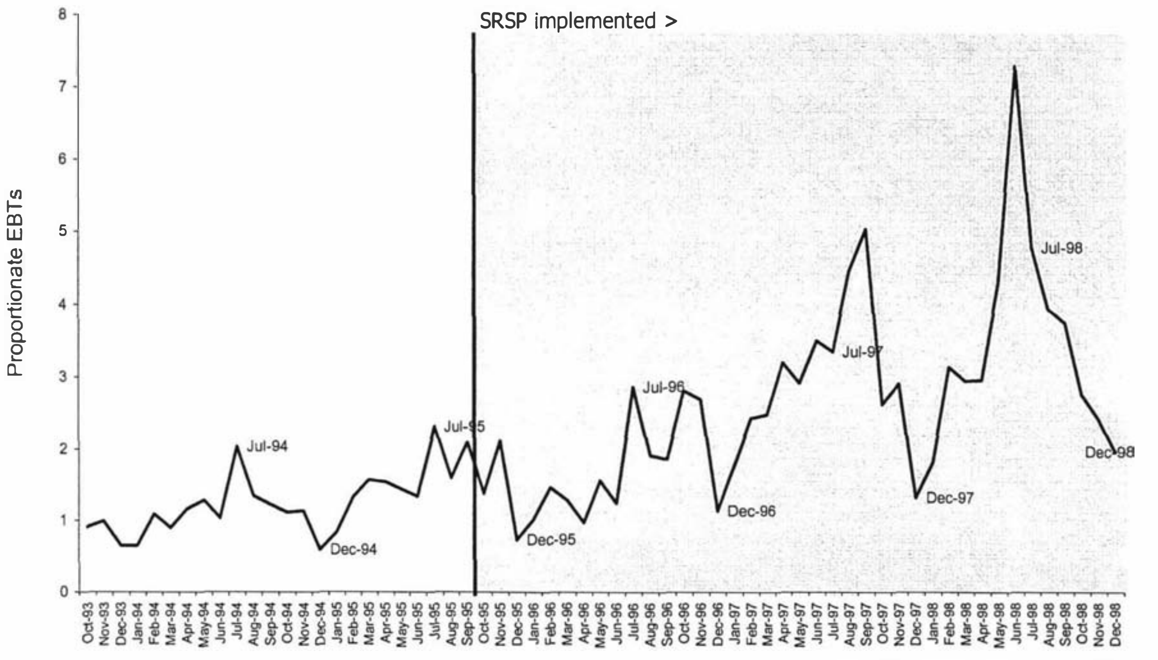
- Dependent variable
    - EBTs
- Independent variables
    - DSRSP

- Sadstock
- Trend
- December dummy variable
- Number of CBTs
- Adstock

The Sadstock estimate was found to be statistically significant and negative, while December was the only other significant estimate. From these findings, Tay concluded that the SRSP had changed the structural relationship between advertising and drink-driving behaviour. Furthermore, Tay claimed that the SRSP advertising had a greater impact in reducing drink-driving behaviour than road safety advertising in general.

2.7.2 Criticisms of Tay's (1999) Models

Tay maintains that only one seasonal dummy variable representing December is necessary in the model to capture the effects of underlying seasonal factors on the number of EBTs. This would be a reasonable argument if the month of December was the only underlying seasonal feature in the EBT data (Macpherson, 2003). However, this claim does not take into account the number of CBTs conducted for the same period. EBTs are largely a function of the number of CBTs. Figure 2 on the next page taken from Macpherson (2003) indicates that when the number of tests conducted is taken into account there is a series of regular peaks and troughs in the data – all of which may contain useful information about drink-drive behaviour. While the month of December is a regular month of high levels of EBTs, this is only because there are a high number of tests conducted at this time of the year. The month of December is actually a period of lower levels of drink-driving as a proportion of the number of tests undertaken and the winter month of July is a more prominent indicator of higher levels of drink-driving. Without further analysis it is difficult to determine the whys and wherefores behind this seasonal pattern. However, it would be reasonable to assume that extra tests conducted in December carry with them a strong deterrent effect and that in the months of lower levels of testing, during the winter, the deterrent is either not as strong or negligible. There is enough evidence here to suggest that all of the seasonal dummy variables should be considered for inclusion in the models or at least December *and* July. While the omission of variables from a model may be justified in terms of releasing degrees of freedom, their removal from a model is not justified if they represent important factors and where the model's estimates are sensitive to their inclusion or exclusion.



Source: (Macpherson, 2003)

Figure 2. Monthly EBTs as a proportion of CBTs

Macpherson (2003) also points out that with CBTs also included in Tay's (1999) models it is somewhat surprising that Tay's estimates for the month of December are positive. Figure 2 above suggests they should be negative. Furthermore the plot above demonstrates, as claimed by Macpherson and Lewis (1998) that drink-drive behaviour increased following the introduction of the SRSP - further eroding the credibility of Tay's decision to only use the December seasonal variable.

2.7.3. Conclusions and Implications of Tay's (1999) Models

Tay (1999) consisted of a series of models that included: modifications to the Macpherson and Lewis (1998) models; the testing of the functional form; the extension of the initial model using autoregression; and a test for a structural change in the relationship between the road safety advertising and driving behaviour. Tay found that by removing ten of the eleven seasonal dummy variables that the SRSP advertising had significantly contributed to a reduction in the number of EBTs. Tay also argued that the double-log functional form was the weakest fitting form among a set of four common functional forms. Furthermore, Tay found the presence of autoregression in the data to be inconclusive. Finally, Tay claimed that the SRSP advertising had a greater impact in reducing drink-driving behaviour than road safety advertising in general.

However, there are a number of criticisms of Tay's approach to the evaluation of the SRSP advertising. The decision to exclude the complete set of seasonal variables has been challenged by Macpherson (2003). Consequently, it is argued that Tay's findings are likely to be sensitive to the inclusion of the seasonal variables. Macpherson (2003) also demonstrated that the month of December is insufficient for representing the seasonal nature of EBTs. The absence of the majority of the seasonal variables appears to seriously undermine Tay's (1999) claims.

Tay (1999) does not represent Tay's only evaluation of the New Zealand SRSP and its components. Tay (2001) contained a review of the Cameron and Vulcan (1998) versus White et al (2000a) debate surrounding the evaluation of the SRSP as a whole, and the development of another model largely based on the Cameron and Vulcan quarterly data.

2.8 Tay's (2001) Re-Evaluation of the SRSP.

2.8.1 Another Modeling Approach from Tay

Tay's (2001) study of the effectiveness of the SRSP begins with an assessment of the Cameron and Vulcan (1998) and White et al (2000a) models. After conducting a series of statistical tests, Tay claimed that the inclusion of the trend was a significant improvement on the original Cameron and Vulcan model in terms of the fit of the model. However, Tay did not go as far as addressing the practical issues relating to the need for a trend in the models nor did he endorse the claims that arose from White et al's (2000a) results. On the contrary, Tay offered yet another perspective to the modeling of the SRSP.

Tay began by pointing to *potential* problems with autocorrelation in the data even though the results of the Durbin-Watson statistics he used to test for this issue were, once again, in the inconclusive region. As with his earlier models, Tay approached the issue of autocorrelation by reformulating the model with first-order autoregression using a Generalised Least Squares (GLS) procedure. He did concede, however, that the modification may not be necessary and also ran a standard OLS model using the same specifications. Consistent with his approach in his earlier study, Tay disposed of the seasonal dummy variables that had been non-significant in the previous evaluations. However, the SRSP advertising (Advert) was now represented by a single indicator variable for both years of the campaign. In an attempt to uncover structural change in the underlying trend brought about the SRSP advertising, Tay created a new variable advert-trend, which represented the interaction between the advertising and the trend. To capture and structural change in the trend and the introduction of CBTs, the interaction of CBT and the trend was also included in the model. Tay also concluded, following a series of statistical tests based around improvement to the fit of the model, that new cars was superior to unemployment as an economic indicator. The variables (all at quarterly level) used in Tay (2001) were:

- Dependent variable
  - Serious Crashes
- Independent variables
  - Qtr 3
  - New Cars
  - Trend
  - Compulsory breath tests (CBTs)
  - CBT-Trend
  - Advert
  - Advert-Trend

The results of both the OLS model and the autoregressive model are almost qualitatively and quantitatively the same. It would therefore appear that autocorrelation is not a problem as first suggested by Tay.

Of the independent variables, CBT and CBT-Trend were the only non-significant estimates. The coefficient for the Advert-Trend variable was negative in direction and statistically significant. Tay claims this result indicates that the implementation of the SRSP advertising significantly contributed to a reduction in serious crashes over and above the effect of previous road safety advertising. Tay argued that this was the appropriate interpretation despite the CBT variables being non-significant and the Advert coefficient being positive rather than negative.

2.8.2 Criticisms of Tay's (2001) Re-Evaluation of the SRSP

Macpherson (2003) argues that there are a number of concerns about the validity of Tay's (2001) models. Tay's decision to exclude non-significant predictor variables was not extended to the new moderator effect variables. Moreover, Tay's models are shown to be sensitive to the choice of economic indicator. Each of these criticisms will now be examined.

Tay chose to exclude the dummy variables representing the second and fourth quarters on the basis that they were statistically non-significant; however, Tay then chooses to retain the non-significant CBT and CBT-Trend variables. While this may appear to be a rather trivial matter, Macpherson (2003) found that the final model and its resulting conclusions are sensitive to the presence of these variables. Firstly, the moderator effect of CBT-Trend was tested by checking its significance if it is added to the model. The effect is clearly non-significant and therefore should not be included in the model on this basis alone but there is also an issue of its high collinearity with the Advert-Trend variable. This may or may not be a problem with the estimation of the effects but as CBT-Trend is non-significant the potential difficulties are avoided. The CBT variable is non-significant with or without the inclusion of the CBT-Trend variable, so it is also appropriate, using Tay's own standard, to remove this variable from the model. A beneficial side effect of removing the two non-significant variables is to release some degrees of freedom and slightly increase the statistical power of the models. The model was then re-estimated without CBT and CBT-Trend and the coefficients for both Advert and Advert-Trend were now only marginally significant ($p = 0.09$ for both).

Macpherson (2003) also found another inconsistency in Tay's advertising models. Unfortunately, Tay did not provide any information about the correlations between variables in the final model. Macpherson (2003) points out that a quick examination of the correlations reveals that unemployment has a noticeably higher correlation with serious crashes than the new cars economic indicator that was chosen by Tay ($r = 0.40$ and -.152 respectively). Furthermore, the relationship between unemployment and serious crashes is statistically significant (at the 0.05 level), while the correlation for new cars is non-significant. Tay based the inclusion of new cars in the final model on its performance in Cameron and Vulcan's and White et al's models. However, this same test of performance is not repeated with Tay's models. Unemployment provides the superior fit to serious crashes with Tay's models. Macpherson (2003) argues that using Tay's own standards again; unemployment should replace new cars in the final model.

With unemployment as the economic indicator, it is now necessary to repeat the tests of the moderator effects and the model as a whole. Macpherson (2003) claims that the test for the CBT, trend and CBT-Trend is unchanged with both the individual variables, and therefore the moderator effect, all being statistically non-significant (CBT $p = 0.31$; CBT-Trend $p = 0.33$). However, the estimates for the Advert and Advert-Trend variables are very sensitive to a change in the economic indicator. The two individual variables are no longer statistically significant (Advert $p = 0.44$; Advert-Trend $p = 0.59$). It appears that Tay's claim about the effect of the SRSP advertising campaign was dependent on the choice of new cars rather than unemployment and moreover, the selection of the economic indicator was inappropriate by his own claimed standards.

Macpherson (2003) states that Tay's alternative model, using the measure of the economy based on fit alone, confirms White et al's conclusions that the SRSP campaign has failed to significantly affect driver behaviour.

2.8.3. Conclusions and Implications of Tay's (2001) Models

Tay proposed a modification to the approach taken by Cameron and Vulcan (1998) and White et al (2000) that introduces two new variables. Tay claimed that his models provided support for Cameron & Vulcan's conclusion that the SRSP had significantly reduced the incidence of serious crashes in New Zealand following its introduction. However, Macpherson (2003) has criticised some of modelling decisions and argues that they are also inconsistent with Tay's own standards for selection. It has been argued that when non-significant variables are removed from Tay's models, a practise utilised by Tay when choosing what seasonal effects to include in his models, the key advertising variables are no longer significant. Furthermore, Macpherson demonstrated that Tay's models used the economic indicator that provided the poorest fit to serious crashes. When the questionable variable was replaced with another alternative that was used in Cameron and Vulcan (1998), the estimates for advertising were no longer significant.

The final evaluation of the SRSP to be reviewed was carried out by LTSA researchers Guria and Leung (2004). This large study will now be examined and will be followed by an overall summary and conclusion for Chapter 2.

2.9 Guria and Leung's (2004) SRSP Evaluation

2.9.1 The Guria and Leung (2004) Modeling Approach

Guria and Leung (2004) developed a series of models in an attempt to help clarify the debate surrounding the claimed success of the SRSP and to provide an estimate of the number of deaths saved by the campaign. Guria and Leung created a large series of models using a variety of dependent and independent variables, two estimation procedures, and three levels of data (a 10 year annual series, a 29 year annual series, and a 10 year quarterly series). Data limitations were acknowledged across all the models developed and the intended aim of the study was to capture some consistency in the results rather than rely on the estimates arising from any one model. In total 32 models are reported by Guria and Leung that cover the two time periods, 10 years (annual and quarterly), 29 years (annual only).

Dependent variables used in this study were: fatal crashes, and non-motorcycle fatalities for the annual models, and serious crashes and non-motorcycle serious crashes for the quarterly models. The distinction of non-motorcycle fatalities and serious injuries was made to remove any potential confounding effects due to the declining use of motorcycles over the periods covered by the models. Problems with the reporting rate of serious crashes that may lead to measurement error was raised as the reason they were not used for the annual models and the relatively small number of fatalities was the reasoning provided for not using these in the quarterly models. All the dependent variables were normalized by the traffic volume index (TVI) to take into account the growing traffic volume and possible changes in risk associated with these differences.

A number of independent variables were used in the study but they varied between the annual and quarterly models.

- Trend and seasonal effects (quarterly model only for seasonal effects)
- Unemployment rate
- New car registrations
- Dummy variable to indicate the 1970 oil crisis (annual models only)
- Dummy variable to indicate changes in speed limits for 1973 to 1985, and 1985 onwards (annual models only)
- Number of new vehicles registered (only used in the 29 year annual model)
- Estimated strategic police hours and advertising expenditure
- Dummy variable to indicate CBT and speed camera programmes
- Advertising and enforcement interaction terms

A large proportion of the data used to represent the advertising and enforcement (including their subsequent interactions) in the 29 year models were estimated, as this information was not collected prior to 1990.

Guria and Leung claimed that many of the independent variables were problematic in terms of high levels of correlation. They claimed that if multicollinearity was a problem, using OLS to estimate the effects would lead to inflated estimated standard errors and difficulty in relying on significance testing. To overcome this dilemma, Principle Component Analysis (PCA) was used to create independent versions of the variables and then transformed estimates of the coefficients were calculated along with corresponding standard errors and significance test results. PCA models were run along side standard OLS models to check for consistency between the estimated coefficients and the OLS derived coefficients.

2.9.2 The Guria and Leung (2004) Results

With such a large number of models and configurations, even within models based on the same level of data, it is difficult to summarise the results without completely reproducing the many tables from the study. To simplify matters here, models from each level of data will be discussed, in turn, with possible limitations. Then, the overall nature of the findings across the models and criticisms will be discussed.

2.9.2.1 The 29 Year Annual Models

The 29 year annual models consisted of estimates for the following variables:

- Trend
- Unemployment Rate
- (OIL) Dummy variable for the 1973 Oil crisis
- (D1973) Dummy variable for 1973 speed limit change
- (D1985) Dummy variable for 1985 speed limit change
- New car registrations
- Compulsory breath tests (CBTs)
- (SHindex) Enforcement
- (ADindex) Advertising
- (SHindex * ADindex) Enforcement and advertising interaction
- (SRSP * SHindex) SRSP and enforcement interaction
- (SRSP * ADindex) SRSP and advertising interaction

The OIL variable was statistically non-significant across Fatalities, Non-motorcycle fatalities and fatal crashes so models were run with and without OIL. Otherwise all variables were significant when derived from the PCA analysis while very few were significant when using OLS. Guria and Leung claim that this would be due to the problems of multicollinearity among the independent variables. Unfortunately, no measures are provided about the correlations among the independent variables.

The D1985 estimates are negative when an increase in the speed limit would be expected to result in an increase in fatalities. Guria and Leung claim that the negative value for the D1985 estimates estimate are due to the increased vigilance of the Police when the limit was increased. However, they fail to provide any evidence to support this claim or any reasoning why this effect is not simply accounted for by the enforcement variable SHindex.

Both unemployment and new cars are negative and significant in the PCA models but non-significant in the OLS models. Both of these variables are effectively measuring the same concept, the economy, and it is rather unusual to find them together in the same model for this reason alone. As a result, it is very likely that they are highly correlated with one another and therefore it is no surprise that they are non-significant in the OLS models. Furthermore, Guria and Leung do not explain why an economic indicator is required in the model when the dependent variables are normalized by the traffic volume index (TVI). The TVI would be expected to be highly correlated to the economy however without access to the analysis data this can not be verified. Inclusion in the model of any economic indicators would lead to an upward bias of their impact on the dependent variable. Therefore, the decision to include both the TVI, through normalization of the dependent variables and not one but two measures of the economy, raises questions about the validity of the model's estimates. Furthermore, Guria and Leung claim that the unexpected negative estimate for new cars points to the greater safety of increased imported cars. However, the 29 year period (1971 to 2000) covered by Guria and Leung's models stretches beyond the period import restrictions were relaxed in New Zealand in 1989. To apply this one micro-event to the overall measure of new car registrations is inappropriate and would be better represented by the inclusion of a specific indicator variable.

All the intervention coefficients in the PCA models are negative and significant which is what would be expected if the interventions were effective in reducing road fatalities. However, this is not the case with the OLS estimates and, again, Guria and Leung claim that this is simply due to multicollinearity. From the PCA regression results Guria and Leung claim that the advertising and enforcement have significantly reduced road trauma. Furthermore, because the interactions between the SRSP and the advertising and enforcement are significant, the change in these interventions by the SRSP has resulted in greater benefits than were achieved beforehand. Finally, the interaction between the advertising and enforcement indicates that there is a complementary effect over and above their individual impact on road trauma.

However, there is a question mark over how far the results can be generalised from these models. With only 29 data points for each variable and 12 independent variables, the models easily exceed the recommended ratio of five observations for each independent variable with a ratio of 2.4:1 and is likely to result in the over fitting of the variate to the sample (Hair et al., 1998). It is difficult to extend the results further without validation against another time series. On the other hand, this problem may be reduced by collaborating results from the other models.

2.9.2.2 The 10 Year Annual Models

Clearly, a model with only 10 data points is of limited application but Guria and Leung repeatedly claim that while there are problems with the individual models, consistent results across the models will overcome any shortfalls with the individual models. Despite these claims, the number of independent variables almost exceeds the number of data points at nine to ten or a ratio of 1.1:1 and clearly the variate is again being over fitted to the sample making the results potentially too specific to the sample.

The 10 year annual models used the following independent variables:

- Trend
- Unemployment Rate
- Compulsory breath tests (CBTs)
- (SHindex) Enforcement
- (ADindex) Advertising
- (SHindex * ADindex) Enforcement and advertising interaction
- (SRSP * SHindex) SRSP and enforcement interaction
- (SRSP * ADindex) SRSP and advertising interaction

The trend was significant in all the 10 year annual models suggesting that variables not included in the model have been contributing to a downward trend on road fatalities and crashes. However, unemployment was non-significant except for the model using fatal crashes. Furthermore, in this model, half the intervention variables had signs opposite to what was expected by Guria and Leung. When unemployment was removed, the affected variable's sign reversed and increased in magnitude. On the other hand, when the previously non-significant intervention variables were removed and unemployment retained, unemployment continued to be significant and the other intervention variables became positive. Guria and Leung suggest that there is a possibility that unemployment captured the effects of the other variables it is highly correlated with and therefore should not be included. Without access to the data set it is difficult to say whether this action is based on convenience or good theory. As alluded to before in the discussion of the 29 year models, one would expect that estimates for economic indicators, such as unemployment, would be upwardly biased as a result of the normalization of the dependent variables by the TVI. Unfortunately, further analysis is required before the validity of Guria and Leung's actions and subsequent claims can be more fully assessed.

With unemployment removed from the models, the estimates for the intervention variables are consistent in direction and significance for the PCA regressions. Once again, the OLS results vary in terms of direction, magnitude and significance. Nonetheless, the interplay between the small sample size and the ratio of the number of independent variables, relative to the sample size, may be playing a part in the failure to obtain significant estimates using standard OLS regression.

2.9.2.3 The 10 Year Quarterly Models

The 10 year Quarterly models contained estimates for the following variables:

- Dummy variable for 4th Quarter (S4)
- Trend
- Unemployment Rate
- Compulsory breath tests (CBTs)
- Dummy variable for both the CBT and Speed programmes (CBTSPD)
- Enforcement (SHindex)
- Advertising (ADindex)
- Enforcement and advertising interaction (SHindex * ADindex)
- SRSP and enforcement interaction (SRSP * SHindex)
- SRSP and advertising interaction (SRSP * ADindex)

The seasonal dummy variable for the 4th quarter was significant and positive across all the PCA and OLS regressions, indicating higher levels of risk than other quarters. However, no estimates were provided for the other quarters. The trend was again significant and negative across all the PCA and OLS regression models which are consistent with the previous models.

Once again, the estimates for enforcement and advertising are significant in the PCA regressions but inconsistent and varied in the OLS regression models. In contrast, the interaction term for the SRSP and enforcement is positive and significant rather than negative. Guria and Leung claim that this could be due to poor data quality as they assumed the SHindex and ADindex were the same across all quarters when they were not in reality. One can only assume that the claim of poor data quality was not extended to the other estimates for advertising and enforcement because the estimates were consistent with previous results and claims.

Therefore, it would appear that Guria and Leung are stating the quarterly estimates merely played a confirmatory role to the smaller and possibly inferior 10 year annual and 29 year annual model estimates. The sample size relative to the number of independent variables is higher for the quarterly models at 4:1 than the other two model series so one would assume that the quarterly models would play a leading role in the formation of conclusion as opposed to a supporting role. Guria and Leung did not provide any reasoning for this unusual viewpoint. Furthermore, if Guria and Leung were aware that the assumption of the quarterly advertising and enforcement was incorrect, why did they not simply re-estimate the quarterly numbers to better reflect the actual situation? They acknowledged the use of adstock to represent advertising in their introduction, yet for some unknown reason chose to disregard the measure in favor of estimated expenditure. This decision would appear to undermine the validity of their models and their subsequent claims.

There does not appear to be any obviously apparent reason why Guria and Leung did not chose to use monthly level data for their models. Using their model specifications, the data would be either obtainable or able to be constructed at the lower level but more importantly it would have possibly reduced the issue of multicollinearity and the subsequent complexity in the use of PCA regression. Monthly level data would have provided greater levels of variability, reduced collinearity and greater degrees of freedom.

2.9.3 Conclusions and Implications of Guria and Leung's (2004) Models

At the beginning of the study, Guria and Leung claim that because of data limitations, no single model would be able to provide sufficient confidence, but if the estimates were consistent across the models, confidence would be improved. The study contains constructed data for all the key intervention variables and the quality of the assumptions underlying the development of the data has even been questioned by the authors themselves. They also claim that they were unable to derive the benefits for the advertising and enforcement components as the estimated savings were inconsistent across the models. Guria and Leung eventually concede that no conclusions can be drawn about the advertising or enforcement effects due to problems with multicollinearity and the claimed complementary effects of these two interventions.

Despite these substantive limitations, Guria and Leung (2004) still claim that the results across the models are (p.904) "mostly consistent" and that this somehow suggests "strong validity". What's more, they then claim that the SRSP contributed to an estimated saving of 333 lives and that the package has made a substantial impact on road safety. The conclusions of this study do not match at all well the underlying self-acknowledged reservations and limitations of the study. Without further validation one cannot have confidence in Guria and Leung's (2004) claims.

2.10 Conclusions of Literature Review

Each of the studies that have been reviewed here has attempted to capture the true effect of road safety advertising using a variety of model specifications and estimation techniques. Likewise, each researcher has presented a case for why their model or models is best suited for isolating and estimating the effectiveness of the campaign. However, the studies have produced mixed results when it comes to deciding whether the advertising has resulted in a significant reduction in the road safety statistics.

A major problem is that it is very difficult to compare the studies, as they not only differ on model specification and estimation procedures but they have also used different sets of data and outcome variables. Table 5 on the next page contains a summary of the reviewed evaluations of road safety advertising. The table clearly demonstrates the wide variety in the models and approaches that have been utilised so far in the quest to estimate the effectiveness road safety advertising. While most studies have involved the use of multiple models, the key characteristics have been grouped into the one column to simplify comparison.

From examining Table 5 it is evident that every evaluation of the road safety advertising included at least one model that used the combination of double-log OLS regression. Moreover, each study utilised CBTs as a measure of enforcement activity in at least one model. However, this is as far as the similarity between studies goes, with a myriad of variable combinations and definitions used to represent, not only the advertising, but the road safety system that the campaigns operated within. Indeed, the focus of the debate of the relative merits of the evaluation models has largely centred on the many differences between the models in terms of the variables used to represent the road safety system and the procedures used to estimate it.

Table 5. Summary of Advertising Evaluation Models

	Cameron et al (1993)	M & L (1998)	Cameron & Vulcan (1998)	White et al (2000a)	Tay (1999)	Tay (2001)	Guria & Leung (2004)[2]
Functional Form							
Double-log	x	x	x	x	x	x	x
Log-Linear					x		
Linear-Log					x		
Linear					x		
Estimation							
OLS	x	x	x	x	x	x	x
Autoregression GLS					x	x	
PCA							x
Level							
Monthly	x	x			x		
Quarterly			x	x		x	x
Annual							x
Dependents							
EBTs		x			x		
Serious Crashes			x	x		x	x
HAH Serious Crashes	x						
Fatalities							x
Independents							
Advertising							
- All-theme TARPs	x						
- All-theme Adstock	x	x			x		
- D-Drive TARPs	x						
- D-Drive Adstock	x	x					
- Qualitative			x	x	x	x	x
- Est. Expenditure							x
- Interaction term(s)					x	x	x
Enforcement							
- CBTs[1]	x	x	x	x	x	x	x
- Est. Expenditure							x
- Interaction term(s)					x	x	x
Unemployment	x		x	x			
New Cars			x	x		x	x
Trend	x	x		x	x	x	x
Seasonal Factors							
- All factors	x	x	x	x			x
- Sig. factors only					x	x	
Alcohol Sales	x						
1970s Oil Crisis							x
Significant reduction claimed?	**Yes**	**No**	**Yes**	**No**	**Yes**	**Yes**	**Yes**

1. CBTs or Victorian equivalent, RBTs. **2.** Variables listed are indicative of those used by Guria and Leung (2004).

Rather than digress further into the existing stream of criticisms, claims and counterclaims, the current study will now simply replicate these existing evaluations, where possible, using a single set of data and a series of road safety outcomes. *The key assumption underlying this approach is that if a measure of advertising effectiveness is to be considered robust, we would expect that it would produce estimates that will generalise across not only different forms of road safety advertising, but also across different road safety outcomes.*

The aim of this thesis is to attempt to find some consistency between the approaches that have thus far been advanced to identify a robust measure of the effectiveness of the road safety advertising. The next chapter begins this process by replicating and extending the models put forward to date.

CHAPTER 3. THE REPLICATION AND EXTENSION OF COMPETING MODELS OF ROAD SAFETY ADVERTISING

3.1 Introduction

The research objective of the thesis is to attempt to identify a robust measure of the effectiveness of road safety advertising. To achieve this end the existing models that have been used to evaluate the New Zealand SRSP advertising campaign will be replicated with the longer time series. The replications will also be extended to include a series of road safety outcomes in addition to the measures used by the original authors.

The aim of the analysis is to use the best estimation processes and approaches available and a wide variety of road safety statistics to identify a robust measure of road safety advertising effectiveness. A robust measure of road safety advertising effectiveness will be one that produces advertising estimates that generalise across road safety statistics and subtle changes in model specifications. Therefore, we would expect a robust measure to produce advertising estimates that are consistent in terms of direction and significance. The robustness of all the replicated models will be examined at the conclusion of this chapter.

Before the analysis and results are discussed, the methodology and procedure will be outlined along with a brief description of the road safety outcomes that will be used across all the replications. Independent variables, as specified by the original models, are described separately in Appendix 1 from page 150.

3.2 Methodology

3.2.1 Procedure

The literature review described a series of attempts to evaluate the use of road safety advertising to affect driving behaviour. However, not all of the data is available. Thus the replications are restricted to the following models, for which all data were obtainable:

- Macpherson & Lewis (1998)
- Cameron and Vulcan (1998) and White et al (2000a)
- Tay (1999)
- Tay (2001)

The models used by Guria and Leung (2004) are not replicated here as the majority of the key advertising variables were either estimated using data not available to this author or used calculations that were not detailed in the published material. The inclusion of the trend variable marked the only difference between the Cameron and Vulcan (1998) and White et al (2000a) models. Therefore, the replication of these two studies has been combined here to simplify the discussion of the findings.

Each of these prior studies is simply replicated with the extended time series, October 1993 to December 1998. This data that encompasses the first three years of the SRSP, this period was chosen because it precedes a series of events and initiatives that would have required the inclusion of new variables to the previous model specifications. Further details of the specific composition of the evaluation model will be provided at the beginning of each set of replications.

The outcome measure used was one of the distinguishing factors between the studies and a common point of debate. The outcome measures used in Chapter 3 therefore are:

- Positive evidential breath tests (EBTs)
- Drink-drive convictions
- Serious crashes
- Fatalities
- High alcohol hour serious crashes

A brief explanation of each of the outcomes as well as a description of the specific characteristics of the data over the analysis period will be provided in the following section. The independent variables in Chapter 3 have been defined by the previous studies so are not justified here. However, a discussion of the quantitative independent variables used in the analyses for this chapter is contained in Appendix 1 on page 150.

Please note that the complete output for the replication models is provided in Appendix 2 beginning on page 159.

3.2.2 Data Characteristics

3.2.2.1 Positive Evidential Breath Tests (EBTs)

Positive evidential breath tests (EBTs) are counted in the process of conducting compulsory and mobile breath tests. EBTs are tallied within regions and are not the result of a direct documented reporting process. EBTs were utilised by Macpherson and Lewis (1996, 1998) in their evaluation of the New Zealand SRSP drink-drive television advertising. In an attempt to capture the effect of drink-drive advertising Macpherson and Lewis chose EBTs as a specific measure of drink-drive behaviour as opposed to using a broader overall outcome such as fatalities or serious crashes.

The EBT data (see Figure 3 below) appears to follow a fairly predictable pattern up to about October 1996 – the point where the original Macpherson and Lewis study concluded. At this stage there is a very noticeable increase in the number of EBTs; a level largely sustained through to the end of the series in December 1998. Positive EBTs for the year ending September 1996 actually decreased by 23%, but this was followed by an 83% increase for the year ending October 1997, settling down to a meagre 2% for the year ending October 1998. Such a noticeable increase may be indicative of a major policy change and this may prove to be problematic for the use of this outcome for modelling the effects of the road safety advertising. Macpherson and Lewis (1996, 1998) suggest that an increase in EBTs may be explained in terms of: greater levels of enforcement, simple over-counting, gains in efficiency of testing procedures, or higher levels of drink-driving, or some combination of these.

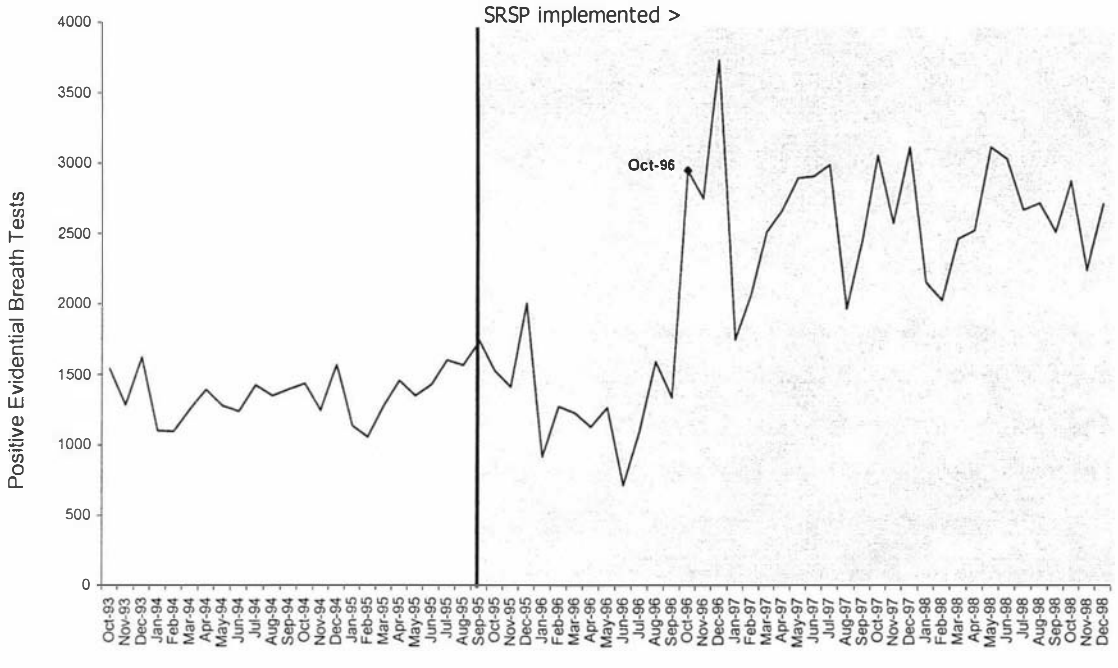


Figure 3. Positive Evidential Breath Test (EBTs) October 1993 to December1998

3.2.2.2 Drink-Drive Convictions

Drink-drive conviction data was not available to Macpherson and Lewis for their study as there is a substantial lag between committing an offence and the subsequent conviction in a court of law. Furthermore, not all positive EBTs will end up being processed as a conviction due to problems with the administration and collection of the EBT data. In addition, a small number of EBTs are rejected on technical grounds in the legal process that follows the positive test. Drink-drive convictions are easily validated and are collected as part of the tracking and monitoring of offending by the Ministry of Justice in New Zealand. Therefore, convictions for driving with excess alcohol are likely to be a more stringent measure of the level of drink-driving behaviour than EBTs for any given period. Drink-drive convictions are collated here from offences coded A101 through to A331. Conviction data is recorded for the date of the offence – not the date of the conviction which can occur up to six months after the offence.

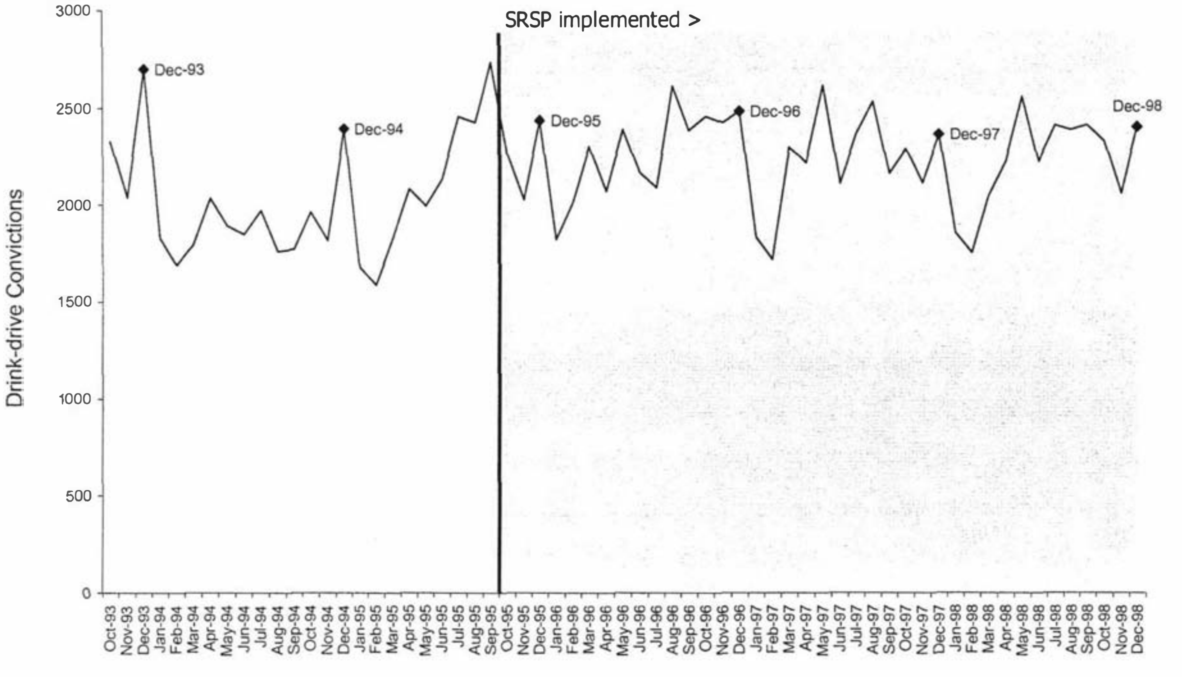


Figure 4. Drink-drive Convictions – October 1993 to December 1998

Across the time series there appears to be an upward trend (see Figure 4). The data also contains a noticeable pattern preceding the introduction of the television campaign with peaks of offending in December being followed by troughs in February. Following the introduction of the SRSP, January and February remain as the months with the lowest levels of drink-drive convictions but December is less evident as a period of greater levels of drink-drive behaviour. Annual spikes of drink-drive offending occurred in August 1996, May 1997 and May 1998. Such patterns are likely to be culmination of both driver behaviour and planned enforcement activity of Police – possibly in anticipation of changes in driver behaviour.

Another point of interest in Figure 4 is the absence of a peak in drink-drive convictions that corresponds to the substantial peak in EBTs (Dec-96). As drink-drive convictions result from a clearly documented legal process, it is expected that they are likely to be a more robust measure of drink-drive behaviour than EBTs.

3.2.2.3 Serious Casualty Crashes

Another dependent variable that has been used in the modelling of road safety initiatives is serious casualty crashes (Cameron et al., 1993; Guria & Leung, 2004; Newstead, Cameron et al., 1995a). A serious casualty crash is typically defined as if as a result of the accident a person requires hospitalisation.

Unlike EBTs, data for serious crashes was available from January 1990 (see Figure 5). While the availability of EBT data sets the analysis period for all the replications, the complete time series for serious crashes provides us with an overview of the long term patterns of this road safety statistic. It would appear from the graph that serious crash numbers have been gradually trending down well before the introduction of the SRSP advertising campaign.

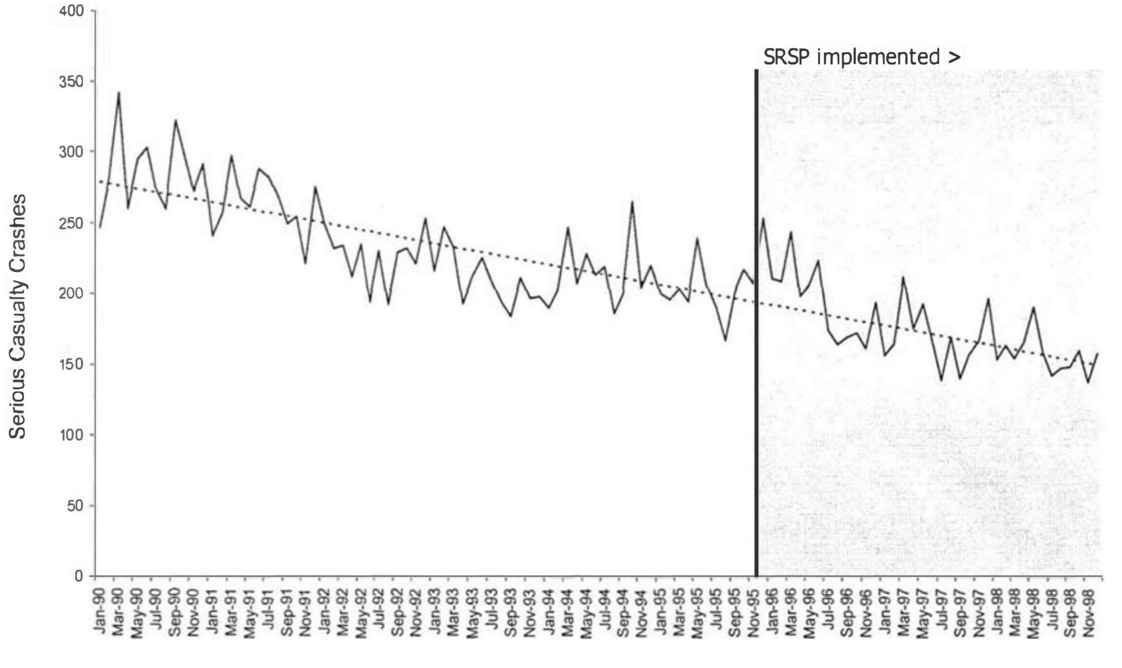


Figure 5. Serious Crashes – January 1990 to December 1998

A closer inspection of the analysis period (see Figure 6 below) indicates a peak in December 1995, shortly after the start of the SRSP advertising campaign, followed by a continuation of the gradual downward trend evident in the longer time series in Figure 5. There does not appear to be a pronounced seasonal pattern in serious crashes with peaks and troughs occurring at a number of different times of the year.

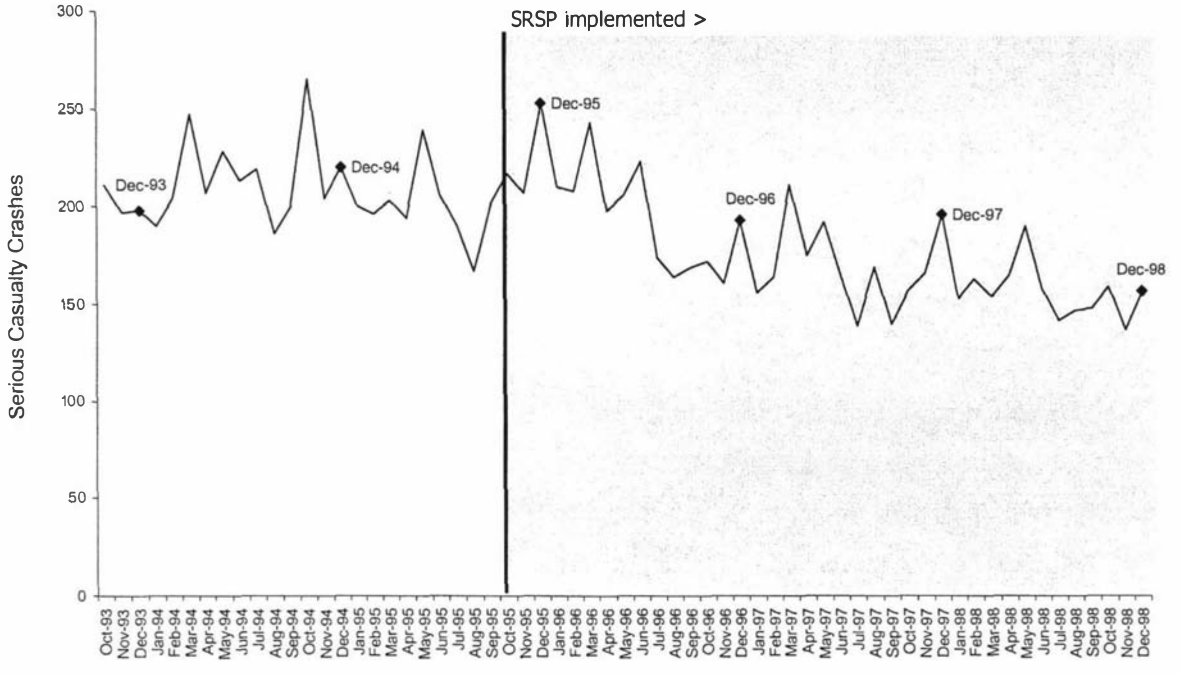


Figure 6. Serious Crashes – October 1993 to December 1998

3.2.2.4 Fatalities

The vast majority of studies undertaken in the general modelling of road accidents have used the number of accidents with fatalities or injuries, or the number of injuries or fatalities (Hakim et al., 1991). While fatalities present some statistical problems because they provide smaller numbers than injuries, their use is often pursued as there are fewer problems with the reporting criteria-completeness of data for fatalities compared to injuries. In addition, there has been a preference exhibited by policymakers, the media, and the general public for the analysis and reporting of fatalities (Newstead at al, 1995). This preference is hardly surprising in the context of road safety where the main focus of the majority of campaigns is first and foremost to reduce the incidence of fatalities. Moreover, fatalities are frequently used in media statements by Government officials and politicians alike as a measure of the effectiveness of road safety campaigns.

Figure 7 below provides a narrower perspective of New Zealand's annual fatalities from road accidents than that provided by Figure 1 on page 15. The number of road deaths had been is gradual decline from the late 1980s and this pattern has largely continued following the implementation of the SRSP campaign.

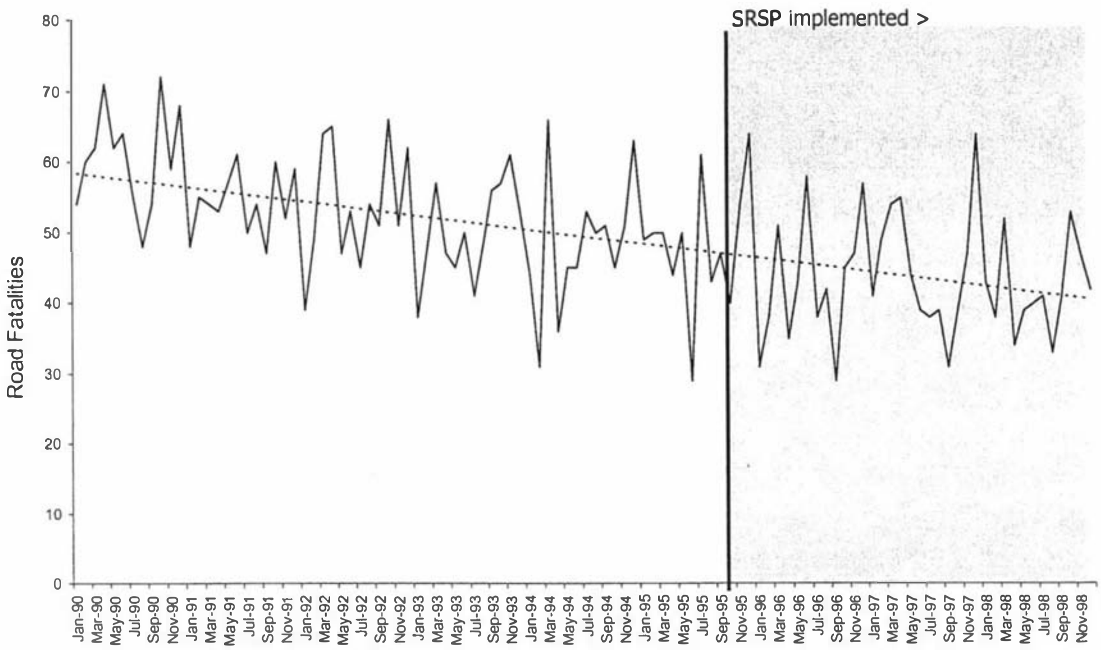


Figure 7. Monthly Road Fatalities January 1990 to December 1998

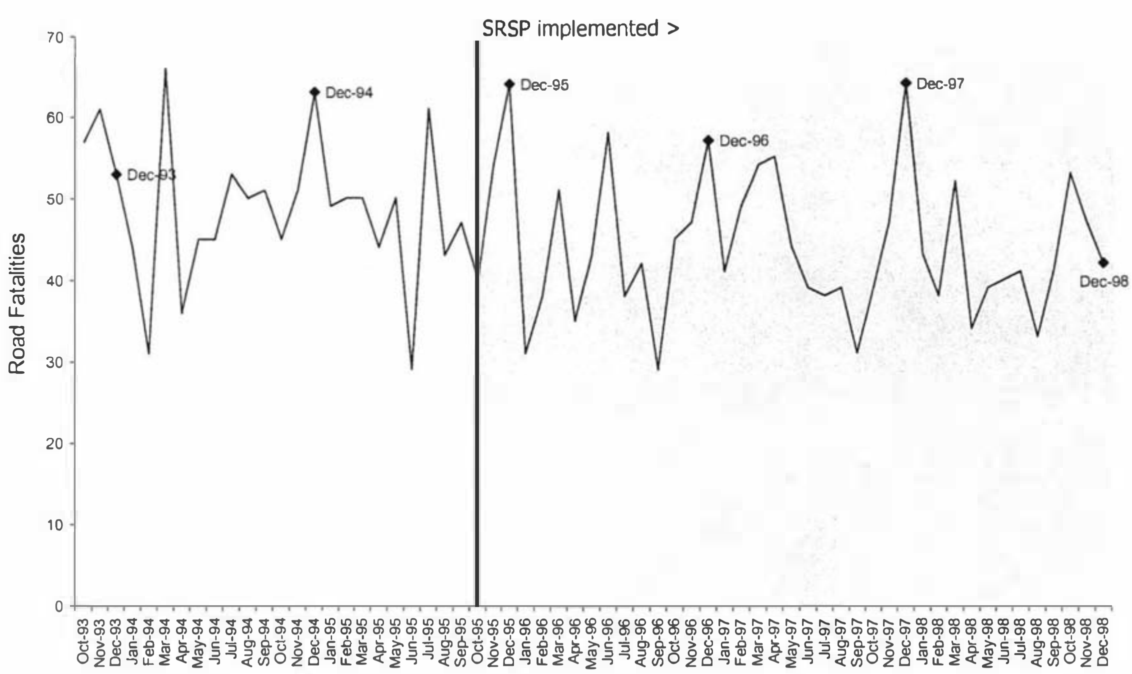


Figure 8. Monthly Road Fatalities – October 1993 to December 1998

The gradual downward trend is still noticeable when fatalities are viewed at the monthly level (see Figure 8 above). Also visible is a reasonably consistent peak for the month of December – the annual Christmas holiday period.

3.2.2.5 High Alcohol Hour Serious Crashes

Serious crashes can be further broken down into those that occur in high-alcohol hours and those that occur in low alcohol hours. The definition has been used previously to target periods when certain types of accidents are more likely to occur (Cameron et al, 1993). Low alcohol hours are used to test the effects of anti-speeding initiatives, whereas high alcohol hours are used to test the effects of anti-drink drive initiatives. The time of day definitions tend to vary from country to country. For example, low alcohol hours in Victoria have been defined as: 6am to 6pm Monday to Thursday; 6am to 4pm Friday, 8am to 2pm Saturday, and Sunday 10am to 4pm. These are periods when the percentage of drivers killed or admitted to hospital with a blood alcohol content exceeding 0.05%, was below 4 %.

The high alcohol hours are the converse of these periods during which about 38% of driver serious casualties had blood alcohol content exceeding 0.05% (Diamantopoulou et al., 1998). However, the definition of high alcohol hours in New Zealand is a much narrower period of time. Cameron and Vulcan (1996) define the New Zealand high alcohol hours as 10pm to 4am Monday to Thursday and 10pm to 6am Friday to Sunday. High alcohol hour serious crashes has been used as an explanatory variable in a number of evaluations (Cameron et al., 1993; Cameron & Vulcan, 1998; Tay, 2003a).

As with serious crashes, the number of high alcohol hour crashes has been in gradual decline from the early 1990s (see Figure 9 on the next page). However, there is a suggestion that numbers were edging up again just prior to the introduction of the SRSP advertising with a peak evident around December 1995. Following this peak, numbers have continued their previous downward trend.

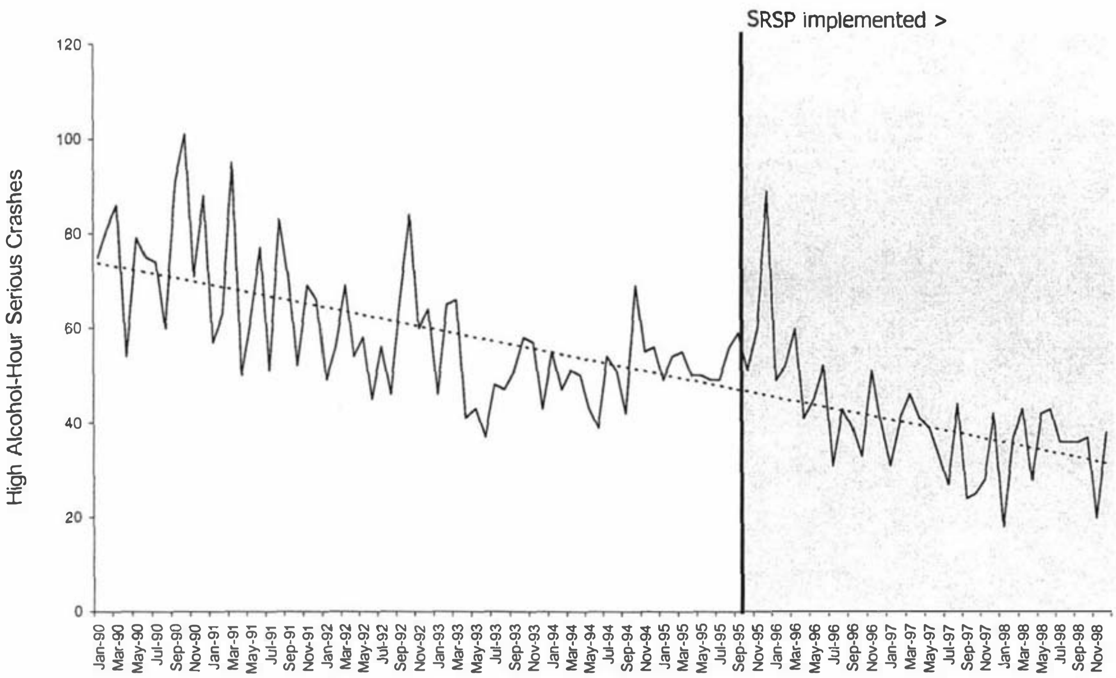


Figure 9. High Alcohol Hour Serious Crashes – January 1990 to December 1998

The study period initially reveals little in the way of a seasonal pattern (see Figure 10). Still, with closer examination the jagged profile of the time series suggests some regularity. Following the introduction of the SRSP advertising campaign, the months of March, June-July, and December feature as periods of higher crash rates. Furthermore, these months are typically followed by periods of lower crash rates – hence the uneven contour.

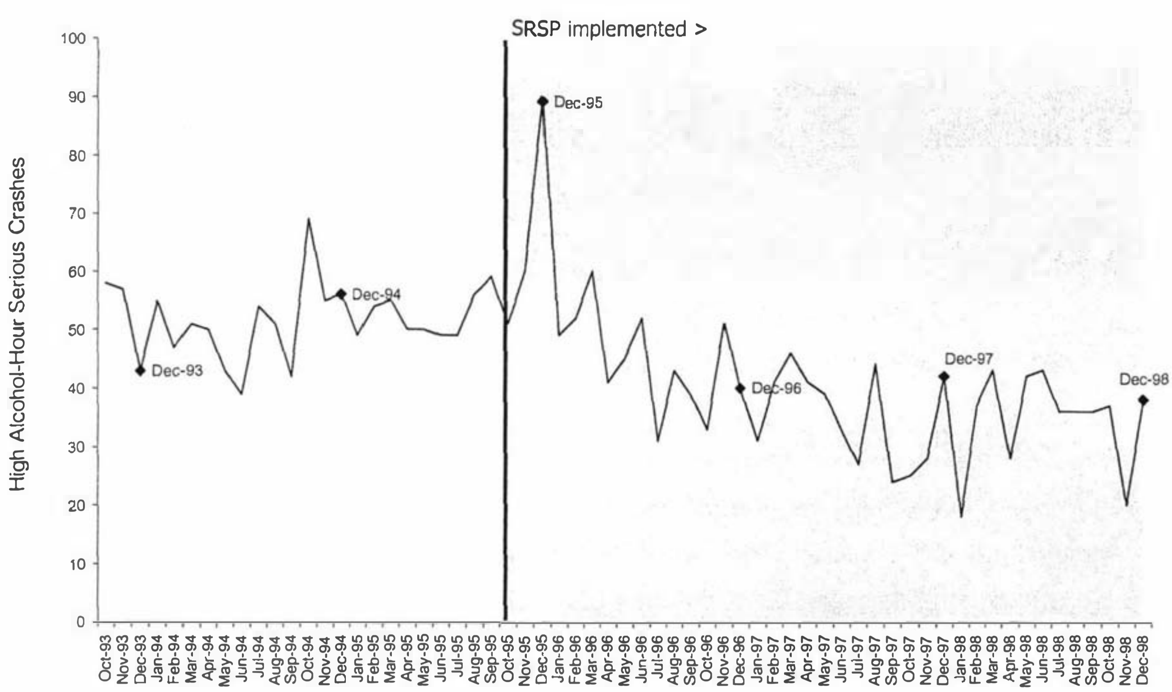


Figure 10. High Alcohol Hour Serious Crashes – October 1993 to December 1998

Other road safety outcomes are available for the period in question such as alcohol-related crashes and derivatives of fatalities such as alcohol-related fatalities. However, the analysis is only concerned with the measures utilised in the evaluations to be replicated. Further road safety outcomes are examined in the analysis in Chapter 5.

Brief descriptions of quantitative independent variables, as specified by the original evaluation models, are provided in Appendix 1 from page 150.

3.3 The Replication of Macpherson and Lewis's (1998) Models

3.3.1 Introduction

The basic model used by Macpherson & Lewis (1998) took the functional form of:

$$Y_1 = f(x_1, x_2, x_3, x_{4-15})$$

Equation 5

Where, for example:

Y_1 = Positive Evidential Breath Tests (EBTs)

x_1 = Adstock representing advertising

x_2 = Compulsory breath tests (CBTs)

x_3 = Trend effects

x_{4-15} = Seasonal effects

f = double-log function

Two models were developed by Macpherson and Lewis, one model – Model (a) – using all road safety advertising (all-theme) and one model – Model (b) – using drink-drive advertising specifically. The same approach will be taken here for each of the road safety outcomes.

Both the dependent variable and the independent variables are transformed by the natural logarithm (to base e; where e = 2.7182818284). Typically, road safety relationships are assumed to be multiplicative (Hakim et al, 1991); however there is a mathematical problem with estimating such relationships with linear regression. Linear regression assumes that there is an additive relationship between the predictor variables. The solution is to simply transform the multiplicative relationship to an additive relationship by taking the logs of both the dependent and independent variables prior to modelling.

The time series used by Macpherson and Lewis covered the period October 1993 to September 1996 and used monthly level data, giving a total of 36 observations. The time series for the current study extends the period analysed through to December 1998 (63 observations) so encompasses the first three years of the SRSP campaign.

Standard OLS regression was used to estimate the first two models using EBTs as the outcome; one using the all-theme version of Adstock - Models 1(a) - and one using drink-drive adstock – Model 1(b). Each model is then repeated using the four remaining road safety outcomes in the following order: drink-drive convictions, serious crashes, fatalities, and high alcohol hour serious crashes. Otherwise, the model specifications are identical to the original study. To summarise, for the replication of Macpherson and Lewis (1998) there will be two models - Models (a) and (b) – for each of the five road safety outcomes:

(a) All-theme adstock, CBTs, Trend, eleven seasonal dummy variables
(b) Drink-drive adstock, CBTs, Trend, eleven seasonal dummy variables

The results for each of the road safety outcomes will be compared with the original findings from Macpherson and Lewis (1998). However, comparisons for the Macpherson and Lewis replications will be limited to the adstock, CBT and trend estimates. The seasonal estimates are not considered important in the context of the research objective of this thesis – to identify a robust measure of *advertising* effectiveness.

3.3.2 Positive Evidential Breath Tests (EBTs)

Macpherson and Lewis (1998) used EBTs as the road safety outcome in their evaluation models so the following pair of replications represents the closest replication of the original study.

Table 6 on the next page provides a comparison of the original findings from Macpherson and Lewis for all SRSP road safety advertising themes Model (a) with the replicated model 1(a) using the extended time series.

From the summary statistics it can be seen that Model 1 (a) has a slightly better fit to EBTs than the original Model (a) with an adjusted R^2 of .66 compared to .53.

A comparison of the new estimates from the extended time series with the original findings indicates that there are few meaningful differences. When compared to the original estimates it is very clear that there are only minor differences. CBTs continue to have a positive and significant effect on the number of positive breath tests across both models.

Table 6. Macpherson & Lewis (1998) Replication – EBTs and All-Theme

	Regression Coefficients & Statistics	
	Model (a)	**Model 1(a)**
Independent Variables[1]		
Adstock (All-theme)	**-.04**	**-.01**
CBTs	.45*	.54**
Trend	.01	.02**
Summary Statistics		
R^2	.72**	.73**
Adjusted R^2	.53	.66

1. Both models included eleven seasonal estimates that are not provided here. The full results are provided on page 1S9. **Model (a)** results are taken from the original study from Macpherson & Lewis (1998). **Model 1 (a)** is a replication of Macpherson & Lewis (1998) using the longer time series. **CBTs** = Compulsory breath tests. * Statistically significant at 0.0S level. ** Statistically significant at 0.01 level.

However, one noticeable change with the longer data set is that the trend is now a significant and positive contributor to EBTs. This result indicates that some long term phenomenon is resulting in increasing levels of drink-driving.

At this point it is interesting to note that in contrast to common practise (Hakim et al., 1991), Macpherson and Lewis (1998) did not use an economic indicator in their road safety models. The reasoning for this was that the unemployment variable was highly correlated to the trend (r = 0.90). As the trend was more closely related to EBTs, unemployment was dropped from the model. In effect, the trend now also represents the economic indicator – the number of unemployed.

Most importantly in the context of this thesis, the conclusion about the effect of the SRSP road safety advertising does not change with the addition of more data. Using this model there is no evidence that the general road safety advertising has an effect on drink-driving behaviour as represented by the level of positive evidential breath tests (EBTs). While both advertising estimates are negative (-.04 and -.01) neither is statistically significant at the 0.05 level. To clarify this statement, it should be noted that a positive advertising coefficient would indicate that the advertising had been unsuccessful in reducing the number of EBTs. Likewise, a negative but statistically insignificant coefficient would also indicate that the advertising had not affected the number of EBTs. However, a negative and significant advertising estimate would support the LTSA claim that the road safety advertising had affected driver behaviour and subsequently road accidents and fatalities. The results of this replication support the previous finding from Macpherson and Lewis, that the general SRSP road safety advertisements did not reduce drink-drive behaviour.

Consistent with the original study, the analysis was repeated using the specific drink-drive adstock variable (see Table 7 below). It appears that focusing solely on the effects of the SRSP drink-drive advertisements has not led to a change in the estimation of its effectiveness. There is no discernable difference between the advertising estimates from the original study – Model (b) and the estimates using the extended time series – Model 1(b). Moreover, the advertising estimate for Model 1(b) is statistically insignificant.

Consistent with Model 1(a), the trend estimated in Model 1(b) is significant and positive using the longer time series. These findings suggest that factors that are gradually increasing over time, which are not explicitly accounted for by other variables in the model, are significantly contributing to higher levels of EBTs. Similarly, CBTs are estimated to be significantly contributing to an increase in EBTs in Model 1(b) as they were in the original models and in Model 1(a).

Table 7. Macpherson & Lewis (1998) Replication – EBTs and Drink-Drive

	Regression Coefficients & Statistics	
	Model (b)	**Model 1(b)**
Independent Variables[1]		
Adstock (drink-drive)	**-.02**	**-.03**
CBTs	.42*	.53**
Trend	.01	.02**
Summary Statistics		
R^2	.69**	.74**
Adjusted R^2	.49	.66

1. Both models included eleven seasonal estimates that are not provided here. The full results are provided on page 160. **Model (b)** results are from the original study by Macpherson & Lewis. **Model 1 (b)** is a replication of Macpherson & Lewis using the longer time series. **CBTs** = Compulsory breath tests. ***Statistically significant at 0.05 level. **** Statistically significant at 0.01 level.

The two close replications of Macpherson and Lewis (1998) have confirmed the original findings that there is no evidence to support claims that the SRSP advertising has led to changes in drink drive behaviour as measured by EBTs. The next pair of replications will estimate the SRSP advertising effect using drink-drive convictions as the road safety outcome.

3.3.3 Drink-Drive Convictions

Other researchers (Bliss et al., 1998; Cameron & Vulcan, 1998; Guria, 1999; Guria & Leung, 2004; Tay, 1999, 2003a) have suggested that the use of EBTs in the Macpherson and Lewis (1998) evaluation was inappropriate. Furthermore, Macpherson & Lewis (1998) alluded to difficulties in the use of EBTs as a measure of drink-drive behaviour and suggested that drink-drive convictions (by date of offence) might be more appropriate. However, up-to-date conviction data was not available at the time of the original analysis. In an initial attempt to address the limitations of EBTs, the current study repeats the analysis with drink-drive convictions as the dependent variable and once again alternating between the general (all-theme) and specific (drink-drive) advertising. Table 8 provides a comparison of the estimates from the original Macpherson and Lewis models using EBTs – (a) and (b) – with each of the corresponding new models that use drink-drive convictions as the dependent variable - models 2(a) and 2(b).

Table 8. EBTs and Drink-Drive Convictions

	Regression coefficients and statistics			
	Model (a)	**Model 2(a)**	**Model (b)**	**Model 2(b)**
Dependent Variable				
Positive EBTs	**x**		**x**	
Drink-drive convictions		**x**		**x**
Independent Variables[1]				
Adstock (All-theme)	**-.04**	**.04***		
Adstock (drink-drive)			**-.02**	**.03***
CBTs	.45*	.01	.42*	.03
Trend	.01	.01	.01	.01*
Summary Statistics				
R^2	.72**	.66**	.69**	.66**
Adjusted R^2	.53	.56	.49	.55

1. All models included eleven seasonal estimates that are not provided here. The full results are provided on pages 161 and 162. **X** denotes the presence of the corresponding variable. * Statistically significant at 0.05 level. ** Statistically significant at 0.01 level.

The models using drink-drive convictions as the road safety outcome – Models 2(a) and 2(b) - have provided a slightly higher measure of fit compared to the original Macpherson and Lewis models with adjusted R^2 values of .56 and .55 respectively (see Table 8).

CBTs are no longer significant when using drink-drive convictions as the road safety outcome. Furthermore, the trend estimates while unchanged in terms of magnitude, are only significant for Model 2(b) using drink-drive advertisements. As was found in model 1(b) (see Table 7), model 2(b) suggests that factors that are trending upwards over time are significantly contributing to small increases in drink-drive behaviour.

By changing the dependent variable from EBTs to convictions the SRSP advertising campaign is now found to have a significant, though positive, effect on drink-drive behaviour. The findings for models 2(a) and 2(b) is the same – both models have resulted in significant and positive advertising estimates (.04 and .03 respectively). Therefore the conclusion drawn from both of these models is that an increase in advertising is resulting in *higher* levels of drink-drive behaviour. This counterintuitive claim could be explained simply by an increase in advertising coinciding with an anticipated increase in drink-drive behaviour – an issue that will be revisited in the specification of models and the estimation procedure in Chapter 5. Alternatively, this finding could be interpreted as an indication that drink-drive convictions are increasing despite the SRSP advertising campaign.

3.3.4 Serious Crashes

Continuing with the extension of Macpherson and Lewis (1998), the dependent variable was changed to serious crashes - as used by Cameron and Vulcan (1998) and consequently by White et al (2000a) and Tay (2001). A serious crash is defined as if as a result of a road accident a person requires hospitalisation. Serious crashes have often been used in road safety models as the estimates can be converted into policy directives and cost and benefit statements. Using Graham's (1998) classification of SRSP outcomes, serious crashes would be considered an overall outcome.

Once again, the findings below are presented to provide a comparison of the original estimates using EBTs as the dependent variable against the new estimates using another road safety outcome – serious crashes.

Table 9. **EBTs and Serious Crashes**

	Regression coefficients and statistics			
	Model (a)	**Model 3(a)**	**Model (b)**	**Model 3(b)**
Dependent Variable				
Positive EBTs	x		x	
Serious Crashes		x		x
Independent Variables[1]				
Adstock (All-theme)	**-.04**	**-.01**		
Adstock (drink-drive)			**-.02**	**.004**
CBTs	.45*	-.04	.42*	-.04
Trend	.01	**-.01****	.01	**-.01****
Summary Statistics				
R^2	.72**	.71**	.69**	.71**
Adjusted R^2	.53	.62	.49	.62

1. All models included eleven seasonal estimates that are not provided here. The full results are provided on pages 163 and 164. **X** denotes the presence of the corresponding variable. *Statistically significant at 0.05 level. **Statistically significant at 0.01 level.

The fit of the Macpherson and Lewis models (adjusted R^2 of .62) to serious crashes is only slightly less than that obtained in the EBT models 1(a) and 1(b).

Using serious crashes as a dependent variable in the Macpherson and Lewis models implies that the most significant impact is produced by trending factors. Moreover, the sign of the coefficient suggests that the effect of the trend is to reduce serious crashes, rather than increase serious crashes, as estimated in the models based on EBTs and convictions. Unlike the models using drink-drive outcomes (EBTs and convictions), models 3(a) and 3(b) indicate that the enforcement has been ineffective. Both estimates for CBTs, while negative in direction, are non-significant at the 0.05 level.

The use of serious crashes, rather than EBTs in the Macpherson and Lewis models has not altered the original conclusion from Macpherson and Lewis (1998) - SRSP advertising appears to have no significant effect on driver behaviour and the resulting statistics. Both advertising estimates are non-significant with the drink-drive estimate being positive rather than negative in direction.

Using the crash based road safety statistic, serious crashes, a measure argued by other researchers as superior to EBTs (Bliss et al., 1998; Cameron & Vulcan, 1998; Guria & Leung, 2004; Tay, 2001), has produced varying and non-significant estimates of the effect of the SRSP advertising campaign. Furthermore, the findings using serious crashes have produced conclusions regarding the campaign's effectiveness that are largely consistent with those argued for in the original study.

3.3.5 Fatalities

The Macpherson & Lewis analysis was repeated with the use of fatalities. This is another measure of driving behaviour that, using Graham's (1998) classification, is an overall outcome. For obvious reasons, fatalities are often used by policy makers and the media when making claims about the effectiveness of road safety initiatives. While this measure is useful from a policy perspective it is expected to be of limited use for modelling the effectiveness of the SRSP advertising.

Like previous tables in this section, Table 10 on the next page compares the original estimates using EBTs with the findings for the same model using fatalities as the road safety outcome. The variables in Models 4(a) and 4(b) only account for 30% of the variation in fatalities. The lowest level of explanation using the Macpherson and Lewis models thus far. However, this result is not unexpected for such a broad measure of road safety that is likely to include a large random component.

Table 10. EBTs and Fatalities

	Regression coefficients and statistics			
	Model (a)	Model 4(a)	Model (b)	Model 4(b)
Dependent Variable				
Positive EBTs	x		x	
Fatalities		x		x
Independent Variables[1]				
Adstock (All-theme)	**-.04**	**-.02**		
Adstock (drink-drive)			**-.02**	**-.02**
CBTs	.45*	.10	.42*	-.09
Trend	.01	-.002	.01	-.002
Summary Statistics				
R^2	.72**	.45**	.69**	.46**
Adjusted R^2	.53	.30	.49	.30

1. All models included eleven seasonal estimates that are not provided here. The full results are provided on pages 165 and 166. **X** denotes the presence of the corresponding dependent variable. *Statistically significant at 0.05 level. **Statistically significant at 0.01 level.

The CBT estimates using fatalities compared to EBTs are non-significant. Both estimates are smaller with the all-theme Model 4(a) producing a positive coefficient while the drink-drive Model 4(b) producing a negative coefficient. Once again, trending factors are contributing to a reduction in the road safety outcome though, like the CBT estimates, the effect is non-significant.

The only two independent variables that are statistically significant in the fatality-based replications are the months of March and December (the results for the seasonal variables are provided on pages 165 and 166). These two months are associated with significantly higher levels of road accident fatalities.

The effect of the SRSP advertising is negative in direction but non-significant in both the fatality-based models. Using this outcome, road safety advertising, either the general all-theme or drink-drive advertisements, has resulted in a statistically non-significant reduction in fatalities.

Changing the road safety statistic from EBTs to fatalities has produced a model that, in terms of fit, is inferior to the outcomes tested so far here. Furthermore, the fatality-based models have produced advertising estimates that are consistent with the original study, regardless of the type of SRSP advertisements used to represent the campaign.

3.3.6 High Alcohol Hour Serious Crashes

Serious crashes can also be broken down into those that occur in high-alcohol hours and those that occur in low alcohol hours. The definition is used to target periods when certain types of accidents are more likely to occur – generally interpreted as speed-related crashes in low alcohol hours and drink-driving related crashes in high alcohol hours. The distinction between time periods has been used in previous evaluations of the Victorian campaign (Cameron et al., 1993; Cameron & Vulcan, 1998; Tay, 2003a) but a slightly different definition is used in New Zealand. In New Zealand high alcohol hours are considered to be between 10pm and 4am, Monday to Thursday, and between 10pm and 6am Friday to Sunday. It is expected that this intermediate outcome measure will not be as precise as other drink-drive outcomes – EBTs and convictions. Serious crashes during high alcohol hours also include a large number of non-alcohol related crashes – just less of these types of crashes occur during high alcohol hours than other time periods.

Table 11. EBTs and High Alcohol Hour Serious Crashes

	Regression coefficients and statistics			
	Model (a)	**Model 5(a)**	**Model (b)**	**Model 5(b)**
Dependent Variable				
Positive EBTs	x		x	
HAH Serious crashes		x		x
Independent Variables[1]				
Adstock (All-theme)	**-.04**	**-.04**		
Adstock (drink-drive)			**-.02**	**-.05**
CBTs	.45*	-.22	.42*	-.24
Trend	.01	**-.01****	.01	**-.01****
Summary Statistics				
R^2	.72**	.54**	.69**	.54**
Adjusted R^2	.53	.40	.49	.40

1. All models included eleven seasonal estimates that are not provided here. The full results are provided on pages 167 and 168. **X** denotes the presence of the corresponding variable. **HAH Serious Crashes** = High Alcohol Hour Serious crashes. *Statistically significant at 0.05 level. ** Statistically significant at 0.01 level.

Table 11 above compares the estimates using High Alcohol Hour serious crashes with those obtained from the original Macpherson and Lewis (1998) study using EBTs as the outcome. The results are very similar to those obtained using serious crashes (see Table 9), except that the model explains much less of the variation in the outcome measure (adjusted R^2 of .40 compared to .62). Using the high alcohol hour distinction for serious crashes has seen no change in the estimate for the trend compared to the overall serious crash measure. Trending factors are again highly significant in reducing the crash numbers. Likewise, the CBT estimates are negative and non-significant in Models 5(a) and 5(b) as they were in Models 3(a) and 3(b).

The advertising estimates were again non-significant for both types of SRSP advertisements. The road safety advertising was not effective in reducing the number of high alcohol hour serous crashes. Moreover, the high alcohol hour based models have produced advertising estimates that are consistent with those from the original study and pointed to other factors being responsible for the continuing decline in high alcohol hour serious crashes.

3.3.7 Summary of Replications of Macpherson and Lewis (1998) Models

The original model estimated by Macpherson and Lewis (1998) found no evidence to support the LTSA's claims that the introduction of the SRSP road safety advertising had led to improvements in driver behaviour and consequently a lower level of road accidents and fatalities. Table 12 provides a summary of the estimated effects for the replications using the five road safety outcomes. Model numbers ending in (a) relate to the all-theme advertising content, while model numbers ending in (b) relate to the drink-drive advertisements.

To assist the interpretation of the summary table it should be noted at this point that references to "positive" and "negative" are in terms of the direction of the estimated relationships and are not to be confused with an interpretation of the practical implications of the finding. For example, while an advertising estimate may be positive in direction, policymakers would consider the implications of this result to be a "negative" reflection of their efforts. This would mean that an *increase* in the road safety measure is associated with an increase in the level of SRSP advertising. Thus, a positive advertising estimate is an indication that the campaign has been ineffective and, therefore, unsuccessful at reducing the road accident statistics.

Table 12. Summary of Estimated Effects from Replications of Macpherson & Lewis

	Road Safety Outcome									
	EBTs		**Drink-drive Convictions**		**Serious Crashes**		**Fatalities**		**HAH Serious Crashes**	
	1(a)	1(b)	2(a)	2(b)	3(a)	3(b)	4(a)	4(b)	5(a)	5(b)
Variables										
SRSP Advertising	-	-	+	+	-	+	-	-	-	-
CBTs	+	+	+	+	-	-	+	-	-	-
Trend	+	+	+	+	-	-	-	-	-	-

Shaded cells indicate a statistically significant effect at the 0.05 level. (a) = all-theme. (b) = drink-drive.

While the majority (70%) of estimates for the SRSP advertising indicate that it has reduced the road safety outcomes, the only significant effects using the Macpherson and Lewis model are positive in direction – Models 2(a) and 2(b) using drink-drive convictions.

Enforcement as represented by CBTs appears to be positively related to the EBT-based outcomes in Models 1(a) through to 2(b), and largely negatively related to the crash-based outcomes of serious crashes, fatalities and high alcohol hour crashes in Models 3(a) to 5(b).

Across all the road safety outcomes except fatalities, the trend is the most common significant contributor to changes in the road safety statistics. Factors that are gradually trending upwards over time are contributing to an increase in EBT-based outcomes, and contributing to a decrease in crash-based outcomes –with the exception of fatalities.

Changing the type of advertisements to represent the SRSP road safety advertising appears to have little, if any, effect on the estimates with few differences between the all-theme (a) and drink-drive (b) models evident across the replications.

Despite changing the road safety outcome measures and the type of SRSP advertisements, the results of the replications in terms of the advertising effects are inconclusive. At this stage in the proposed analysis process, there is no indication that this model will provide a robust measure of the effectiveness of the advertising.

The next approach that was developed to evaluate the effectiveness of the SRSP campaign was Cameron and Vulcan (1998). This model will be the focus of the next series of evaluations along with the modified model proposed by White et al (2000a) as an improvement of Cameron and Vulcan's attempt.

3.4 The Replication of Cameron and Vulcan's (1998) and White et al's (2000a) Evaluation of the SRSP Campaign

3.4.1 Introduction

In 1998 Cameron and Vulcan were commissioned by the LTSA to develop a quantitative model to evaluate the effectiveness of the overall New Zealand Supplementary Road Safety Package (SRSP). Contrary to the findings of Macpherson and Lewis (1998), Cameron and Vulcan concluded from their analyses that the SRSP advertising campaign had been successful in reducing the number of serious crashes. Indifferent to their own previous research (Cameron et al., 1993; Cameron & Newstead, 1993a, 1993b; Cameron & Newstead, 1996; Cameron et al., 1995a, 1995b; M. Cameron et al., 1994) and the approach undertaken by Macpherson and Lewis (1998), the MUARC researchers chose to represent the effects of the overall SRSP campaign as a step function using two dummy variables to represent the first two years of the campaign. The Cameron and Vulcan models spanned from the beginning of 1990 to the middle of 1997 using quarterly data which amounted to 30 observations. Cameron and Vulcan chose to use the total number of serious crashes as the dependent variable in the evaluation of the NZ campaign, which is similar to the high and low alcohol serious crashes variable used in their previous modelling of the Victorian campaign. For reasons unknown, two models were specified, one using unemployment as the economic indicator, and one using new car registration as the economic indicator. Each of the models contained the following variables:

- Dependent Variable
  - Serious crashes
- Independent Variables
  - Compulsory breath test (CBT) dummy variable
  - SRSP dummy to indicate mid 95 to mid 96
  - SRSP dummy to indicate 2nd half 96 to mid 97
  - New car registrations, or Unemployment rate
  - Three seasonal dummy variables to denote three last quarters (Q2, Q3, and Q4)

All variables were transformed by the natural logarithm thereby creating double-log models. This transformation is common in the modelling of road safety data.

3.4.2 Specification of Replication Models

Consistent with the previous replication, the original models will be extended to include models using other road safety outcomes (listed below). As Cameron and Vulcan (1998) utilised serious crashes as the dependent variable, this section will begin with models using this outcome. From the initial two models, the dependent variable will be changed to: EBTs, drink-drive convictions, fatalities, and high alcohol hour serious crashes, in that order.

The current time series includes monthly level data for the period October 1993 to December 1998 so encompasses the first three years of the campaign – 1995 to 1998. As a result, each year of the SRSP campaign will now be represented by three dummy variables rather than the two required by Cameron and Vulcan.

However, a notable omission from the list of independent variables in Cameron and Vulcan's (1998) evaluation was a trend term. The exclusion of a trend term was challenged by White et al (2000a). Furthermore, White et al (2000a) demonstrated that the conclusions from Vulcan and Cameron (1998) were sensitive to the presence or absence of the trend. To address this issue and to serve as a replication of White et al's (2000a) model specification, two further models that include the trend will be estimated for each road safety outcome. The replication in the current study differs from the original Cameron & Vulcan (1998) and White et al (2000a) studies by utilising monthly rather than quarterly data. The use of monthly level data in the current study should only serve to provide a finer perspective and greater precision than that afforded by quarterly data. Furthermore, the CBT program is represented by actual monthly counts rather than a dummy variable as was the case with the original study. A dummy variable for CBTs was not possible here as the beginning of the CBT program was prior to the start of the new time series (October, 1993). Therefore, the dummy variable would have been a constant across the complete time series.

In summary there will be four models for each of the five road safety outcomes:

a) CBTs, SRSP 95/96, SRSP 96/97, SRSP 97/98, New Cars, Seasonal dummies
b) CBTs, SRSP 95/96, SRSP 96/97, SRSP 97/98, Unemployment, Seasonal dummies
c) CBTs, SRSP 95/96, SRSP 96/97, SRSP 97/98, New Cars, Seasonal dummies, and Trend
d) CBTs, SRSP 95/96, SRSP 96/97, SRSP 97/98, Unemployment, Seasonal dummies, and Trend

The results for each of the road safety outcomes will be presented in a series of tables. The first two columns of each table - Models (a) and (b) will contain the replications relating to Cameron & Vulcan (1998), and the remaining two columns - Models (c) and (d) will contain the estimates from the replication of White et al (2000a).

3.4.3 Serious Crashes

The dependent variable chosen by Cameron and Vulcan to model the effects of the New Zealand SRSP campaign, and subsequently by White et al in their re-evaluation was serious casualty crashes. Therefore, Models 6(a) and 6(b) represent the closest replication of the original evaluation and Models 6(c) and 6(d) represent the closest replication of the original re-evaluation by White et al.

Table 13. Replications of Cameron and Vulcan's Evaluation & White's Re-Evaluation of the NZ SRSP – Serious Crashes

	Regression coefficients and statistics			
	Model 6(a)	**Model 6(b)**	**Model 6(c)**	**Model 6(d)**
Independent Variables				
CBTs	.11	.17*	.01	.01
SRSP – 95/96	.13**	.03	.10*	.06
SRSP – 96/97	-.04	-.13**	.002	-.03
SRSP – 97/98	.17**	.15**	-.03	-.01
New Car registrations	-.37**		-.07	
Unemployment		-.20		-.19
Trend			-.01**	-.01**
Summary Statistics				
R^2	.69**	.64**	.76**	.77**
Adjusted R^2	.51	.59	.68	.67

* Statistically significant at 0.05 level. ** Statistically significant at 0.01 level. **Note:** Full results provided on pages 169 to 172.

The first model - 6(a) - indicates that the first year of the SRSP is having a significant but positive effect on serious crashes, whereas the second year has had no significant impact, but then the third year is also estimated to have had a significant but positive effect on crashes. The direction of the estimates of the effect of the campaign for each year does not change when another economic indicator is used. However, changing the indicator from new cars to unemployment - see Model 6(b) - results in the SRSP being estimated as statistically significant for both the second and third years of the campaign. Consequently, both Models 6(a) and 6(b) are relatively consistent with the original Cameron and Vulcan findings that the campaign increased in effectiveness from the first year to the second year. But the increasing effectiveness of the campaign does not appear to have continued into the third year of the SRSP advertising campaign.

The inclusion of a trend effect – Models 6(c) and 6(d) – has repeated the findings of White et al (2000a). The campaign is estimated to have little to no effect with only one year, SRSP 95/96, being significant at the 0.05 level. Also consistent with White's findings, factors trending upwards over time are significant in reducing the incidences of serious casualty crashes. Neither new car registrations nor unemployment have significantly affected serious crashes when the trend is included. However, in the original evaluation by White et al – and in 6(a) for new cars – both indicators were estimated to significantly reduce crash numbers.

The four closest replications of the original Cameron and Vulcan (1998) and White et al (2000a) studies have resulted in little change to the initial conclusions. When only considering the direction of the estimates, the replication of Cameron and Vulcan supports the claim that the campaign has been effective in the second year. In contrast, the replication suggests that the campaign has been ineffective in the third year – see 6(a) and 6(b). The replication of White et al's (2000a) model that includes the simple addition of a trend term seriously challenges Cameron and Vulcan's underlying model assumptions and their subsequent claims.

It is possible the above findings are dependent on the modeller's choice of road safety outcome. The next replication uses EBTs as the road safety outcome to see whether the same conclusion would be reached with a different outcome measure.

3.4.4 Positive Evidential Breath Tests (EBTs)

In the previous evaluation of Macpherson and Lewis (1998) the use of EBTs and drink-drive convictions failed to uncover any elements that contributed to a significant reduction in either of the road safety outcomes. The repeated use of EBTs as the road safety outcome across two separate model specifications will assist in our understanding of the effectiveness of the SRSP advertising campaign.

Table 14 contains the estimates from the application of EBTs to the Cameron and Vulcan (1998) and White et al (2000a) models. Models 7(a) to 7(d) contain ample significant estimates but few of these are reducing the number of EBTs – most factors estimated are positive, thus are leading to higher levels of drink-drive behaviour rather than a reduction. The only exceptions are found in Models 7(a) and (c) where the first year of the SRSP has resulted in a significant reduction in drink-driving. On the other hand, these two models contain significant estimates of gains in drink-driving for the second and third years of the SRSP campaign, indicated by the significant but positive coefficients.

Table 14. Replications of Cameron et al's Evaluation & White's Re-Evaluation of the NZ SRSP – EBTs

	Model 7(a)	Model 7(b)	Model 7(c)	Model 7(d)
Independent Variables				
CBTs	.06	-.03	.34*	.33**
SRSP – 95/96	**-.25****	-.084	-.15*	-.14
SRSP – 96/97	**.42****	**.56****	.30**	.32**
SRSP – 97/98	**.62****	**.58****	.21*	.26**
New Car registrations	.65**		-.24	
Unemployment		.28		.26
Trend			**.01****	**.01****
Summary Statistics				
R^2	.78**	.75**	.88**	.88**
Adjusted R^2	.71	.67	.83	.83

* Statistically significant at 0.05 level. ** Statistically significant at 0.01 level. **Note:** Full results provided on pages 173 to 176.

Factors that trend upward over time and the number of CBTs are also estimated to significantly contribute to higher levels of drink-drive behaviour – a repeat of the findings in Models 1(a) and (b) from the Macpherson and Lewis replication on page 57. Once again, both these findings may be explained in relation to EBTs. Increases in the number of CBTs are timed with the anticipated increase in drink-drive behaviour. If this is correct, then this synchronous relationship presents a problem for the use of a single equation such as used here and in the other replications. This is an issue that will be re-visited in Chapters 4 and 5.

3.4.5 Drink-drive Convictions

The results of using drink-drive convictions as the outcome measure are shown in Table 15. Once again, the result is very similar estimates to the findings of the models using EBTs (see Table 14). This result is not altogether unexpected as drink-drive convictions largely originate from positive evidential breath tests.

Models 8(a) and (b) estimate similar effects for the SRSP and CBT variables. The number of CBTs is having a negative effect on drink-drive convictions although this is not statistically significant. In contrast the SRSP campaign has had a significant positive effect on drink-drive behaviour - with only the one exception being the second year of the campaign for Model 8(a). Furthermore, neither of the economic indicators are significantly affecting drink-driving. Both models provide a moderate level of explanation of drink-drive convictions.

Table 15. Replications of Cameron and Vulcan's Evaluation & White's Re-Evaluation of the NZ SRSP – Drink-Drive Convictions

	Model 8(a)	Model 8(b)	Model 8(c)	Model 8(d)
Independent Variables				
CBTs	-.02	-.02	.05	.04
SRSP – 95/96	**.11****	**.12****	**.13****	**.12****
SRSP – 96/97	**-.13****	**.14****	**.10****	**.10***
SRSP – 97/98	**.08***	**.08***	-.02	.03
New Car registrations	-.04		-.26*	
Unemployment		.14		.13
Trend			**.003****	.002
Summary Statistics				
R^2	.68**	.68**	.72**	.70**
Adjusted R^2	.56	.57	.62	.59

* Statistically significant at 0.05 level. ** Statistically significant at 0.01 level. **Note:** Full results provided on pages 177 and 180.

In Model 8(c), new car registrations now have a significant negative impact on drink-driving, while the estimate for unemployment in Model 8(d) is almost identical to Model 8(b). The new trend variable is statistically significant for the model using new car registrations only. Moreover, the estimates in both Models 8(c) and (d) are noticeably smaller than those for the comparable Models 7(c) and (d) (see Table 14). However, the factors that are trending upwards over time are only significantly related to an increase in drink-drive behaviour when using new car registrations as the economic indicator.

The introduction of the trend term in Models 8(c) and (d) makes little difference to the estimates for the first two years of the SRSP campaign – the campaign is still having a significant but positive effect on driving behaviour. However, now the third year of the campaign has had little if no effect on driver's behaviour.

The use of EBTs and drink-drive convictions produce estimates that are a distinct from those found by Cameron and Vulcan (1998), White et al (2000), and the subsequent replications of those studies. The differences may be simply explained by the outcomes themselves. While road crashes continued to gradually decline over the study period, drink-drive behaviour measured by the number of positive EBTs and the eventual drink-drive convictions increased over that same period. As the implementation of the SRSP advertising campaign coincided with an increase in drink-driving, it is not surprising that the relationships between these actions are positive. Likewise, the trend now represents the factors that are not represented explicitly in the model but which are also gradually increasing over time – hence the positive relationship.

The next series of replications are based on road fatalities, therefore it is expected that the estimates will be similar to those found using the broader categorisation of serious crashes.

3.4.6 Fatalities – Models 9(a) to 9(d)

Table 16 on the next page contains the estimates of the extension of Cameron and Vulcan and White et al's models to include the use of fatalities as the measure of outcome.

As expected, the use of this overall outcome has produced no statistically significant effects among the key variables of interest here. Moreover, the models are a weak explanation of the overall variation in road fatalities with the largest Adjusted R^2 of .27 or 27%. Once again, this result is not unexpected and underpins the limitations of such global measures for judging such initiatives. If we disregard the significance of the estimates the results appear to be supportive of the claim that the SRSP advertising has led to a reduction in fatalities over its first three years. Unlike previous models here, the inclusion of a trend – Models 9(c) and 9(d) – does not affect this finding. Factors that are trending upwards over time are estimated to be reducing fatalities – a similar finding to Models 6(c) and 6(d) using serious crashes (see Table 13). But notably, none of the estimates in any of these four models are statistically significant.

Table 16. Replications of Cameron and Vulcan's Evaluation & White's Re-Evaluation of the NZ SRSP – Fatalities

	Model 9(a)	Model 9(b)	Model 9(c)	Model 9(d)
Independent Variables				
CBTs	.12	.13	.09	.09
SRSP – 95/96	-.03	-.07	-.04	-.06
SRSP – 96/97	-.04	-.07	-.03	-.05
SRSP – 97/98	-.10	-.10	-.06	-.06
New Car registrations	-.06		.03	
Unemployment		-.18		-.17
Trend			-.001	-.001
Summary Statistics				
R^2	.45**	.45**	.46**	.46**
Adjusted R^2	.26	.27	.25	.26

* Statistically significant at 0.05 level. ** Statistically significant at 0.01 level. **Note:** Full results provided on pages 181 to 184.

3.4.7 High Alcohol Hour Serious Crashes

The final replications of Cameron and Vulcan (1998) and White et al (2000a) involve the use of another intermediate road safety outcome – high alcohol hour serious crashes. Once again, the expectation is that this outcome will provide a more precise measure of drink-drive behaviour than the overall crash statistic, serious crashes.

Table 17. Replications of Cameron and Vulcan's Evaluation & White's Re-Evaluation of the NZ SRSP – High Alcohol Hour Serious Crashes

	Model 10(a)	Model 10(b)	Model 10(c)	Model 10(d)
Independent Variables				
CBTs	.04	.13	-.14	-.15
SRSP – 95/96	**.22****	.06	.16	.11
SRSP – 96/97	**-.09**	**-.23***	-.01	-.05
SRSP – 97/98	**-.37****	**.34****	.11	.09
New Car registrations	-.67*		-.09	
Unemployment		-.23		-.21
Trend			**-.01****	**-.01****
Summary Statistics				
R^2	.51**	.45**	.58**	.58**
Adjusted R^2	.34	.26	.43	.43

* Statistically significant at 0.05 level. ** Statistically significant at 0.01 level. **Note:** Full results provided on pages 185 to 188.

The pattern of results in Table 17 closely mirrors those from Models 6(a) to (d) (see Table 13). The inclusion of a trend variable produces non-significant estimates for the SRSP campaign and significant trend estimates. This finding gives further support to White et al's arguments that Cameron and Vulcan's (1998) model specification was sensitive to the presence of a trend and the factors represented by this variable. Furthermore, as was claimed by White et al, the trend is the significant contributor to the reduction road safety accident statistics.

3.4.8 Summary of Models 6(a) to 10(d)

The nature of the findings and patterns that were evident in the replications of Macpherson and Lewis (1998) has been repeated here in the replications of Cameron and Vulcan (1998) and White et al (2000a). Across the estimated Models 6(a) to 10(d) the results are, once again, inconclusive in regards to the effectiveness of the SRSP advertising campaign. The findings have been split over two tables. Table 18 contains the direction and significance estimated effects of the replications of Cameron and Vulcan's models. Table 19 contains the direction and significance of the estimated effects of the replications of White et al – the key difference between the tables being the inclusion of a trend term in the later models.

Table 18. Summary of Estimated Effects from Replications of Cameron & Vulcan

	Road Safety Outcome									
	Serious Crashes		**EBTs**		**Drink-drive Convictions**		**Fatalities**		**HAH Serious Crashes**	
	6(a)	6(b)	7(a)	7(b)	8(a)	8(b)	9(a)	9(b)	10(a)	10(b)
Variables										
SRSP 95/96	+	+	-	-	+	+	-	-	+	+
SRSP 96/97	-	-	+	+	+	-	-	-	-	+
SRSP 97/98	+	+	+	+	+	+	-	-	-	-

Shaded cells indicate a statistically significant effect at the 0.05 level. (a) Includes new cars. (b) Includes unemployment.

From Table 18 if we disregard the statistical significance of the advertising estimates, 47% of effects indicate a reduction in the road safety statistics following the introduction of the SRSP campaign. Using the same perspective applied to the findings in Table 19, 57% of the advertising effects indicate that the road safety statistics reduced following the implementation of the SRSP campaign.

However, taking into account the statistical significance of the advertising estimates, Table 18 shows that 74% of the significant advertising effects indicate that the campaign has not been effective in reducing the road safety outcomes. If we focus solely on the significant advertising estimates in Table 19 on the next page (i.e. ignore the trend estimates), 40% indicate that the implementation of the SRSP advertising resulted in a reduction in the road safety outcomes. Thus, the inclusion of the trend variable into the models has slightly increased the number of significant negative SRSP estimates. This is contrary to the original White et al (2000a) findings where the inclusion of the trend resulted in fewer if any significant SRSP estimates. Nonetheless, the majority of SRSP estimates here, with or without the trend also being present, indicate that the implementation of the SRSP campaign has been ineffective in reducing the road safety statistics.

Table 19. Summary of Estimated Effects from Replications of White et al

	Road Safety Outcome									
	Serious Crashes		**EBTs**		**Drink-drive Convictions**		**Fatalities**		**HAH Serious Crashes**	
	6(c)	6(d)	7(c)	7(d)	8(c)	8(d)	9(c)	9(d)	10(c)	10(d)
Variables										
SRSP 95/96	+	+	-	-	+	+	-	-	+	+
SRSP 96/97	+	-	-	-	-	+	-	-	-	-
SRSP 97/98	-	-	+	+	-	+	-	-	+	+
Trend	-	-	+	+	+	+	-	-	-	-

Shaded cells indicate a statistically significant effect at the 0.05 level. (c) Includes new cars. (d) Includes unemployment.

Viewing the results from the perspective of the road safety outcome used and focussing only on the advertising effects, the EBT-based models (EBTs and convictions – Models 7a, 7d, 8c, 8d) produced noticeably more significant estimates than the other crash-based outcomes (fatalities, serious and high alcohol crashes – Models 6c, 6d, 9c, 9d, 10c, 10d). Of the significant advertising estimates in the EBT-based models, 44% were negative and 56% were positive. Only models 7c and 7d produced any consistency in the pattern of the three advertising estimates across the two models using different economic indicators. For these models, the campaign was estimated to be effective for the first two years (though the first year of the SRSP is statistically insignificant in Model 7d) and positive, and therefore ineffective, in the third year.

The EBT-based models failed to replicate the original Cameron and Vulcan (1998) and White et al (2000a) findings. These models – 7(a,b,c,d) and 8(a,b,c,d) – indicated, to at least some degree, that both the SRSP and the trend have *both* contributed significantly to an *increase* in drink-driving. Moreover, the contrast between the crash-based outcomes and the EBT-based outcomes is consistent with those found in the replication of Macpherson and Lewis (see summary Table 12 on page 65). Across the two series of replications undertaken at this point, the use of crash-based models indicates that the trend is a significant factor in the reduction in crash-based outcomes while the trend significantly contributes to an increase in drink-drive behaviour in the EBT-based models. The counterintuitive findings that the SRSP campaign has led to an *increase* in road safety outcomes will be the revisited in Chapters 4 and 5.

The next series of models will replicate the models from Tay's (1999) evaluation of the SRSP campaign. Tay put forward these models to address what he claimed to be deficiencies in the Macpherson and Lewis (1998) assessment of the road safety advertising's effect on driver behaviour.

3.5 Replication of Tay's (1999) Evaluation of the SRSP Road Safety Advertising

3.5.1 Introduction

In 1999 Tay re-analysed the data from Macpherson and Lewis (1998) and consequently claimed that, following some modifications to the model and the estimation process, the road safety advertising campaign was successful in reducing the level of drink-driving in New Zealand. Tay's modifications can be broken down into the following elements:

- The use of only a general measure of road safety advertising,
- A subtle re-specification of Macpherson and Lewis's basic model,
- The testing of the functional form,
- The use of first-order autoregression,
- The testing for a structural change in the relationship between the advertising and the road safety outcome.

3.5.1.1 A General Measure of Advertising

Macpherson and Lewis (1998) used a pair of models to estimate the effectiveness of the New Zealand road safety advertising. These differed in the one respect; they switched between a general (all-theme) measure of the advertisements and a specific (drink-drive) measure of the road safety advertisements. Macpherson and Lewis found that the conclusions drawn from both models were the same. Therefore, Tay (1999) chose to focus only on the re-analysis of the broader measure of the advertising. The assumption underlying Tay's use of all SRSP road safety advertisements (all-theme) is that focusing solely on the specific drink-drive messages results in an under-representation of the amount of SRSP road safety advertising at any one time. The treatment of messages used the SRSP campaign was very similar across all the types of advertisements. Therefore, given the similarity of the images and messages, the effect of each type of advert is assumed, by Tay, to spill over into all other driving behaviours.

Consequently, the replication of Tay (1999) will also focus solely on the general (all-theme) measure of road safety advertising.

3.5.1.2 Tay's Basic Model Re-specification

Tay (1999) also claimed that ten of the estimated eleven monthly dummy variables were statistically non-significant using the original Macpherson and Lewis (1998) models. However the results from Macpherson and Lewis (1998) show that this assumption appears to have been incorrect. In the original study only three of the seasonal variable are non-significant; February, June, and December. Therefore, it is not clear why Tay excluded all of the monthly dummy variables except December. Another aspect of this decision was his mistaken interpretation of the level of drink-driving in this month. Tay concluded from the raw EBT data that drink-driving regularly peaked in December. However, Figure 2 on page 15 taken from Macpherson (2003) shows that, when taking the number of tests into account, the month of December is actually a period of lower than average drink-drive behaviour. Despite these issues, the original specification of the explanatory variables in Tay's models will be maintained in the following replication and extensions.

3.5.1.3 Tay's Test of the Functional Form

Tay made another modification to the Macpherson and Lewis (1998) approach by testing the functional form of all his models. Tay (1999) tested four functional forms. They were:

- Double-log
- Log-linear
- Linear-log
- Linear

However, Tay's own analysis found minimal differences between the fits achieved and, more importantly, no practical differences between the estimates and conclusions drawn between the four functional forms.

To simplify the replications to follow, Tay's functional forms were re-tested here. If, once again, the differences between the functional forms are found to be minimal, then just the one functional form can be used for the replication of each of Tay's models. While Tay (1999) analysed the functional form for each of his models without finding any practical differences in the conclusions, little is to be gained by repeating the exercise here if the findings are repeated.

The basic model using the four functional forms, as specified by Tay (1999), were re-estimated using the longer time series and are shown in Table 20 below.

Table 20. Tay's Different Functional Forms using EBTs as the Outcome

	Regression coefficients and statistics			
	Model 11(a)	**Model 11(b)**	**Model 11(c)**	**Model 11(d)**
Functional Form				
Double-log	x			
Linear-log		x		
Log-linear			x	
Linear				x
Independent Variables				
Adstock (All-theme)	-.01	-1.76	.000	-.20
CBTs	.35**	662.99**	3.992E-06**	.01**
Trend	.02**	35.46**	.02**	38.64**
December	-.06	-83.02	-.31	-630.14
Summary Statistics				
R^2	.65**	.67**	.68**	.70**
Adjusted R^2	.63	.65	.66	.68

Note: All models above are using EBTs as the dependent variable. *Statistically significant at 0.05 level. **Statistically significant at 0.01 level. **Note:** Full results provided on pages 189 to 192.

Using the adjusted R^2 as a point of comparison, there is no substantive difference between the models. In each of the models, CBTs and the trend are significant and positive. Furthermore, the conclusions you would draw from each of the models above are identical; there is no evidence to suggest that the advertising has resulted in a significant reduction in the road safety statistics – none of the advertising estimates are statistically significant. This finding reflects Tay's own findings in so far that the estimates are consistent across the models using the four functional forms.

The double-log is the most common functional form for the analysis of road safety data (Hakim et al., 1991) and has been used for all the replications undertaken up to this point in this thesis. The continuing use of this functional form is not only consistent with best practice, but enables a more straightforward comparison between all the replications. As a result, the double-log functional form will be used for the replications of Tay (1999) beginning with the replication of the Tay's basic model using the five road safety statistics – Models 12(a) to 12(d) on page 80.

3.5.1.4 Tay's Use of First-order Autoregression

Tay also suspected that because the Macpherson and Lewis (1998) analysis used time series data that autocorrelation may be present. On the other hand, after calculating Durbin Watson statistics, Tay concluded that the he was unable to conclusively determine the presence of autocorrelation in the data. Despite this, Tay still re-analysed the Macpherson and Lewis data using first-order autoregressive estimation.

With a principle of completeness in mind, the first-order autoregressive model will be replicated here in the current study – in Models 13(a) to 13(e) on page 81.

3.5.1.5 Tay's Test for a Structural Change

Lastly, Tay re-analysed his four functional forms in an attempt to detect any evidence of a structural change between the level of advertising and drink-driving. To test whether the implementation of the SRSP had resulted in a change in the level of EBTs, two additional variables were created - DSRSP and Sadstock. DSRSP is a dummy variable that assumes a value of zero for observations that were before the implementation of the SRSP (October 1995) and a value of one for observations after the implementation. Sadstock is the interaction term between DSRSP and Adstock and Tay argued that this variable would estimate the presence of a structural change in the relationship between drink-driving behaviour and advertising after the launch of the SRSP. Once again, Tay chose to use first-order autoregressive estimation for these models.

The test for a structural change is repeated here using the five different road safety statistics – Models 14(a) to (e) on page 83.

3.5.2 Overview of the Tay (1999) Replications

To summarise, the model specification of the testing of functional forms, the estimation of the basic model and the initial first-order autoregressive models will use the following independent variables:

- All-theme Adstock
- Compulsory breath tests (CBTs)
- Trend
- December dummy variable

The structural change models will consist of the following 'additional' independent variables:

- DSRSP
- Sadstock

Each model will be extended once again by using the five road safety statistics in the following order:

(a) Positive evidential breath tests (EBTs) - as per Tay's (1999) evaluation
(b) Drink-drive convictions
(c) Serious crashes
(d) Fatalities
(e) High alcohol hour serious crashes

Consistent with the previous replications here, the data is at monthly level and covers the period October 1993 to December 1998.

3.5.3 Replications of Tay's (1999) Basic Model

Table 21 on the next page contains five replications of what Tay (1999) referred to as the 'basic' model. The models only differ in terms of the road safety statistics used as the dependent variable. Tay used EBTs in his evaluation so this is specified in the first model of this series – Model 12(a) – and therefore represents the closest replication of the basic model. Please note that Model 12(a) is identical to Model 11(a) in Table 20.

Model 12(a) indicates that the trend and CBTs are the only significant factors affecting driving behaviour. This result is consistent with the findings in Model 1(a) from the Macpherson and Lewis replications (see page 57) that includes all the seasonal dummy variables. Furthermore, it is would appear Models 12(b) to (e) are not too dissimilar to the corresponding models in the replication of Macpherson and Lewis – see Models 2(a) to 5(d) on pages 59 to 64. Model 12(b), based on drink-drive convictions, points to the month of December being the only variable of significance. This is an almost identical finding as Model 2(a) (see page 161 for the complete results). However, as would be expected with 10 seasonal variables omitted, Model 12(b) explains substantially less of the variation in convictions (adj. R^2 of .23 compared to .56) than Model 2(a). Furthermore, Model 12(b) also differs from Model 2(a) in that it does not estimate a significant effect for the SRSP advertising. The earlier replication estimated that the advertising was related to a significant increase in drink-drive behaviour.

Table 21. Tay's (1999) Basic Model using Different Road Safety Statistics

	Regression coefficients and statistics				
	Model 12(a)	**Model 12(b)**	**Model 12(c)**	**Model (12d)**	**Model (12e)**
Dependent Variable					
EBTs	x				
D-drive convictions		x			
Serious crashes			x		
Fatalities				x	
HAH serious crashes					x
Independent Variables					
Adstock (All-theme)	**-.01**	**.03**	**-.01**	-.02	**-.04****
CBTs	**.35****	-.041	.06	.12	-.14
Trend	**.02****	.002	**-.01****	-.002	**-.01****
December	-.06	**.19***	.09	.15	.30*
Summary Statistics					
R^2	.65**	.28**	.58**	.24**	.46**
Adjusted R^2	.63	.23	.55	.19	.42

HAH = High Alcohol Hour. *Statistically significant at 0.05 level. **Statistically significant at 0.01 level. **Note:** Full results provided on pages 193 to 195.

Models 12(c) and (e) are similar in the respect that they all indicate that trending factors are significantly reducing the road safety outcome. Once again, these findings are consistent with the corresponding Macpherson and Lewis replications – Models 3(a), 4(a), and 5(a). However, Model 12(e) now differs from Model 5(a) of the Macpherson and Lewis replication as it now estimates a significant reduction in high alcohol hour crashes due to the road safety advertising. In summary, the Macpherson and Lewis replication failed to reveal a significant reduction using all the monthly dummy variables and Tay's decision to remove the monthly dummy variables other than December has already been questioned here. Therefore, it would appear that the advertising estimate is sensitive to the inclusion or omission of the significant seasonal variables.

Factors that trend upwards over time were again a significant factor in the increase of EBTs and the reduction in serious and high alcohol hour crashes.

3.5.4 Replications of Tay's (1999) Autoregressive Model

Tay (1999) anticipated that the time series data used in the analysis may exhibit autocorrelation. However, autocorrelation is not a problem in the actual estimation of model effects. The presence of autocorrelated data will only affect the standard errors of the estimates and any subsequent tests of their precision (Lewis, 1975). Even so, for the sake of completion Tay's (1999) first-order regressive model has been replicated using EBTs and then re-analysed using the remaining four road safety statistics (see Table 22 below).

Table 22. Tay's (1999) Autoregressive Model using Different Outcomes

	Regression coefficients and statistics				
	Model 13(a)	**Model 13(b)**	**Model 13(c)**	**Model 13(d)**	**Model 13(e)**
Dependent Variable					
EBTs	x				
D-drive convictions		x			
Serious crashes			x		
Fatalities				x	
HAH serious crashes					x
Independent Variables					
Adstock (All-theme)	**-.07**	**.01**	**-.01**	-.03	**-.05**
CBTs	**.23****	.03	.07	.11	-.14
Trend	**.02****	.003	**-.01****	-.001	**-.01****
December	.16	.20**	.09	.17	**.31***
Summary Statistics					
Rho	.63	.52	.13	-.19	.11
R^2	.53**	.40**	.52**	.28**	.40**
Adjusted R^2	.48	.35	.48	.22	.35
Durbin Watson	2.00	1.89	2.04	2.02	2.03

* Statistically significant at 0.05 level. ** Statistically significant at 0.01 level. **Note:** Full results provided on pages 197 to 201.

As found by Tay (see page 30), the Durbin Watson statistics for all of the models in Table 22 above indicate that there is no conclusive evidence of positive first-order serial correlation in the time series (n = 63, k = 4 at the 0.01 level of significance). All of the calculated Durbin Watson statistics are close to 2 and well above the upper limit of the test (d_u) indicating that we can accept the null hypothesis that $p = 0$ - there is no evidence of either positive or negative autocorrelation (Ramanathan, 1998).

Unsurprisingly, given the results of the Durbin Watson test for autocorrelation, the findings in Table 22 above are very similar to those found using Tay's basic model in (page 80). Models 13 (a) through to (e) mirror the findings and conclusions derived from the results of the replication of Tay's basic model. The only departure from the findings of the previous series of replications of Tay's basic model is the insignificance of the advertising estimate for Model 13(e).

Overall, the use of Tay's recommended autoregressive modification to the Macpherson and Lewis model has resulted in no significant estimates of a reduction in road safety outcomes as a result of the introduction of the road safety advertising. Moreover, the results indicate that factors other than SRSP advertising are significantly affecting road safety statistics.

3.5.5 Replications of Tay's (1999) Structural Change Model

Tay's last series of models tested for the presence of a structural change in the relationship between EBTs and the road safety advertising after the implementation of the SRSP. Tay maintains that without a test for structural change, the estimates for the advertising will just indicate whether drink-drive advertising in general (pre and post SRSP) has had any impact on drink-driving behaviour and will not provide any indication of the success or failure of the advertising associated with the SRSP.

To estimate a structural change Tay created two new variables, DSRSP and Sadstock. A statistically significant and negative coefficient for Sadstock will indicate that the SRSP advertising has had a larger impact than road safety advertising in general. A non-significant Sadstock and a significant and negative coefficient for DSRSP would indicate that the SRSP campaign has been effective in reducing road safety statistics without changing the structural relationship between advertising and the outcomes. Once again, the EBT model – model 14(a) – represents the closest replication and was subsequently repeated using the series of statistics.

Table 23. Tay's (1999) Structural Change Model using Different Outcomes

	Regression coefficients and statistics				
	Model 14(a)	**Model 14(b)**	**Model 14(c)**	**Model 14(d)**	**Model 14(e)**
Dependent Variable					
EBTs	x				
D-drive convictions		x			
Serious crashes			x		
Fatalities				x	
HAH serious crashes					x
Independent Variables					
Adstock (All-theme)	.07	.03	**-.06***	-.03	**-.11***
Sadstock	**-.39****	-.13	.06	-.001	-.01
DSRSP	2.33	.88	-.23	.004	.36
CBTs	**.25****	.03	.07	.11	-.13
Trend	**.02****	.002	**-.01****	-.001	**-.02****
December	.15	.20**	.08	.17	.30*
Summary Statistics					
Rho	.59	.50	-.001	-.184	-.01
R^2	.59**	.45**	.64**	.28**	.51**
Adjusted R^2	.54	.37	.59	.19	.45

* Statistically significant at 0.05 level. ** Statistically significant at 0.01 level. **Note:** Full results provided on pages 202 to 206.

Model 14(a) using EBTs indicates that CBTs and trending factors have significantly increased the level of the road safety statistics – in this instance drink-driving. This result is similar to the EBT-based models in the previous replications here – see Models 12(a) and 13(a). However, none of the other models in Table 23 repeat this finding.

Factors that trend upwards over time have significantly reduced road safety statistics in two of the models – 14(c) and (e). Once again, this finding is consistent with previous replications in the current study that have utilised these outcomes – see Models 3(a), 3(b), 5(a), 5(b), 6(c), 6(d), 10(c), 10(d), 12(c), 12(e), 13(c), and 13(e). The reducing effect of the trend is consistent and prominent across all the model specifications and estimation procedures when using serious and high alcohol hour crashes.

In Table 23 above, only one model contains a significant estimate for the Sadstock, the EBT Model 14(a). This model suggests that there is a structural change in the relationship between the advertising and driver behaviour following the introduction of the SRSP. The post-SRSP implementation advertising has had a larger impact than road safety advertising prior to that period.

The insignificance of the DSRSP variable in all the models here strongly indicates that the implementation of the SRSP on its own has not had an impact on driving behaviour. However, the raw Adstock estimate is significant for Models 14(c) and (e). It would appear from these models that the SRSP advertising has significantly reduced serious crashes and high alcohol hour serious crashes. The actual estimates are very similar to those found in the previous replications here although in many of those models the advertising variable was not statistically significant – see Models 3(a), 5(a), 13(c), 13(d), and 12(c). In contrast to the previous replications, the all theme adstock estimates are only now significant with the presence of the DSRSP and Sadstock variables. Moreover, neither the DSRSP nor Sadstock variables are statistically significant in Models 14(c) or (e). Therefore, the sensitivity of the adstock estimates to the inclusion of the questionable DSRSP and Sadstock variables weakens the findings.

3.5.6 Summary of the Replications of Tay (1999)

Tay (1999) claimed that the SRSP advertising had significantly reduced the level of drink-driving in New Zealand across the period October 1993 to October 1996. However, using a longer time series, October 1993 to December 1998, that encompasses the first three years of the SRSP, and a series of road safety statistics, the results of the reanalysis presented in Tables 21 to 23 do not provide a consistent estimate of the advertising's effectiveness.

The summary of the findings from the replication of Tay's (1999) models have been split over two tables. Table 24 contains the estimated effects and their direction for Tay's basic model – Model 12 series - and the autoregression model – Model 13 series - whereas Table 25 contains the estimated effects for Tay's structural change model – Model 14 series.

Table 24. Summary of Estimated Effects from Replications of Tay's (1999) Basic Model and Autoregression Model

	Road Safety Outcome									
	EBTs		**Drink-drive Convictions**		**Serious Crashes**		**Fatalities**		**HAH Serious Crashes**	
	12(a)	13(a)	12(b)	13(b)	12(c)	13(c)	12(d)	13(d)	12(e)	13(e)
Variables										
Advertising	-	-	+	+	-	-	-	-	**-**	-
CBTs	**+**	**+**	-	+	+	+	+	+	-	+
Trend	**+**	**+**	+	+	**-**	**-**	-	-	**-**	**-**
December	-	+	**+**	**+**	+	+	+	+	**+**	**+**

Shaded cells indicate a statistically significant effect at the 0.05 level. (12) Basic model. (13) Autoregression model

Table 24 shows that while the majority of the estimates for the advertising indicate a reduction in the road safety statistics, only one model – 12(e) – produced a significant effect. In a repetition of the findings from the other replications, factors trending upwards have significantly increased EBTs and significantly reduced serious and high alcohol hour crashes. The month of December is related to an increase in the road safety statistics in all but one of the models in Table 24, but the effect is only significant for the conviction and high alcohol hour crash based models.

Table 25. Summary of Estimated Effects from Replications of Tay's (1999) Structural Change Model

	Road Safety Outcome				
	EBTs	**Drink-drive Convictions**	**Serious Crashes**	**Fatalities**	**HAH Serious Crashes**
	14(a)	14(b)	14(c)	14(d)	14(e)
Variables					
Adstock	+	+	**-**	-	**-**
Sadstock	**-**	-	+	-	-
DSRSP	+	+	-	+	+
CBTs	**+**	+	+	+	-
Trend	**+**	+	**-**	-	**-**
December	+	**+**	+	+	**+**

Shaded cells indicate a statistically significant effect at the 0.05 level.

In Table 25 the estimated effects for the trend and the month of December have remained unchanged from the previous replications of Tay (1999) despite the changes in the model's specification. Tay's (1999) original model estimated a significant interaction between the advertising and the SRSP (Sadstock) thereby indicating the SRSP advertising had a larger impact than the pre-SRSP advertising. This result has only been repeated in the EBT model – Model 14(a) – here. Once again, there is no consistency in the findings across the proposed modelling approaches or the road safety statistics in terms of the effectiveness of the advertising.

The final replication in this thesis is of Tay's (2001) model of the SRSP campaign that was developed as an improvement to the approached used by Cameron and Vulcan (1998) and White et al (2000a).

3.6 Replication of Tay's (2001) Evaluation of the SRSP Road Safety Advertising

3.6.1 Introduction

Following on from Cameron and Vulcan's (1998) evaluation of the SRSP and the subsequent modification of their approach by White et al (2000a), Tay put forward yet another version of the model. Tay claimed his model showed that the SRSP advertising had led to a greater decline in serious crash numbers than was evident prior to the implementation of the campaign. In order to come to this conclusion Tay created some new interaction terms, CBT-trend, and Advert-trend.

CBT-trend was a combination of a dummy variable for the introduction of CBTs - from April 1993 – and the trend variable. A significant and negative value for CBT-trend would indicate an increase in the existing decline in crash numbers following the introduction of the CBT campaign. Similarly, he created the Advert-trend variable by combining a dummy variable to represent the SRSP advertising – from October 1995 – and the trend. A significant and negative value for the Advert-trend variable would indicate an increase in the existing decline in crash numbers following the introduction of the SRSP advertising. While the CBT-trend variable in Tay's model was non-significant, the Advert-trend was both significant and negative. Tay argued that this showed that the SRSP advertising had been successful over and above the existing downward influences on crash numbers.

3.6.2 Specification of Replication Models

Tay (2001) used serious crashes as the dependent variable in his modification of Cameron and Vulcan (1998) and White et al (2000a). Consistent with the other replications here, five road safety statistics will be used in the replications in the following order:

(a) Positive evidential breath tests (EBTs) - as per Tay's (1999) evaluation
(b) Drink-drive convictions
(c) Serious crashes
(d) Fatalities
(e) High alcohol hour serious crashes

Serious crashes – model 15(c) will represent the closest replication.

The following independent variables are used in each model:

- New car registrations
- Trend
- Compulsory breath tests (CBTs)
- CBT-Trend
- Advert
- Advert-trend
- July, August, and September dummy variables

Note that CBTs is represented here in the replication as monthly CBTs. As was the problem in the previous replication of Cameron & Vulcan (1998) and White et al (2000a), it was not viable to use a dummy variable for CBTs as the program was implemented prior to the beginning of the analysis data set. The change to the CBT variable will also affect the calculation of the CBT-trend variable.

Moreover, monthly data is used here, as opposed to the quarterly data used in the original study, to maintain consistency with the other replications. As a result, the third quarter seasonal dummy variable used by Tay is replaced with three monthly dummy variables to represent the same period.

3.6.3 Discussion of Replication Models

Table 26 on the next page contains the results from the replication and extension of Tay's (2001) model of the SRSP campaign. Model 15(e) using high alcohol hour serious crashes includes a significant negative estimate for Advert-trend to support Tay's original claim. Two other models contain a negative value for this variable – Models 15(b) using convictions and 15(c) using serious crashes – but neither is significant. Moreover, the other significant estimates from the series are positive – CBTs (Model 15a using EBTs, and Model 15b using convictions) and Advert (Model 15b using convictions, Model 15c using serious crashes, and Model 15e using high alcohol hour serious crashes). The significant estimates for Advert suggests that the campaign has resulted in an increase in convictions, serious crashes and high alcohol hour serious crashes. Likewise, the level of CBTs is related to increases in EBTs and drink drive convictions. The latter may be explained by the coinciding of increases and decreases in the number of breath tests with expected increases and decreases in crash numbers and drink-drive behaviour. Once again, the issue of the possibility of two-way relationships in the data will be discussed in Chapters 4 and 5.

Unlike the other models in this series, the trend is only estimated to have a significant effect on drink-drive convictions. However, this finding is possibly the result of the use of two trend interactions in the same model that will account for most of the trend's explanation in the dependent variables. Likewise, as pointed out by Macpherson (2003), the Advert-trend and Advert variables are potentially sensitive to the inclusion or omission of the CBT and CBT-trend variables, and Tay's choice of new car registrations as the economic indicator rather than the number of unemployed.

Table 26. Tay's (2001) Model using Different Outcomes

	Regression coefficients and statistics				
	Model 15(a)	**Model 15(b)**	**Model 15(c)**	**Model 15(d)**	**Model 15(e)**
Dependent Variable					
EBTs	x				
D-drive convictions		x			
Serious crashes			x		
Fatalities				x	
HAH serious crashes					x
Independent Variables[1]					
New Cars	.03	-.04	.02	.27	.15
Trend	.02	.05*	-.01	-.02	.09
CBT	**.39****	**.30****	-.001	.14	.28
CBT-Trend	-.001	-.004	.001	.002	.01
Advert	-.20	**.32***	**.23***	-.16	**.54****
Advert-Trend	.01	-.01	-.01	.003	**-.02****
Summary Statistics					
Rho	.59	.37	.02	-.14	-.13
R^2	.55**	.45**	.67**	.27**	.57**
Adjusted R^2	.46	.34	.61	.18	.49

1. Models also include three seasonal variables (July, August, and September) to represent the 3rd Quarter.
* Statistically significant at 0.05 level. ** Statistically significant at 0.01 level. **Note:** Full results provided on pages 207 to 211.

3.6.4 Summary of Replication of Tay (2001)

Once again, despite varying the road safety statistic used as the dependent variable little consistency can be found within this series of replications. Looking across all the advertising estimates (Advert and Advert-trend) there is little consistency in either the direction or significance of the effects. Likewise, when splitting the advertising estimates between EBT-based models and crash-based models, there is still no consistency in the measures of advertising effects.

3.7 Summary of the Replications

If a measure is to be considered robust we would expect to see some consistency in the estimates produced using that approach. In order to detect whether this is the case, it is necessary to compare the various models. To this end, Table 27 contains a summary of the advertising estimates taken from the replications that have been undertaken here. The results from the replications will be discussed first in terms of the road safety outcomes and then, more importantly, in terms of the advertising models that have been replicated.

Table 27. Summary of Advertising Effects across the Replications and Outcomes

	Road Safety Outcome				
	EBTs	**Drink-drive Convictions**	**Fatalities**	**Serious Crashes**	**HAH Serious Crashes**
Replications					
Macpherson & Lewis					
• All-theme Adstock	-	+	-	-	-
• Drink-Drive Adstock	-	+	-	+	-
Cameron & Vulcan					
Model (a)[1]					
• SRSP 95/96	-	+	-	+	+
• SRSP 96/97	+	-	-	-	-
• SRSP 97/98	+	+	-	+	-
Cameron & Vulcan					
Model (b)[2]					
• SRSP 95/96	-	+	-	+	+
• SRSP 96/97	+	+	-	-	+
• SRSP 97/98	+	+	-	+	-
White et al					
Model (a)[1]					
• SRSP 95/96	-	+	-	+	-
• SRSP 96/97	+	-	-	+	-
• SRSP 97/98	+	-	-	-	+
White et al					
Model (b)[2]					
• SRSP 95/96	-	+	-	+	-
• SRSP 96/97	+	+	-	-	-
• SRSP 97/98	+	+	-	-	+
Tay (1999)					
• All-theme Adstock[3]	-	+	-	-	-
• All-theme Adstock[4]	-	+	-	-	-
• All-theme Adstock[5]	+	+	-	-	-
• Sadstock	-	-	-	+	-
• DSRSP	+	+	+	-	+
Tay (2001)					
• Advert	-	+	-	+	+
• Advert-trend	+	-	+	-	-

1. Model with new cars as the economic indicator. **2.** Model with unemployment as the economic indicator. **3.** Advertising from Tay's basic model. **4.** Advertising from Tay's autoregression model. **5.** Advertising from Tay's structural change model. Shaded cells indicate a statistically significant effect at the 0.05 level.

3.7.1 Positive Evidential Breath Tests (EBTs) and Drink-Drive Convictions

Drink-drive convictions are the result of positive breath tests and the vast majority of these will be in the form of EBTs, so it is not surprising that these two EBT-based statistics have produced similar estimates of the SRSP advertising effectiveness. Of all the significant effects produced across the replications, EBTs and convictions account for 56%. However, only 24% of these significant EBT-based effects indicate a reduction in drink-drive behaviour resulting from the advertising. Therefore, models using EBT-based measures of success largely indicate that the road safety advertising is related to a significant *increase* in drink-drive behaviour. The SRSP advertising has *not* been effective in changing driver behaviour using this measure.

3.7.2 Fatalities

Models based on fatalities produced quite contrasting findings to the EBT-based models. It is not surprising, given the nature of road fatalities, that there are no significant estimates for any of the models. The occurrence of a road fatality will contain a large random component, so this broad outcome is unlikely to be useful for estimating the effectiveness of road safety initiatives. Despite this limitation, road fatalities are commonly used in claims made by policy makers regarding the effectiveness of road safety advertising and enforcement. In terms of the direction of the coefficients, all but two of the estimates from fatality models were negative - albeit non-significant. Using this outcome as the measure of success, it would appear that the SRSP advertising has been unsuccessful at reducing their incidence.

3.7.3 Serious Crashes and High Alcohol Hour Crashes

Serious crashes and its subcategory, high alcohol hour serious crashes, have featured prominently in previous evaluations of the Victorian advertising campaign and have found favour with policy makers as they are regularly translated into cost and benefit functions. When these statistics are used to assess the SRSP campaign, the results are inconclusive. Estimates of *increases* in crashes account for 50% of all the significant effects produced using these two crash-based statistics. If significance is disregarded, the proportion of positive effects to all estimated effects for these two outcomes reduces to 39%. In addition, serious and high alcohol hour crash-based models have resulted in fewer significant estimates than the EBT-based models.

No consistency was found across all the road safety outcomes used in the replications. However, some uniformity was found when the outcomes were divided into EBT-based and crash-based measures. EBT-based models indicate that the SRSP advertising was likely to result in an increase in drink-drive behaviour, whereas crash-based models were, as a whole, inconclusive. The next step in this summary is to review the robustness of the advertising models.

3.7.4 Replicated Advertising Models

The consistency of the results for each of the advertising models is the principle focus of the research objective. If a measure of road safety advertising is to be considered as robust, we would expect that the estimates would generalise across similar road safety statistics.

3.7.4.1 Macpherson and Lewis

Of the ten advertising estimates produced in the Macpherson and Lewis replications, only two were significant and, furthermore, they were positive. However, of all the advertising estimates produced using the Macpherson and Lewis models, seven (70%) were negative indicating a reduction in the statistics, albeit a non-significant reduction.

3.7.4.2 Cameron and Vulcan and White et al

The replications of Cameron and Vulcan's two advertising models produced more significant estimates than any of the other models here (63% of all significant effects). Most of the significant effects for Cameron and Vulcan's models were positive (74%) indicating an upturn in the road safety statistics following the implementation of the advertising.

However, as we have seen with the review of White et al (2000a) and the corresponding replications, the Cameron and Vulcan models may be over-estimating the effect of the SRSP advertising campaign. The replications undertaken here of White et al suggest that the Cameron and Vulcan models are very sensitive to the inclusion or omission of a trend variable. When a trend is included in the Cameron and Vulcan model 50% of the SRSP estimates are now significant and of these, 27% indicate a significant *decrease* in the road safety outcome and therefore an effective campaign.

The results are inconsistent in terms of direction or significance across either the Cameron and Vulcan or the White et al models that have been replicated here. Neither advertising model provides a robust measure of advertising effectiveness.

3.7.4.3 Tay (1999)

The only significant advertising estimates using this series of models were negative in direction, indicating that the SRSP advertising had been successful at reducing the incidence of drink-drive behaviour. However, these estimates only make up 12% of all the estimated advertising effects for this series. The results are even less compelling when considered in terms of the road safety outcome used for the replications of Tay (1999) with only one significant advertising estimate for the EBT, Serious crash and HAH serious crash models.

3.7.4.4 Tay (2001)

Across the five road safety outcomes, three of the advertising estimates (Advert) produced in the replication of Tay (2001) were significant and positive. These estimates indicate the campaign has been ineffective in reducing drink-drive behaviour. While the two models using fatalities and EBTs as the outcome were insignificant, this measure of advertising effectiveness is possibly the most consistent of those carried out in this series. Disregarding the use of fatalities, that failed to produce any significant advertising estimates regardless of the measure used, 75% of the Advert estimates were significant and positive. However, only one estimate for the structural change variable was significant and, unlike the other estimates for the advertising as a whole, negative in direction.

3.7.5 Conclusions

One thing is clear from the replications of the SRSP advertising models; there is no clear pattern or consistency in findings whatever way you look at the results. While each model has been put forward by its developers as an accurate snapshot of the effectiveness of the SRSP advertising, there is no way to decide which is the most accurate or reliable on the basis of the results produced from this series of replications and extensions. The models have been carefully reproduced using a single set of data and then extended across a wide variety of road safety outcomes, and there is little to no consistency in the findings. This view doesn't change even if we divide the road safety statistics into EBT-based and crash-based outcomes. As a result, despite the series of replications and extensions there has been little progress in finding a robust measure of the road safety advertising's effectiveness.

However, in hindsight all of the models advanced thus far by the researchers and replicated here share one common limitation that may restrict their ability to capture the effect of the

SRSP campaign. All the models are single equation models. A single equation model is suitable for estimating relationships where there is a clear direction of causality from the independent variables to the dependent variable. However, some of the results here give us good reason to believe that a number of two way relationships may exist within the elements we have accounted for in the models. This possibility appears to have escaped the attention of the majority of the road safety advertising researchers to date but it was alluded to by Macpherson and Lewis (1996) and subsequently by Lewis (2001).

Across the replications undertaken here using a wide variety of approaches and road safety statistics, a substantial number of estimated SRSP advertising and enforcement (CBT) effects have been found to be positive in direction. However, these positive estimates suggest that increases in advertising and enforcement have led to increases in road safety statistics such as serious crashes and EBTs. On the face of it, this finding appears incongruous. However, there is a simple explanation. Policy makers, faced with limited resources, will co-ordinate higher levels of advertising and enforcement with expected increases in road accidents and related driving behaviours. In effect, the co-ordination of road safety initiatives with anticipated increases in road accidents represents a two-way relationship. This causes a problem for single equation methods, such as those utilised so far by the researchers attempting to estimate the effect of the SRSP campaign. Single equation models are unable to take into account two-way relationships. Instead two-way relationships require the use of a multiple or simultaneous equation modelling procedure.

The next chapter introduces two stage least squares, a procedure that under certain conditions will produced unbiased estimates of a multiple equation system. In Chapter 5, two stage least squares (2SLS) will be used to estimate a series of models in a further attempt to identify a robust measure of road safety advertising effectiveness.

CHAPTER 4. TWO STAGE LEAST SQUARES (2SLS)

4.1 Introduction

This chapter introduces two stage least squares as a multiple equation alternative to the single equation methods that have been utilised so far in the modelling of road safety advertising.

The rationale for using 2SLS will be provided along with an outline of why this approach is more suitable than single equation methods for estimating two-way relationships. The 2SLS estimation process will then be described.

4.2 Rationale

In the previous chapter we saw that many of the estimates for the SRSP advertising and enforcement contained positive coefficients. These findings suggest that increases in road safety advertising and enforcement were associated with increases in road safety statistics, such as the number of serious crashes and drink drive convictions. However, this seemingly nonsensical result can be easily explained. Policymakers will endeavour to use their limited resources in the most efficient manner possible. To this end, it is reasonable to assume that periods of higher levels of enforcement and advertising will be timed to coincide with periods where it is anticipated that the levels of risky driving behaviours will also be higher.

The seasonal pattern of road safety statistics was noted previously (see section 3.2.2 on page 48). Figure 11 and Figure 12 confirm the coordination of increases in advertising and enforcement with expected increases in road accidents following the implementation of the SRSP. Figure 11 matches monthly advertising (all-theme TARPs) with monthly road fatalities.

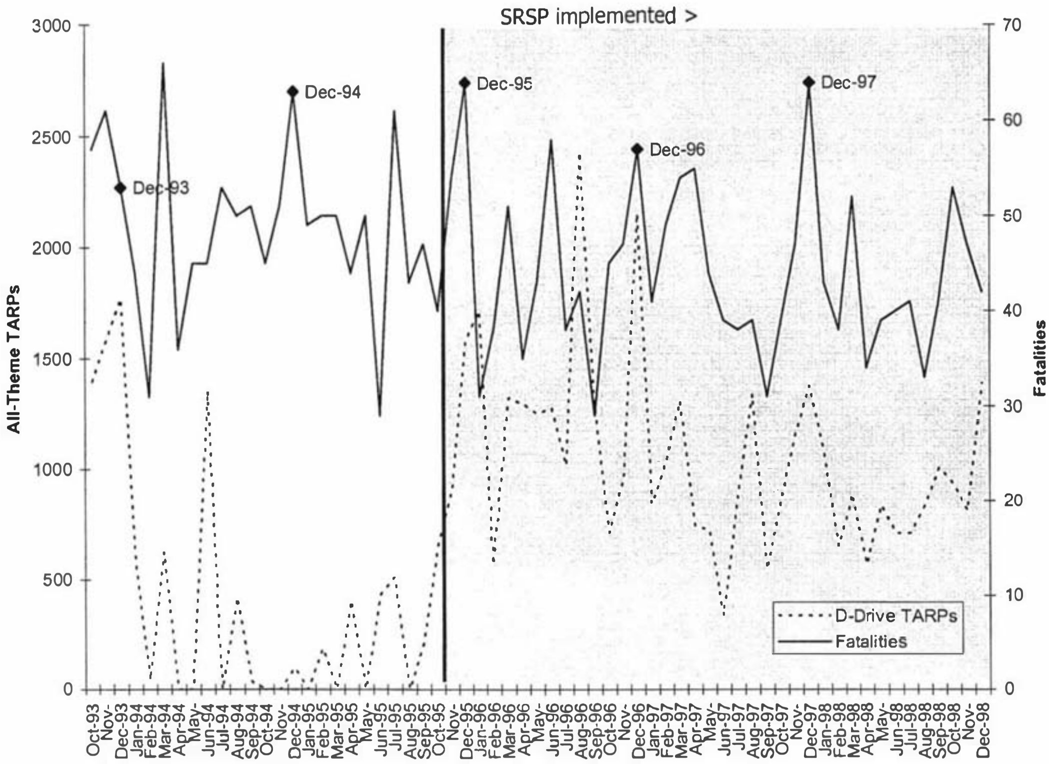


Figure 11. Comparison of Drink-Drive TARPs and Fatalities

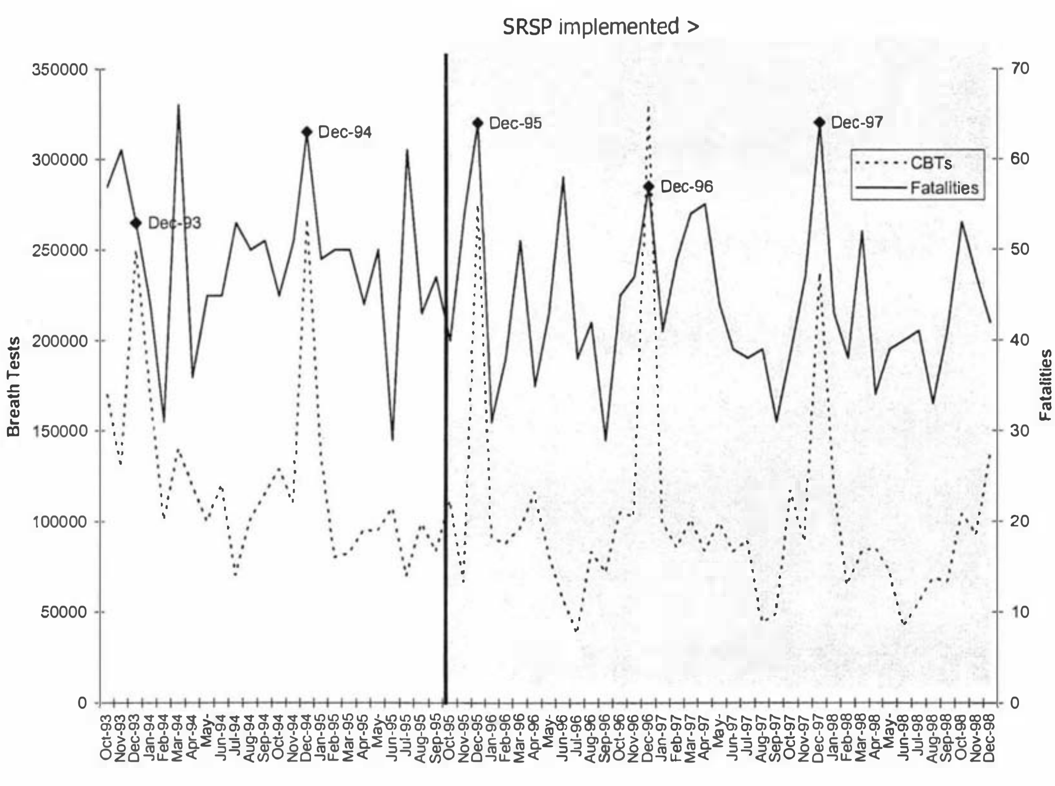


Figure 12. Comparison of CBTs and Fatalities

Figure 12 matches the monthly levels of enforcement (CBTs) with the monthly levels of road fatalities. The coordination of enforcement to periods of higher risk (greater numbers of fatalities) is clear from the plot.

Therefore, the relationship between the enforcement (and advertising) and fatalities is, effectively, two-way. Not only is enforcement related to fatalities but fatalities are, in turn, related to enforcement. This situation of simultaneity presents a problem for the modelling of the relationship, especially with the single equation models that have been advanced thus far. The presence of two-way relationships, or simultaneity, renders the use of single equation estimation inappropriate (Johnston, 1963; Ramanathan, 1998). As will be demonstrated in the next section, the use of single equation methods to estimate a multiple equation system will lead to biased and imprecise estimates.

4.3 Single Equation Bias and 2SLS

The full statistical model of the basic approach used by previous researchers that has been replicated and discussed so far can be represented by the equation below:

$$Y_1 = f_1(x_1, x_2, x_3, x_4, x_{5-16}, e_1)$$

Equation 6

Under the classical assumptions, OLS estimators are best (minimum variance) linear unbiased estimators (BLUE). One of the major underpinning assumptions required to achieve unbiased estimates is that the explanatory variables (the *x*'s) are independent from the disturbance term (e_1). If this assumption does not hold, OLS estimators are known to be biased.

However, some of the explanatory variables in this basic model are likely to be endogenous variables, that is, the levels of CBTs and Adstock are themselves likely to be determined within the decision making system used by the law enforcement agencies. For example, the number of tests carried out (CBTs) over a particular time period is probably determined by how the agencies think drivers will behave at different times of the year. The same applies to Adstock. The equation determining Y_1 should probably be written:

$$Y_1 = f_1(Y_2, Y_3, x_3, x_{4-15}, e_1)$$

Equation 7

Where Y_2 and Y_3 (previously x_1 and x_2 in Equation 6), are CBTs and Adstock

Similar expressions can be written for these two (now endogenous) variables.
Where Y_2 and Y_3 (previously x_1 and x_2), are CBTs and Adstock

$$Y_2 = f_2(Y_1, Y_3, x_3, x_6, x_7, e_2)$$

Equation 8

$$Y_3 = f_3(Y_2, Y_1, x_{4-15}, x_7, x_8, e_3)$$

Equation 9

There are now three equations, called structural equations, in the system. The parameters of these equations are known as structural parameters. Since, in this system, Y_1 is dependent on e_1 (Equation 6), and Y_2 is dependent on Y_1 (Equation 7), e_1 must be dependent on Y_2, and the basic assumption is broken for estimating Equation 6.

For instance, writing Equations 7 and 8 in their linear form (without the constants for convenience of expression), and calling them Equations 10 and 11:

$$Y_1 = (a_{12}Y_2 + a_{13}Y_3 + b_{13}x_3 + b_{14-15}x_{4-15} + e_1)$$

Equation 10

$$Y_2 = (a_{21}Y_1 + a_{23}Y_3 + b_{23}x_3 + b_{26}x_6 + b_{27}x_7 + e_2)$$

Equation 11

It can easily be seen by substituting equation 11 for Y_2 in equation 10 that Y_2 is a function of the error term e_1.

The same applies to equations 7 and 8. It is therefore not appropriate to estimate the parameters of any of the structural equations with a single equation least squares model.

The solution is to form a new set of equations, called reduced form equations, which express all the endogenous variables in terms of exogenous variables only, and estimate the parameters of these reduced form equations. This can always be done because there are three equations (6, 7 and 8) and three unknowns (Y_1, Y_2 and Y_3).

It is the structural parameters that are of most interest; in particular the effect of advertising and it is thus important to be able to derive the structural estimates from the reduced form estimates, and this is where a problem may arise, known as the "identification" problem.

If it is not possible to derive the structural estimates of the parameters in an equation from the estimates of the reduced form estimates, the equation is said to be "under identified". If it is possible to derive unique values of the structural estimates of parameters, the equation is said to be "exactly identified". If more than one estimate of any of the parameters of a structural equation can be derived, the equation is said to be "over identified". The conditions for identification are well known and were set out by Johnston (1963) as the "rank condition" of identifiability.

> *"For any relation in a system to be identified, the rank of the matrix of coefficients of variables excluded from that relation must equal the total number of relations minus one".*

For the purposes of this argument, the "rank" is the number of excluded variables. If the number of excluded variables is less than the "*the total number of relations minus one*", then the equation (*relation* in Johnston's terminology) is over identified.

The system described is over identified and two stage least squares (2SLS) is a recognised technique for deriving estimates of the parameters of an over identified equation. In essence, in stage 1 of 2SLS each of the endogenous variables is regressed on all the exogenous variables, and the "predicted" values of the endogenous variables from each of these regressions are computed. The second stage then estimates the structural equations as they stand, but with the raw data of the endogenous variables replaced by these "predictions".

Modern routines, such as those used by SPSS, are much more efficient than the procedure described above at estimating the 2SLS estimates, but the effect is the same.

4.4. Application of 2SLS

While 2SLS has been predominantly used by researchers in the field of economics, it has also been utilised in a large variety of research situations – for example: alcohol, drugs and violent crime (Markowitz, 2000), technology diffusion (Xu, 2000), contraceptive use (Bollen, Guilkey, & Mroz, 1995), product development (Shih & Venkatesh, 2004), crime trends (Triggs, 1997), University funding (Payne, 1999), privatisation of firms (Li & Rozelle, 2001), income distribution (Silverstone & Gibson, 2003), union membership (Koeller, 2001), labour market forces (Astor & Houseman, 2005), political campaign strategies (Reeves, Chan, & Nagano, 2004), auto insurance (Grace, Klien, & Philips, 2001), direct-to-consumer advertising (Ling, Berndt, & Kyle, 2002), and measuring the relationship between vehicle speed and income levels (Fosgeraus, 2005).

A comprehensive literature search indicates 2SLS has never been applied to the evaluation of road safety initiatives, or even more specifically, to the evaluation of road safety advertising.

4.5 2SLS Variable Definitions

2SLS modelling requires the analysis variables to be divided into four discrete classifications:

- Endogenous dependent variables
- Endogenous explanatory variables
- Exogenous explanatory variables
- Exogenous instrumental variables.

A variable is endogenous in a 2SLS model if it is at least partly a function of other parameters in the model. This is as opposed to an exogenous variable that is not determined by other parameters and variables in the model but is set external to the system being modelled and any changes to these variables comes from external forces. Of the set of endogenous variables, one is chosen to be the dependent variable – for this thesis the variable will be a road safety outcome. The remaining endogenous variables are specified as explanatory variables and are therefore the dependent variables in the first stage of the 2SLS estimation process.

An exogenous variable is not determined by other parameters and variables in the model but is set external to the system being modelled and any changes to these variables come from external forces. The type of variables that would be classified as external to the road safety system would be seasonal factors and trend factors and variables used as economic indicators.

Instrumental variables are exogenous variables used in the first stage of the 2SLS procedure to create the 'instruments'. Effectively, the first stage of the 2SLS procedure involves a series of regression equations where the instruments are regressed against the endogenous explanatory variables. In the second stage of the 2SLS procedure the dependent variable is regressed not on the original endogenous explanatory variable but on the predictions arising from the first stage. The predicted versions of the endogenous explanatory variables represent the exogenous variation in the original explanatory variables.

4.4 Conclusion

The use of single equation estimation methods such as OLS will lead to biased estimates if the analysis situation or system contains simultaneous equations between the variables of interest. Two stage least squares is an appropriate method for estimating a mutliple equation system and will lead to better estimates of the effectiveness of the road safety advertising. The results of the replications provide enough reason to suggest the existence of at least two relationships that are simulataneous (two-way) – the relationship between enforcement and road safety statistics, and the relationship between the advertising and the road safety statistics. Furthermore, we can also logically deduce from the situation that policymakers will target increases in both enforcement and advertising to periods where they expect risky driving behaviours will be greater.

Therefore, the next chapter will explore the use of 2SLS estimation in the evaluation the effect of the SRSP advertising campaign on a series of road safety outcomes using a single set of data. Once again, the objective of this chapter will be to identify a robust measure of the effectiveness of the road safety advertising.

CHAPTER 5. 2SLS MODELS FOR ROAD SAFETY ADVERTISING

5.1 Introduction

This chapter will explore the use of 2SLS in the estimation of the effects of the SRSP advertising campaign. The 2SLS models will use the same data set as was used for all the replications reported in Chapter 3 and once again the time series will span from October 1993 through to December 1998 encompassing the first three years of the SRSP campaign.

However, before the findings of the 2SLS models are discussed, the data rationale and characteristics will be examined. The data section will be followed by the procedure used for the estimation of the 2SLS models of the road safety advertising.

5.2 Data for 2SLS Models - Rationale and Characteristics

The variables to be used in the 2SLS models will be divided into the following categories:

- Endogenous dependent variables
- Endogenous explanatory variables
- Exogenous explanatory variables
- Exogenous instrumental variables.

The following notation will be used to identify the variables:

- Endogenous dependent and explanatory variables denoted as Y_{nk}
- Exogenous explanatory variables denoted as x_{nk}
- Exogenous instrumental variables as z_{nk}.

Unlike the models analysed in Chapter 3, the 2SLS models are not based on a previous study and therefore their specification is required to be justified. As a consequence, the following variable sections will serve two purposes: one, to introduce and describe the variables, and two, to provide the rationale for the variables inclusion in the 2SLS advertising evaluation models.

5.2.1 Endogenous Dependent Variables

Chapter 3 explored, among other issues, the use of a series of road safety outcomes. This chapter extends this approach slightly in the context of 2SLS modelling. The road safety statistics are the central focus of each specific evaluation model of the road safety advertising. Therefore, the road safety outcomes are hypothesised in the current study to be a function of other variables in the model – hence they are endogenous. The choice of road safety outcomes for Chapter 5 is determined partly by previous research into the effectiveness of road safety advertising and partly by usage by policy makers. EBTs (Y_{1a}), drink-drive convictions (Y_{1b}), serious crashes (Y_{1c}), fatalities (Y_{1d}), and high alcohol hour crashes (Y_{1e}) have each been discussed in detail in Chapter 3 (see page 48). These statistics will again be used in the 2SLS section of the analysis on the same basis that they were used in Chapter 3. In addition to these variables, the 2SLS analysis will include the following road safety outcomes:

- Alcohol-related Serious Crashes (Y_{1f})
- Alcohol-related Fatalities (Y_{1g})

These variables will each in turn be described and their characteristics examined.

5.2.1.1 Alcohol-Related Serious Crashes (Y_{1f})

Traffic crash reports (TCR's) are generated for any traffic accident attended by a Police Officer. The definition of whether a crash is alcohol-related is typically formed as part of an Officer's self-assessment at the time or following subsequent blood tests. Tay (2003) expressed a number of concerns about the validity and reliability of alcohol-related crashes as a measure of drink-drive behaviour. As the severity of the crash increases, the percentage of drivers that are blood tested decreases. Therefore, the majority of the classifications of accidents as alcohol-related rely on the attending Police officer's judgment. Even using the blood alcohol limit (BAC) to attribute cause is also of dubious value because the presence of an illegal blood alcohol level does not necessarily mean that this was the actual cause of the accident. Despite these potential limitations the use of alcohol-related serious crashes may offer a slightly different perspective of the effectiveness of the SRSP advertising that has not been captured by the other alcohol-related outcomes that have been used so far in Chapter 3. For example, high-alcohol hour serious crashes include a large number of non-alcohol related accidents and therefore may underestimate the effect of drink-drive advertisements on drink-drive behaviour.

Data for alcohol-related serious crashes was available from January 1990 through to December 1998 (see Figure 13). As with serious crash numbers, it is clear from the graph that alcohol-related crashes have also been in decline since well before the implementation of the SRSP television advertising campaign.

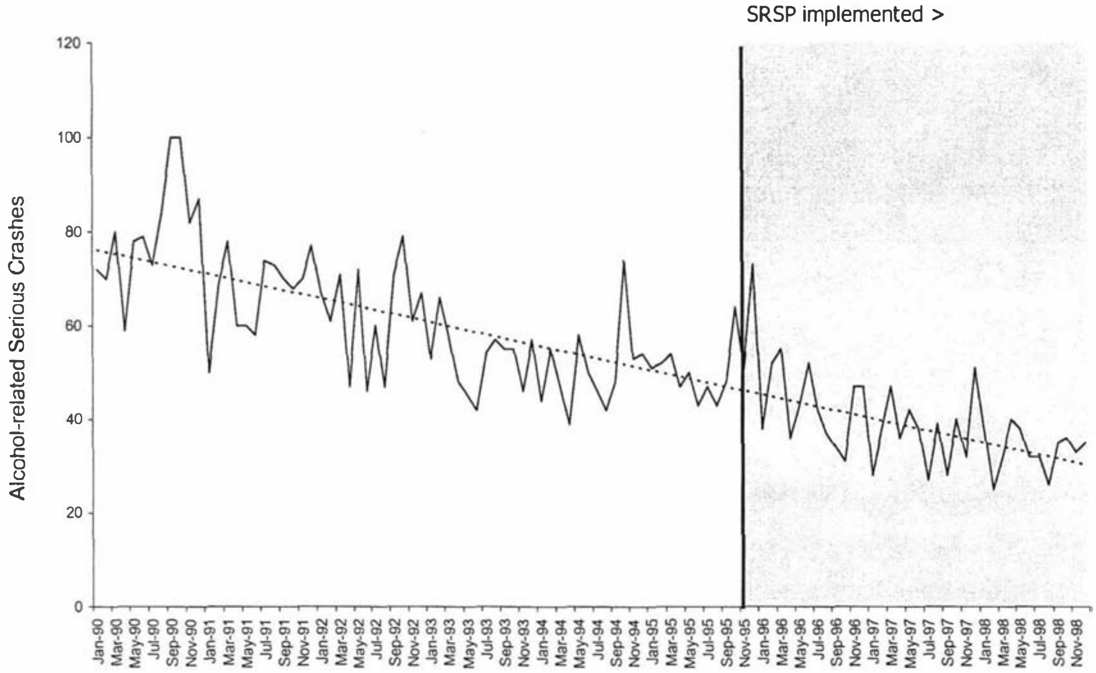


Figure 13. Alcohol-Related Serious Crashes – January 1990 to December 1998

For the analysis period, alcohol-related crashes, peaked in December 1995 and have reduced to lower levels ever since (see Figure 14). A number of peaks are evident in the data with months of higher levels of alcohol-related crashes generally followed directly after by months with lower levels – hence the jagged profile. However, there is a suggestion of lower levels of variation and a slight downward trend from December 1995 onwards that is possibly a continuation of the trend highlighted in Figure 13.

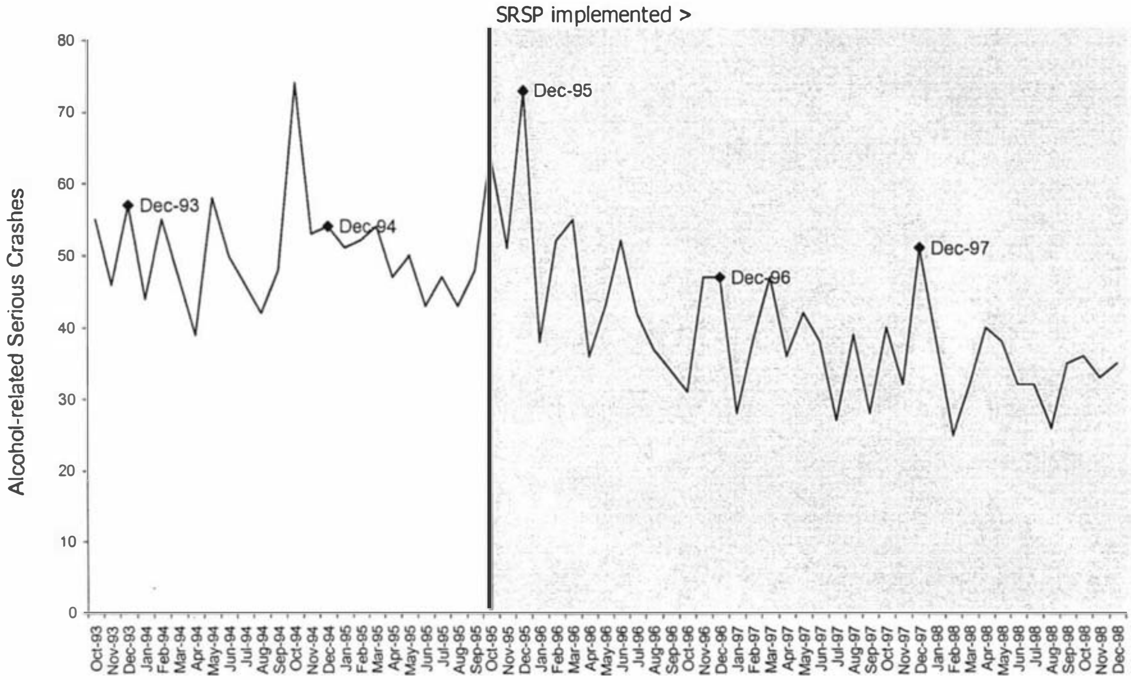


Figure 14. Alcohol-Related Serious Crashes –October 1993 to December 1998

5.2.1.2 Alcohol-Related Fatalities (Y_{1g})

Road accident fatalities can be broken down further into a series of categories based on the likely cause of the accident. Alcohol-related fatalities are road accident fatalities that are either classified by the attending Police officer's self-assessment at the time of the accident or following subsequent blood tests. The limitations raised by Tay (2003) about alcohol-related serious crashes equally apply to fatalities. More specifically for road fatalities, Tay (2003) has suggested that as the severity of the accident increases the reliance on subjective assessment of the cause of the accident also increases. As a result, the classification of fatalities as alcohol-related is largely based on the subjective assessment of the attending police officer. Despite, these potential limitations, narrowing the focus to another alcohol-related measure may help isolate the effects of the SRSP advertising that may not be discernable using broader outcomes.

Since January 1990 monthly alcohol-related fatalities, like other crash statistics in New Zealand, have been gradually trending downwards and this trend has largely continued following the introduction of the SRSP campaign in October 1995 (see Figure 15 on the next page).

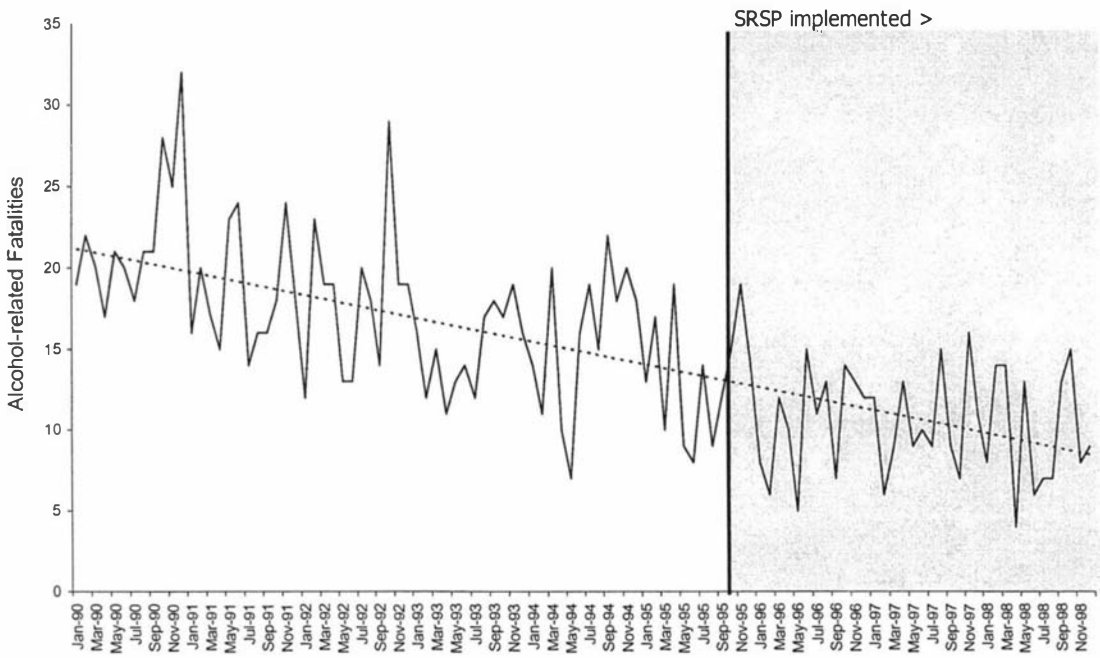


Figure 15. Alcohol-Related Fatalities – January 1990 to December 1998

In Figure 16 alcohol-related fatalities show a similar pattern to the total number of road fatalities. However, on closer inspection, the month of December does not feature as prominently as it does with overall fatalities. It would appear that alcohol-related fatalities tend to peak in the month of November. The period after October 1995 has noticeably less variation than before and the downward trend illustrated in Figure 15 appears to be leveling off slightly.

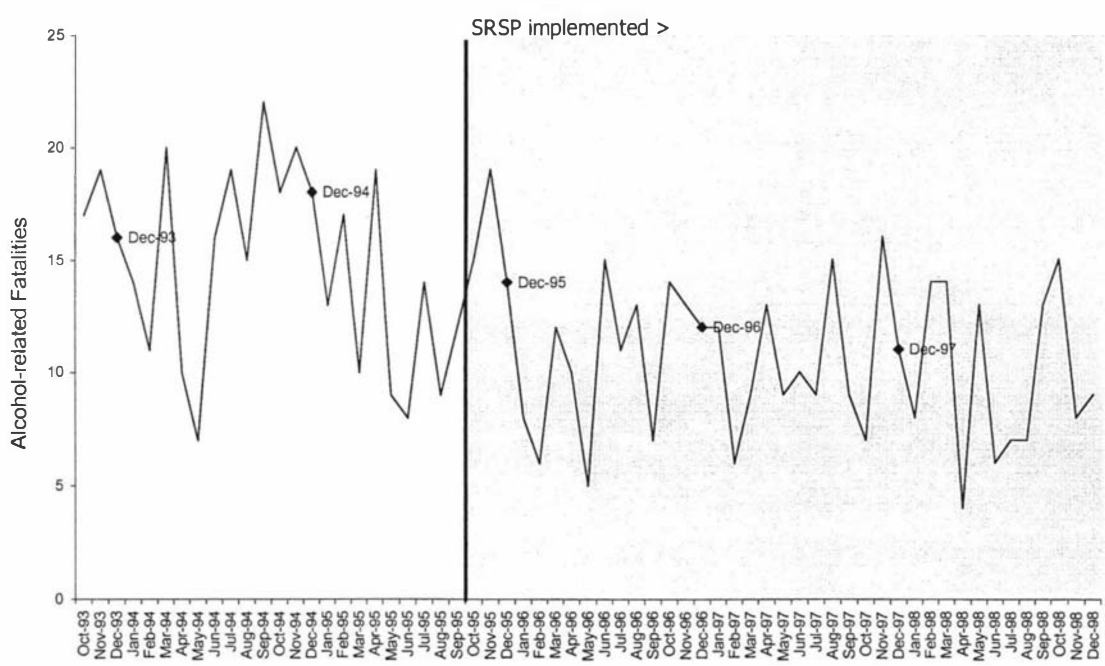


Figure 16. Monthly Alcohol-Related Fatalities – October 1993 to December 1998

5.2.1.3 List of Endogenous Dependent Variables

In summary, the Endogenous dependent variables to be used in this chapter is as follows:

- EBTs (Y_{1a})
- Drink-drive convictions (Y_{1b})
- Serious crashes (Y_{1c})
- Fatalities (Y_{1d})
- High alcohol hour serious crashes (Y_{1e})
- Alcohol-related serious crashes (Y_{1f})
- Alcohol-related fatalities (Y_{1g})

5.2.2 Endogenous Explanatory Variables

The remaining endogenous variables in the 2SLS models will be CBTs (enforcement) and a measure of advertising. The planning of Police and LTSA's limited resources assigned to the two elements of the SRSP will be set to coincide with periods when it is anticipated that levels of poor driving will be higher. For example, CBTs and SRSP advertising regularly increased during the pre-Christmas period in anticipation of an expected increase in drink-drive behaviour. Therefore, using the EBT outcome as an example, not only are EBTs partly a function of CBTs and the SRSP advertising, but both the SRSP advertising and CBTs are also partly a function of EBTs. All these variables are partly explainable by parameters within the system and are therefore, by definition, endogenous.

However, there are some issues with these variables that need to be discussed in the context of their use in 2SLS.

Firstly, the issue of the separation of the SRSP advertising and enforcement effects will be examined and then the alternative measures of road safety advertising will be discussed.

5.2.2.1 Separation of SRSP Advertising and Enforcement

Advertising and enforcement make up the two key components of the SRSP campaign. While the focus of the current study is to estimate the effects of the advertising campaign, it is necessary to separate out the effect of the advertising from the effect of the enforcement. The separation of enforcement and advertising presented difficulties in the analysis of the Victorian campaign as the two countermeasures were strongly aligned with one another.

This alignment of enforcement and advertising was one of the key characteristics of the Victorian road safety campaign. Fortunately, from a modeling perspective, previous evaluations of the New Zealand SRSP have shown that the two elements were not closely linked or necessarily as supportive in the New Zealand campaign as they were in the Victorian campaign (Macpherson & Lewis, 1998; Tay, 2004, 2005a). Therefore, advertising and enforcement are able to be represented separately in the 2SLS models, as they were in the single equation models in Chapter 3.

5.2.2.2 Adstock versus TARPs

Cameron et al (1993) and Newstead et al (1995a) claim that the most reliable relationships estimated in their models were those where the TAC advertising was represented by adstock as opposed to simple TARPs. However, Hooley and Wilson (1998) have argued that adstock is likely to overestimate the effect of the advertising because it is often serially correlated with the dependent variable and the error term. They also suggested the inclusion of a trend and seasonal factors in the advertising model could lead to better estimates. Broadbent (1979; 1988) acknowledged this potential problem with adstock and suggested that it was preferable to look at the trend and seasonal effects separately rather than attempt to estimate their effect as part of the lagged advertising term. This approach is consistent with that used in many of the reviewed evaluations (Cameron et al, 1993: Macpherson and Lewis, 1996, 1998) and the OECD (1997) principles.

While it is expected that adstock is a better representation of the levels of exposure to the advertising at any one time, it represents a complication when specifying the structural model for the 2SLS procedures. Factors that will be likely to have an effect on the levels of advertising will bear a greater relationship to the raw TARPs than the adstock version of the advertising. To take this potential problem into account, both forms of advertising are run separately against each dependent variable. Therefore, if the identification of an advertising effect is contingent on the form used to represent the advertising then it will still be captured by models containing the appropriate structure.

5.2.2.3 Advertising Represented by a Step Function

White et al (2000) has suggested that the better performance of adstock over TARPs may be simply because the adstock data more closely resembles a simple step function than the TARPs data as the contrast is very high between the levels of advertising before and after the campaign was implemented. White et al (2000) demonstrated that the level of adstock used in the Victorian campaign was easily replaced with a simple dummy variable (step function) without altering the model's conclusions. They then argued that a step function is better representation of the advertising than using adstock. The underlying assumption when using adstock is that the relationship is quantitative and that the changes in the monthly level of advertising will have a corresponding effect on the levels of the measured road safety outcome. However, if the adstock estimates are comparable with a step-function's estimates, then the monthly levels are irrelevant and all claims of certain responses to specified levels of advertising are misleading.

In a 2SLS model it is not possible to represent the SRSP advertising as a qualitative (dummy) variable. All endogenous explanatory variables must be quantitative, as they are treated as dependent variables in the separate regressions that form part of the first stage of the calculation of the estimates. Therefore, a step function is not technically appropriate to represent the SRSP advertising in the 2SLS models. For this reason, a step function will not be used to represent the road safety advertising.

5.2.2.4 Summary of Endogenous Advertising and Enforcement Variables

As with Chapter 3, the SRSP campaign will be represented by two classifications of road safety advertising content. All-theme will be used to represent the overall SRSP advertising campaign during the analysis period, namely, drink-drive, speeding, and seat belt restraint. Likewise, drink-drive will be used to represent the advertisements solely aimed at curbing drink-drive behaviour.

In summary, SRSP enforcement will feature in all the 2SLS models while the SRSP advertising and enforcement will be represented in separate models by the alternative measures.

The complete list of explanatory endogenous variables for the 2SLS models are:

- All-theme TARPs (Y_{2a})
- Drink-drive TARPs (Y_{2b})
- All-theme adstock (Y_{2c})
- Drink-drive adstock (Y_{2d})
- Compulsory breath tests (CBTs) (Y_3)

5.2.3 Exogenous Explanatory Variables

The following variables have been specified as exogenous to the road safety system being analysed and also classified as explanatory variables:

- Number unemployed (x_4)
- New car registrations (x_5)
- Trend (x_6)
- Monthly seasonal dummy variables (x_{7-17})

The rationale for the inclusion of each of the exogenous explanatory variables into the 2SLS models will now be discussed.

5.2.3.1 Unemployment (x_4)

The monthly rate of unemployment is used here as the proxy for economic conditions. Using the OECD (1997) road safety modelling principles, an economic indicator represents part of the socio-economic factor that has been shown to influence aggregate road safety data. The number of unemployed has been found to be negatively related to fatalities and serious injury accidents (Hakim et al., 1991; Newstead, Cameron et al., 1995a) and to EBTs (Macpherson & Lewis, 1998) and serious crashes in New Zealand (Cameron & Vulcan, 1998; White et al., 2000a). It is hypothesised that the number of unemployed will have a similar relationship with the dependent variables to be used in the 2SLS models. That is, an increase in the rate of unemployment will act as an indication of people's ability to purchase alcohol and their total mileage driven (Hakim et al., 1991).

Economic conditions are clearly exogenous in that they are determined external to the road safety system being modelled but they are expected to have an effect on the endogenous dependent variables used in the 2SLS models – the road safety outcomes. The pattern of Unemployment data over the analysis period has been provided in Figure 20 on page 157.

5.2.3.2 New Car Registrations (x_5)

New car registrations have occasionally been used in road accident modeling as an economic indicator (Cameron & Vulcan, 1998; White et al., 2000a). However, the OECD (1997) expert group on road safety modeling argues that the size and structure of the transportation sector has been found to influence road accident data. This would suggest that the number of new cars is an indication of exposure when modeling road accidents. But the number of cars on the road would not be expected to increase exposure to be caught drink-driving. On the other hand, the number of cars on the road could possibly increase the probability of being involved in an accident. Therefore, for the EBT-based models – Models 16(a-d) in Table 29 and Models 17(a-d) in Table 30 – new cars will not be included, whereas for the remaining models, new car registrations will be included in the 2SLS models to represent the OECD (1997) transportation-exposure factor. Note that new car registrations could be interpreted in the EBT-based models as another economic indicator but unemployment is already included in these models for that purpose.

Once again, the number of registered cars is clearly an exogenous variable in terms of the 2SLS modeling process. However, like unemployment, new car registrations is expected to have an effect on the road safety outcomes, as discussed above, so should be included in the 2SLS models. The pattern of new car registrations over the analysis period has been provided in Figure 21 on page 158.

5.2.3.3 Seasonal Factors ($x_{7\text{-}17}$)

Seasonal variation is represented by monthly dummy variables for 11 of the 12 months (February to December). For example, the March dummy variable was coded 1 for March and 0 in the other seasonal dummy variables representing the remaining 10 months. All months can not be represented in the models as they would perfectly explain one another. Monthly dummies are included in order to explain residual seasonality in the dependent variables over a year. When included, the dummies may represent residual variation in, for example, EBT data, due to the effect of winter sport socialising, the effects of holiday periods such as Christmas, or the differing number of days in each month, none of which are explicitly included in the 2SLS models fitted here.

Seasonal effects are clearly exogenous to the road safety system but are expected to affect driving behaviour and accident rates.

5.2.3.4 Trend (x_6)

The role of the general trend factor is quite different from the seasonal dummy variables. The residual variation in the data represented by the trend is due to factors which vary slowly over time in a monotonically increasing or decreasing fashion. For example, some of the gradually increasing factors that *may* be represented by the general trend component are, population increases, driver licensing increases, increasing safety of vehicles, gradual and continual improvement in the efficiency of enforcement efforts or, any other time variant, non seasonal factor. The trend component of the models represents the average effect of all these other non-seasonal factors which are not explicitly included in the 2SLS models.

To account for factors gradually increasing over time the trend variable was simply coded 1 for the first month of the series, October 1993, and 2 for the second month of the series, November 1993 and so on for each of the months ending with the coding of 63 for December 1998.

Like seasonal factors, trend factors are clearly exogenous to the road safety system, but are expected to have an impact on driver behaviour and accident rates as represented by the dependent variables in the 2SLS models.

5.2.4 Instrumental Variables (z_i)

A condition of the 2SLS procedure is that the instrumental variables must have a direct or indirect relationship to the endogenous explanatory variables. However, the instrumental variables must not have a direct casual relationship to the endogenous dependent variable. Variables that are related to the dependent variable are not candidates as instruments as they will be correlated with the error term. To avoid this situation, exogenous variables representing lagged effects of the dependent variable will not be included in that particular model. For example, lagged EBTs are not used as an instrumental variable in models that explain the variation in EBTs.

Exogenous explanatory variables, such as unemployment and the trend, are also added to both the first stage models, as instruments, and second stage models, as explanatory variables, to improve the precision of the estimation and to avoid simultaneous equations bias (Maddala, 1977). The exogenous explanatory variables have already been discussed on Page 110 so they are not repeated in this section. Please note that these variables will retain their notation as explanatory variables (x_i) even though they are also treated as instrumental variables in the 2SLS estimation process.

The instrumental variables (with the exception of the exogenous explanatory instruments) will now be discussed under the following headings:

- Lagged Advertising
- Lagged Enforcement
- Lagged Road Safety Outcomes

5.2.4.1 Lagged Advertising

It is hypothesised here that current and future advertising will be a function of new advertising objectives and past advertising. The level of advertising used in the previous year is expected to affect the levels used in the following year (the current year). It is reasonable to assume that the advertising agency or the LTSA would take into account the previous year's level of advertising when planning future advertising for the same period of time in the following year.

TARPs are used to represent advertising in the instruments as TARPs form the raw units for the purpose of media planning. Therefore, the advertising instrumental variables are:

- All-theme TARPs – 12 month lag (z_{18})
- Drink-drive TARPs - 12 month lag (z_{19})

Lagged advertising is matched to the theme used as the endogenous explanatory variable in the model (all-theme or drink-drive). In the 2SLS models with All-theme TARPs (Y_{2a}) or All-theme Adstock (Y_{2c}) specified as the endogenous explanatory variable, the corresponding variable, All-theme TARPs – 12 month lag (z_{18}) will be specified as the advertising instrumental variable.

5.2.4.2 Lagged Enforcement

The SRSP advertising campaign was run in conjunction with enforcement activity (CBTs) in line with the Victorian blueprint. As with the SRSP advertising, it is anticipated that past levels of enforcement will affect the planning of future levels of enforcement. Moreover, the level of enforcement for the previous year and the previous month would also be able to be factored into the Police's decision-making process. Therefore, previous levels of enforcement are represented in all the models by 1 month and 12 month lags of CBTs.

- CBTS – 12 month lag (z_{26})
- CBTS – 1 month lag (z_{27})

5.2.4.3 Lagged Road Safety Outcomes

Increases or decreases in the levels of advertising and enforcement will be inextricably related to road safety statistics from the previous year and, when the information is obtainable, sometimes even from the previous month. For example, information about the previous month's levels of EBTs is available to the Police and the LTSA as they will have ready access to this information. On the other hand, conviction data from the previous month is not available for the following month's planning as there is a considerable lag between date of the offence and the subsequent conviction. Information relating to road safety outcomes is available at a number of levels and it can be expected that all available information would be taken into account when planning current and future levels of SRSP advertising and enforcement.

The following points should be noted in relation to the choice of lags for the road safety outcomes.

- While information from the previous month's level of EBTs will be actionable for the following month, information about the previous year's positive EBTs will be redundant as they will be replaced in the decision making process by the subsequent drink-drive conviction data.
- One month lags are not specified for Alcohol-related crashes (z_{23}) or fatalities (z_{24}). The amount of time required to compile the data from blood tests and accident reports precludes this information being utilised for the planning of the following month's enforcement and advertising.
- Similarly, one month lags are not specified for road injuries, serious crashes or high-alcohol hour serious crashes as this data is based on hospital admission data. The time required for the reporting of hospital admission data again precludes this information being utilised for the planning of the following month's enforcement and advertising.

Therefore, the exogenous instrumental variables relating to road safety outcomes used in the 2SLS modelling process here are:

- Drink-drive convictions - 12 month lag (z_{20})
- Fatalities - 12 month lag(z_{21}) and 1 month lag (z_{22})
- Alcohol related crashes - 12 month lag (z_{23})
- Alcohol-related fatalities 12 month lag (z_{24})
- Road injuries - 12 month lag (z_{25})
- Positive evidential breath tests (EBTs) - 1 month lag (z_{26})
- Serious crashes – 12 month lag (z_{29})
- High alcohol hour serious crashes – 12 month lag (z_{30})

5.2.4.4 Fit of Instrumental Variables

Clearly, the data used here in the instrument estimation is not exhaustive but is limited to information supplied by the NZ Police and the LTSA. It is expected that other factors may influence the decision making process for both advertising and enforcement and while these will not be explicitly accounted for in the models, the variables that are included will account for a significant proportion of the information used.

To this end, OLS models were also run to estimate the fit of the instrumental variables to the two endogenous explanatory variables in each model – advertising and enforcement. In each OLS regression, the endogenous explanatory variable was regressed against all the instrumental variables for that particular model. The fit was judged using the R^2 values from the regression models. Clearly to be useful the instrument variables must be related to the endogenous variables and the R-square value is used here as a measure of that association. An R^2 greater than 0.10 for the instruments against the endogenous variable is considered an appropriate level of explanation for the purposes of 2SLS (Bollen, 1996; Stock & Watson, 2003). All the models in the current study have produced R^2 values for the instrumental variables well above 0.10 with the lowest R^2 being .52 for Model 19(c) of Fatalities. The R^2 values for the instrumental variables to the endogenous explanatory variables are provided with the tabulated model statistics for each series of models.

5.2.5 Functional Form of 2SLS Models

Typically the model structure for the study of road safety statistics is multiplicative, where a double-log transformation is used (Hakim et al., 1991). The double-log function has proved useful when establishing the particular influence of certain factors on the outcome of road trauma, such as fatalities, serious casualty crashes, and positive breath tests (Cameron et al., 1993; Hakim et al., 1991; Macpherson & Lewis, 1998; Thoresen et al., 1992). However, research conducted by Zlatoper (1987) suggested that the double-log functional form performed the poorest among a set of alternative functional forms. Further work on this issue was carried out by Tay (2000) as part of his evaluation of the New Zealand SRSP. Conversely, Tay concluded that there was little, if any difference in the resulting estimates and conclusions between the functional forms used. This view has been given further credence in the results from the replication of Tay's (1999) evaluation.

Therefore, the double-log function has been used again for all the 2SLS models. All variables, with the exception of the Trend, have been transformed using the natural logarithm (*e*).

The complete list of variables utilised in the 2SLS analysis is provided in Table 28.

Table 28. Complete List of Variables for 2SLS Models.

Endogenous variables	
Dependent	
Positive evidential breath tests (EBTs) (Y_{1a})	Drink-drive convictions (Y_{1b})
Serious Crashes (Y_{1c})	Fatalities (Y_{1d})
High Alcohol Hour Serious Crashes (Y_{1e})	Alcohol-related Serious Crashes (Y_{1f})
Alcohol-related Fatalities (Y_{1g})	
Explanatory	
All-theme TARPs (Y_{2a})	Drink-drive TARPs (Y_{2b})
All-theme Adstock (Y_{2c})	Drink-drive Adstock (Y_{2d})
Compulsory breath tests (CBTs) (Y_3)	
Exogenous variables	
Explanatory	
Unemployment (x_4)	New car registrations (x_5)
Trend (x_6)	Seasonal dummy - February(x_7)
Seasonal dummy – March (x_8)	Seasonal dummy – April (x_9)
Seasonal dummy – May (x_{10})	Seasonal dummy – June (x_{11})
Seasonal dummy – July (x_{12})	Seasonal dummy – August (x_{13})
Seasonal dummy – September (x_{14})	Seasonal dummy – October (x_{15})
Seasonal dummy – November (x_{16})	Seasonal dummy– December (x_{17})
Instrumental Only	
12 month lag All-themes TARPs (z_{18})	12 month lag Drink-drive TARPs (z_{19})
12 month lag DD convictions (z_{20})	12 month lag Fatalities (z_{21})
1 month lag Fatalities (z_{22})	12 month lag Alcohol related crashes (z_{23})
12 month lag Alcohol related fatalities (z_{24})	12 month lag Road injuries (z_{25})
12 month lag CBTs (z_{26})	1 month lag CBTs (z_{27})
1 month lag Positive evidential breath tests (EBTs) (z_{28})	12 month lag Serious Crashes (z_{29})
12 month lag High Alcohol Hour Serious Crashes (z_{30})	
Note: All variables were transformed using the natural logarithm	

5.3 Procedure for 2SLS models

From the list of variables the 2SLS models were specified in the following manner:

- One series of models was run for each of the road safety outcomes.
    - Positive evidential breath tests (EBTs) – model series 16
    - Drink-drive convictions – model series 17
    - Serious crashes – model series 18
    - Fatalities – model series 19
    - High alcohol hour serious crashes – model series 20
    - Alcohol-related serious crashes – model series 21
    - Alcohol-related fatalities – model series 22.

- Within each series, four models were specified to represent the four combinations of the Adstock or TARPs measure of road safety advertising and the general (all-theme) and specific (drink-drive) content of the advertising. As a result 28 models (4 per series) were created in total.

- Instrumental variables that represent lagged effects of the previous year's advertising have been matched to the corresponding advertising explanatory variables. For example, the previous 12 month's all-theme advertising is always matched to the all-theme explanatory variable.

The complete model specifications for each 2SLS model series is provided in Appendix 2 from page 212.

The findings for each 2SLS model series will be tabulated, described and briefly discussed. At the conclusion of the chapter the overall findings will be examined in more detail. In particular, the following question will be answered:

- Do the conclusions differ between the measures of advertising used as the endogenous explanatory variable?

Once again, the objective of this chapter is to attempt to identify a robust measure of the effectiveness of road safety advertising. A robust measure of advertising will be expected to generalise across the road safety outcomes. Specifically the focus will be on:

1. The significance of the advertising coefficients
2. The advertising coefficient's sign across the form and content used to represent the road safety advertising
3. The pattern of significance and sign of the advertising coefficients across the road safety measures

5.4 2SLS with Positive Evidential Breath Tests (EBTs) – Model 16 Series

In Table 29 below we can observe that all 2SLS models using EBTs provide moderate-to-high levels of fit of the instrumental variables to the endogenous explanatory variables – CBTs and advertising – ranging from .56 to .84. These values are well above the minimum acceptable level of .10 indicating that the instrumental variables are a useful explanation of the variation in the endogenous explanatory variables. Furthermore, the R^2 for the final stage of the 2SLS models are moderate ranging from .63 to .65 indicating a good fit of the predicted variables, from the first stage of the 2SLS process, to the endogenous dependent variable - EBTs.

Table 29. 2SLS Models using EBTs

	Regression Coefficient statistics			
	Model 16(a)	**Model 16(b)**	**Model 16(c)**	**Model 16(d)**
Explanatory Variables[1]				
All-theme TARPs (Y_{2a})	**-.001**			
All-theme Adstock (Y_{2c})		**.01**		
Drink-Drive TARPs(Y_{2b})			**-.004**	
Drink-Drive Adstock(Y_{2d})				**.02**
CBTs (Y_3)	.87**	.82*	.68	.58
Unemployment (x_4)	.41	.41	.42	.48
Trend (x_6)	.02***	.02***	.02***	.02***
Instrumental Variables				
All theme TARPs 12 mth lag (z_{18})	x	x		
Drink-drive TARPs 12 mth lag (z_{19})			x	x
Summary Statistics				
Fit for Advertising (R^2)	.68	.84	.56	.83
Fit for CBTs (R^2)	.83	.83	.82	.82
Adjusted R^2	.63	.63	.65	.65

1. Eleven monthly dummy variables to represent the seasonal factors ($x_{7\text{-}17}$) are also included in the explanatory variables. For a full model specification see Table 37 on page 212* Statistically significant at 0.10 level. ** Statistically significant at the 0.05 level. *** Statistically significant at the 0.01 level. Full results can be found on pages 219 to 222.

CBTs are significantly increasing the number of EBTs for the models that use all the SRSP advertisement themes – Models 16(a) and 16(b). Further investigation is required to understand why CBTs are only significant when accompanied by the all-theme versions of the SRSP advertising and this is beyond the scope of the research objective here. However, positive and significant CBT coefficients are consistent with EBT-based models in Chapter 3 – see Models 1(a), 1(b), 7(c), 7(d), 12(a), 13(a), 14(a), and 15(a). Of these models only one contains the drink-drive version of SRSP advertising, Model 1(b). CBTs were also estimated to be significant and positive with serious crashes in the replication of Cameron and Vulcan (1998) – Model 6(b) – and with drink-drive convictions in the replication of Tay (2001) – Model 15(b).

Another significant factor in all the 2SLS models using EBTs is the positive influence of upwardly trending factors. This finding is consistent with the results from Chapter 3 – Models 1(a), 1(b), 2(b), 7(c), 7(d), 8(c), 12(a), 13(a), 14(a), and 15(b) – as are the positive and significant CBT effects for the All-theme models – Models 1(a), 1(b), 6(b), 7(c), 7(d), 12(a), 13(a), 14(a), 15(a), 15(b).

The models using EBTs have estimated a mixture of positive and negative relationships between the four advertising measures and drink-drive behaviour. However, all the advertising estimates in the EBT 2SLS models are statistically non-significant at the 0.10 level. The models using TARPs – 16(a) and 16(c) – have indicated a non-significant negative relationship between the SRSP advertising and EBTs. Conversely, the models using the Adstock measure of advertising – 16(b) and 16(d) – have estimated a non-significant positive relationship between the SRSP advertising and EBTs.

Overall, the application of 2SLS estimation with EBTs-based models has confirmed some of the findings using EBTs from Chapter 3. That is the results suggest that the SRSP campaign has neither significantly increased nor decreased drink-drive behaviour. There is no evidence to support the claims that the SRSP advertising was effective. Indeed, the results suggest that most of the effects on driving behaviour are due to trending factors and CBTs when all the themes of the SRSP advertising are taken into account.

5.5 2SLS with Drink-Drive Convictions – Model Series 17

Overall, the adjusted R-square estimates for all the 2SLS models in this series were moderately strong. Likewise, the measures of fit for the instrumental variables were all reasonably high indicating that the instrumental variables provided a good explanation of the endogenous enforcement and advertising explanatory variables.

Table 30. 2SLS Models using Drink-Drive Convictions

	Regression Coefficient statistics			
	Model 17(a)	**Model 17(b)**	**Model 17(c)**	**Model 17(d)**
Explanatory Variables[1]				
All-theme TARPs (Y_{2a})		**.02****		
All-theme Adstock (Y_{2c})	**.02**			
Drink-Drive TARPs(Y_{2b})				**.02***
Drink-Drive Adstock(Y_{2d})			**.02**	
CBTs (Y_3)	-.05	-.05	-.02	.05
Unemployment (x_4)	.20*	.16	.19*	.12
Trend (x_6)	.001	.001	.002	.002**
Instrumental Variables				
All theme TARPs 12 mth lag (z_{18})	x	x		
Drink-drive TARPs 12 mth lag (z_{19})			x	x
Summary Statistics				
Fit for Advertising (R^2)	.79	.64	.79	.56
Fit for CBTs (R^2)	.85	.85	.85	.85
Adjusted R^2	.56	.59	.55	.58

1. Eleven monthly dummy variables to represent the seasonal factors ($x_{7\text{-}17}$) are also included in the explanatory variables. For a full model specification see Table 38 on page 213. * Statistically significant at 0.10 level. ** Statistically significant at the 0.05 level. *** Statistically significant at the 0.01 level. Full results can be found on pages 223 to 226.

A similarity between the results for the 2SLS models 17 a,b, and c and the majority of the models using convictions in Chapter 3 is the absence of a significant trend effect – the only exceptions from Chapter 3 are the drink-drive conviction Models 2(b), 8(c), 15(b), and 17(d). The absence of a significant trend effect is in contrast with the findings of the other EBT-based models in Chapter 3 and the 2SLS EBT models in the previous section. It is also in contrast with the *crash-based* models in Chapter 3 where the trend was a prominent, albeit negative, influence on the road safety statistics.

Unemployment is significantly related to increases in drink-drive convictions for the models that use adstock to represent the road safety advertising – Models 17(a) and 17(c). This combination of explanatory variables is unique for this thesis so further investigation would be required before an understanding can be gained of why this has occurred. However, disregarding significance, positive estimates for unemployment are found in all the EBT and conviction 2SLS models. The results suggest that the relationship between drink-drive behaviour and the number of unemployed is likely to be positive. As unemployment increases, the incidence of drink-driving may also increase – indicating a social element to the behaviour as opposed to a financial or economic perspective. More research is required to clarify this finding.

Using TARPs to represent the advertising and drink-drive convictions as the road safety outcome has indicated that increases in SRSP advertising are related to increases in drink-drive behaviour. This result would not be unexpected using a single equation OLS approach as increases in advertising are likely to coincide with anticipated increases in drink-drive behaviour. However, using 2SLS estimation, such a two-way relationship is typically controlled for by the use of instrumental variables such as seasonal factors. Therefore, there must be some other explanation for the positive relationship between the SRSP advertising and drink-drive behaviour when measured by EBT-based outcomes. One possible explanation could be simply that, despite the increases in advertising, drink-drive behaviour as measured by EBTs or drink-drive convictions, also increased over this period.

Neither the drink-drive nor the all-theme adstock estimates were significant in the models using convictions as the road safety outcome.

5.6 2SLS with Serious Crashes – Model Series 18

Table 31 on the next page indicates that the instrumental variables have fitted well with the one minor exception being a slightly lower level of explanation for the instrumental variables against the drink-drive TARPs explanatory variable – see Model 18(d). Overall, the models were moderately strong and statistically significant in the explanation of the variation in the level of serious crashes.

Table 31. 2SLS Models using Serious Crashes

	Regression Coefficient statistics			
	Model 18(a)	**Model 18(b)**	**Model 18(c)**	**Model 18(d)**
Explanatory Variables[1]				
All-theme TARPs (Y_{2a})		**-.01**		
All-theme Adstock (Y_{2c})	**-.02**			
Drink-Drive TARPs(Y_{2b})				**.01**
Drink-Drive Adstock(Y_{2d})			**-.01**	
CBTs (Y_3)	-.13	-.13	-.15	-.13
Unemployment (x_4)	**-.34****	**-.36****	**-.36****	**-.38****
New Car Registrations (x_5)	.02	.03	.03	.12
Trend (x_6)	**-.01*****	**-.01*****	**-.01*****	**-.01*****
Instrumental Variables				
All theme TARPs 12 mth lag (z_{18})	x	x		
Drink-drive TARPs 12 mth lag (z_{19})			x	x
Summary Statistics				
Fit for Advertising (R^2)	.85	.68	.86	.56
Fit for CBTs (R^2)	.86	.86	.85	.85
Adjusted R^2	.66	.66	.66	.69

1. Eleven monthly dummy variables to represent the seasonal factors (x_{7-17}) are also included in the explanatory variables. For a full model specification see Table 39 on page 214. * Statistically significant at 0.10 level. ** Statistically significant at the 0.05 level. *** Statistically significant at the 0.01 level. Full results can be found on pages 227 to 230.

The serious crash-based 2SLS model series sees the inclusion of new car registrations as a representative of the OECD (1997) transportation/exposure factor. It was expected that an increase in the number of vehicles, and therefore an increase in the exposure of motorists, would result in an increase in the number of serious crashes. While all the coefficients for new cars are positive none of them are significant.

Increases in the number of unemployed, are both related to reductions in crash numbers. This result is in contrast to the unemployment estimates for the 2SLS EBT and drink-drive models. However, the negative relationship between economic conditions, as represented by the unemployment variable, is typically related to a reduction in accident rates (Hakim et al., 1991; Harry, 1997). As economic conditions worsen (unemployment increases) disposable income decreases, discretionary expenditure on travel decreases and work-related travel decreases.

Factors that are trending upwards over time are also significantly contributing to reductions in serious crashes. This result is consistent with nearly all of the serious crash models from Chapter 3 – see Models 3(a), 3(b), 6(c), 6(d), 12(c), 13(c), and 14(c). There is a strong suggestion across all of these models that trending factors are influencing the reduction are serious crash numbers.

Using serious crashes as the outcome variable in 2SLS models has resulted in three non-significant estimates of the road safety advertising having a negative effect on crashes and one non-significant estimate that it has a positive effect (see Table 31). Once again, this finding is largely consistent with the results from the replications from Chapter 3. Only two serious crash-based models have produced significant negative advertising estimates – Models 6(b) and 12(c).

Overall, the application of 2SLS estimation with serious crash based models has confirmed the findings using serious crashes from Chapter 3. That is the results suggest that the SRSP campaign has neither significantly increased nor decreased the number of serious crashes. There is no evidence to support the claims that the SRSP advertising was effective. Conversely, the results suggest that most of the effects on serious crashes are due to trending factors and unemployment.

Neither the drink-drive nor the all-theme adstock advertising estimates (Models 17a and 17c) were statistically significant using drink drive convictions as the road safety outcome.

5.7 2SLS with Fatalities – Model Series 19

Using fatalities as a measure of the effectiveness of the SRSP has resulted in none of the key variables of interest being statistically significant (see Table 32 on the next page). Once again, this was a noted feature of the fatality-based models in Chapter 3. Fatality data is expected to contain a large random component making it difficult to obtain significant estimates of other factors as was demonstrated in Chapter 3.

The instrumental variables continued to fit well to the advertising and enforcement explanatory variables with only two noticeably lower results (.66 and .52) for Models 19(a) and 19(c) respectively. However, both these statistics are well above the acceptable level of 0.10 (Bollen, 1996; Stock & Watson, 2003).

In contrast, the 2SLS models overall fitted very poorly with noticeably lower adjusted R^2 values than the previous 2SLS models and all were statistically insignificant at the 0.01 level. However, these measures of fit are consistent with the lower levels obtained for the fatality-based models in Chapter 3. The use of fatalities, while valuable from a policy and publicity perspective, may be impractical from a modelling standpoint.

Table 32. 2SLS Models using Fatalities

	Regression Coefficient statistics			
	Model 19(a)	**Model 19(b)**	**Model 19(c)**	**Model 19(d)**
Explanatory Variables[1]				
All-theme TARPs (Y_{2a})	**.002**			
All-theme Adstock (Y_{2c})		**-.002**		
Drink-Drive TARPs(Y_{2b})			**-.001**	
Drink-Drive Adstock(Y_{2d})				**-.003**
CBTs (Y_3)	.15	.15	.15	.16
Unemployment (x_4)	-.06	-.05	-.06	-.05
New Car Registrations (x_5)	.02	.03	.03	.03
Trend (x_6)	-.002	-.002	-.002	-.002
Instrumental Variables				
All theme TARPs 12 mth lag (z_{18})	x	x		
Drink-drive TARPs 12 mth lag (z_{19})			x	X
Summary Statistics				
Fit for Advertising (R^2)	.66	.85	.52	.85
Fit for CBTs (R^2)	.85	.85	.85.	.85
Adjusted R^2	.25	.25	.25	.25

1. Eleven monthly dummy variables to represent the seasonal factors (x_{7-17}) are also included in the explanatory variables. For full model specification see Table 40 on page 215. * Statistically significant at 0.10 level. ** Statistically significant at the 0.05 level. *** Statistically significant at the 0.01 level. Full results can be found on pages 227 to 234.

If we were to momentarily disregard the issue of statistical significance, it is interesting to note that the direction of some of the estimates is consistent with the 2SLS serious crash models. The estimate for unemployment is negative across all the models, as is the trend coefficients. Furthermore the estimates for new cars are all positive.

Using fatalities as the road safety outcome and 2SLS estimation has resulted in non-significant estimates of the SRSP advertising regardless of the measure used to represent the campaign. The advertising coefficients are all small and non-significant and therefore provide no support for the LTSA claims that the SRSP advertising has been effective in reducing the road toll (Falconer, 1996; Gregg, 1996).

5.8 2SLS with High Alcohol Hour Serious Crashes – Model Series 20

The fit of the 2SLS models is moderate, ranging from an adjusted R^2 of .40 and .43, falling between the low levels obtained for the fatality-based models and the higher levels of the other outcomes analysed using 2SLS thus far (see Table 33).

The fit of the instrumental variables to the endogenous CBT and advertising explanatory variables were all satisfactory. However, the instrumental variables for drink-drive TARPs once again explained the lowest level of fit, though this is still above the R^2 = 0.10 level deemed as acceptable by Bollen (1996).

Table 33. 2SLS Models using High Alcohol Hour Serious Crashes

	Regression Coefficient statistics			
	Model 20(a)	**Model 20(b)**	**Model 20(c)**	**Model 20(d)**
Explanatory Variables[1]				
All-theme TARPs (Y_{2a})	**-.02**			
All-theme Adstock (Y_{2c})		**-.09****		
Drink-Drive TARPs(Y_{2b})			**.003**	
Drink-Drive Adstock(Y_{2d})				**-.09****
CBTs (Y_3)	-.27	-.18	-.32	-.25
Unemployment (x_4)	-.38	-.24	-.39	-.29
New Car Registrations (x_5)	.16	.26	.07	.30
Trend (x_6)	**-.01*****	**-.01*****	**-.01*****	**-.01*****
Instrumental Variables				
All theme TARPs 12 mth lag (z_{18})	x	x		
Drink-drive TARPs 12 mth lag (z_{19})			x	x
Summary Statistics				
Fit for Advertising (R^2)	.68	.85	.56	.86
Fit for CBTs (R^2)	.85	.85	.85	.85
Adjusted R^2	.40	.42	.40	.43

1. Eleven monthly dummy variables to represent the seasonal factors ($x_{7\text{-}17}$) are also included in the explanatory variables. For a full model specification see Table 41 on page 216. * Statistically significant at 0.10 level. ** Statistically significant at the 0.05 level. *** Statistically significant at the 0.01 level. Full results can be found on pages 235 to 238.

The trend variable is significant for all the 2SLS models using high alcohol serious crashes. Factors that trend upwards over time are estimated to be a significant contributor to a reduction in a road safety outcome. This finding is consistent with the majority of trend estimates from the other high alcohol hour models in Chapter 3 – Models 5(a), 5(b), 10(c), 10(d), 12(e), 13(e), and 14(e). In fact, only one of the high alcohol hour crash-based models did not estimate a significant and negative effect for the trend. It would from the results for high alcohol hour crash models that there is strong evidence that factors that are trending upwards over time are contributing to reductions in crash numbers. This finding is consistent with the claims made by Beenstock and Gafni (2000) in their analysis of road accident data from industralised countries.

Like the fatality-based models, CBTs, unemployment, and new cars are non-significant, however the estimated direction of the relationships are consistent with the other crash-based models.

High alcohol hour serious crashes were used in Chapter 3 where only two of the models – Models 12(e) and 14(e) from the replication of Tay (1999) indicated that the SRSP campaign was related to reduction in this outcome. Similar results are found here using the road safety statistic in the 2SLS models using high alcohol hour serious crashes (see Table 33). Three of the advertising coefficients are negative, with two of these being significant – one for each of the adstock measures. These two models suggest that the SRSP advertising has led to a significant reduction in high alcohol hour serious crashes. Conversely, these estimates could represent confirmation of the potential for adstock to overestimate the effectiveness of the advertising as argued by White et al (2000). There is no way of knowing whether the adstock estimates are actually overestimates as we do not know what the true effect is. An examination of the differences between the advertising estimates for the adstock and TARPs variables across the road safety outcomes may shed some light on this possibility. This comparison will be made at the conclusion of the chapter.

The use of high alcohol hour serious crashes as the road safety outcome and the 2SLS modelling has led to mixed advertising estimates. Only two of the estimates have indicated a significant reduction in crash numbers. While these results are supportive of the LTSA claims, they alone do not constitute strong evidence that the advertising has indeed been effective. However, this series of models has once again suggested the underlying trend has played a prominent role in the reduction of high alcohol serious crashes and that this is consistent with previous research of accident data from other industralised countries.

5.9 2SLS with Alcohol-Related Serious Crashes – Model Series 21

The overall measures of fit for the 2SLS models using alcohol-related serious crashes are all moderately strong ranging from an adjusted R^2 of .74 to .78. The exogenous variation in the endogenous explanatory variables and the exogenous explanatory variables explain a large proportion of the variation in alcohol-related serious crashes (see Table 34).

Table 34. 2SLS Models using Alcohol-Related Serious Crashes

	Regression Coefficient statistics			
	Model 21(a)	**Model 21(b)**	**Model 21(c)**	**Model 21(d)**
Explanatory Variables				
All-theme TARPs (Y_{2a})		**-.02**		
All-theme Adstock (Y_{2c})	**-.06*****			
Drink-Drive TARPs(Y_{2b})				**-.002**
Drink-Drive Adstock(Y_{2d})			**-.06*****	
CBTs (Y_3)	-.04	-.08	-.05	-.10
Unemployment (x_4)	**-.33***	**-.42****	**-.37****	**-.43****
New Car Registrations (x_5)	.06	.12	.05	.14
Trend (x_6)	**-.01*****	**-.01*****	**-.01*****	**-.01*****
Instrumental Variables				
All theme TARPs 12 mth lag (z_{18})	x	x		
Drink-drive TARPs 12 mth lag (z_{19})			x	x
Summary Statistics				
Fit for Advertising (R^2)	.85	.68	.85	.56
Fit for CBTs (R^2)	.85	.85	.85	.85
Adjusted R^2	.78	.74	.78	.74

1. Eleven monthly dummy variables to represent the seasonal factors (x_{7-17}) are also included in the explanatory variables. For full model specification see Table 42 on page 217. * Statistically significant at 0.10 level. ** Statistically significant at the 0.05 level. *** Statistically significant at the 0.01 level. Full results can be found on pages 235 to 242.

The fit of the instrumental variables to the endogenous CBT and advertising explanatory variable were also all reasonably high. However, a pattern is starting to emerge with the fit of the instrumental variables to one particular endogenous explanatory variable - drink-drive TARPs (Y_{2b}) – see Model 19(d). So far in the 2SLS models, this variable has consistently achieved the poorest explanation by the instrumental variables. However, the level of fit (.56 in this series) is still well above the 0.10 considered as acceptable by Bollen (1996), therefore, the instrumental variables can be considered as good.

An increase in the number of people unemployed is estimated to significantly reduce the number of alcohol-related crashes. Therefore, as economic conditions worsen (unemployment increases) it is likely that the number of miles driven and discretionary spending are reduced. This finding is consistent with the estimates from the 2SLS models using serious crashes – Models 18(a) to (d).

Once again, the trend has been found to be a significant contributor to the reduction in crash numbers – this time using 2SLS and alcohol-related crashes. The contribution of factors that are gradually increasing over time is proving to be a consistent feature of the road safety models here.

The use of alcohol-related crashes as the road safety outcome in the 2SLS models indicates that the SRSP advertising has resulted in reductions in alcohol-related crashes with two significant estimates. However, once again, these significant estimates are only found in the models using the adstock advertising explanatory variables. While, the significant advertising effects provide some further support for the LTSA claims, the results need to be treated with caution at this stage.

5.10 2SLS with Alcohol-Related Fatalities – Model Series 22

The use of alcohol-related fatalities for the first time in the current study has resulted in relatively low overall levels of fit ranging from an adjusted R^2 of .19 to .21 (see Table 35 on the next page). However, the numbers of monthly alcohol-related fatalities are relatively low compared to the other outcomes used in the current study with the monthly numbers ranging from as little as 4 up to 22. Therefore, it is expected to be difficult to isolate significant effects using this outcome.

Moderate measures of fit for the instrumental variables and the explanatory variables for advertising and enforcement were achieved with drink-drive TARPs again performing the poorest of the four advertising measures. Overall, the R^2 values for all the instrumental variables still indicate that they are good predictors of the endogenous explanatory variables.

Using alcohol-related fatalities as the road safety outcome suggests that factors that are trending upwards over time are significantly reducing the number of road deaths. This finding is in contrast to the non-significant trend estimates for overall fatalities but consistent with other models here using serious crashes, high alcohol related serious crashes, and alcohol-related serious crashes.

Table 35. 2SLS Models using Alcohol-Related Fatalities

	Regression Coefficient statistics			
	Model 22(a)	**Model 22(b)**	**Model 22(c)**	**Model 22(d)**
Explanatory Variables				
All-theme TARPs (Y_{2a})	**-.002**			
All-theme Adstock (Y_{2c})		**.01**		
Drink-Drive TARPs(Y_{2b})			**.05**	
Drink-Drive Adstock(Y_{2d})				**.04**
CBTs (Y_3)	-.57	-.58	-.56	-.73
Unemployment (x_4)	-.08	-.09	-.12	-.09
New Car Registrations (x_5)	.46	.48	.84	.54
Trend (x_6)	-.01***	-.01***	-.01***	-.01***
Instrumental Variables				
All theme TARPs 12 mth lag (z_{18})	x	x		
Drink-drive TARPs 12 mth lag (z_{19})			x	x
Summary Statistics				
Fit for Advertising (R^2)	.68	.84	.57	.86
Fit for CBTs (R^2)	.86	.86	.85	.85
Adjusted R^2	.21	.21	.21	.19

1. Eleven monthly dummy variables to represent the seasonal factors ($x_{7\text{-}17}$) are also included in the explanatory variables. For a full model specification see Table 43 on page 218. * Statistically significant at 0.10 level. ** Statistically significant at the 0.05 level. *** Statistically significant at the 0.01 level. Full results can be found on pages 243 to 246.

In contrast to the trend estimates, all of the advertising estimates from the 2SLS models using alcohol-related fatalities are non-significant. These models suggest that the advertising is not having an effect on drink-drive behaviour as measured by this road safety outcome. The use of alcohol related fatalities does not provide any support for the LTSA claims that the road safety advertising has been effective. Moreover, these models once again suggest that the underlying trending factors are a prominent factor in the reduction of fatalities.

5.11 Summary of 2SLS models

The use of 2SLS estimation in the evaluation of road safety advertising is seen as a logical and technical improvement on the previous attempts to model the effects of the SRSP campaign. Using a single equation, key explanatory variables such as advertising and enforcement are unable to be accurately estimated. These actions are themselves the result of anticipated levels in the road safety statistics such as fatalities and EBTs. Using single equation models to estimate what is a multiple or simultaneous equation system will lead to bias estimates as was demonstrated in Chapter 4.

If a measure of advertising was to be considered robust we would expect the estimates derived from the measure to generalise across outcomes and subtle changes to the model specifications. Clearly, this has not eventuated despite using the technically more appropriate 2SLS estimation procedure. Only 3 of the 7 road safety outcomes used resulted in statistically significant advertising estimates and no one measure of advertising used across these models has resulted in consistent estimates in terms of direction, significance or the conclusions that would be drawn from them. Neither TARPs, adstock, all-theme nor drink-drive measures has been consistently significant across the road safety outcomes. For example, drink-drive conviction models produced indicated significant *increases* in all-theme *TARPs* and drink-drive *TARPs* advertising estimates. Whereas, the models using alcohol related crashes as the road safety outcome produced significant *reductions* in all-theme *adstock* and drink-drive *adstock* advertising estimates. The only consistency across the significant effects is the matching of the measure found to be significant for each specific road safety outcome. For example, for drink-drive convictions, the advertising estimates for the all-theme *TARPs* and the drink-drive *TARPs* were both found to be significant.

Table 36. Comparison of Advertising Estimates across the Road Safety Statistics

	Road Safety Outcomes						
	EBTs	**Drink-drive Convictions**	**Serious Crashes**	**Fatalities**	**HAH Serious Crashes**	**Alcohol-Related Crashes**	**Alcohol-Related Fatalities**
Advertising Variables							
All-theme TARPs	-	+	-	+	-	-	-
All-theme Adstock	+	+	-	-	-	-	+
Drink-Drive TARPs	-	+	+	-	+	-	+
Drink-Drive Adstock	+	+	-	-	-	-	+

Shaded cells indicate a statistically significant advertising effect at the 0.10 level.

Despite the use of the more appropriate multiple equation 2SLS estimation, various models using a range of outcomes and a range of forms of advertising and instruments, the results are still inconclusive. Moreover, in terms of the research objective of this thesis – that is, to identify a robust measure of road safety advertising effectiveness – none of the estimated effects for any of the advertising measures generalises across the road safety statistics.

CHAPTER 6. CONCLUSIONS

6.1 Introduction

The objective of this research was to attempt to determine whether a robust measure of the effectiveness of a road safety advertising campaign can be identified using the econometric analysis of non-experimental data. In the last three decades, road safety advertising has grown in prominence as a tool in the fight to reduce the impact of road accidents on society. Two countries that have been at the forefront in the use of marketing in road safety are Australia and New Zealand. The accident data from both countries has been the subject of a series of statistical modelling evaluations, and some of these studies have formed the basis of claims made by government officials regarding the overall effectiveness of the road safety advertising campaign. However, the results have been sometimes conflicting, and there has been much debate over the form and variables used in the models. A major problem in resolving these conflicts, however, is that the different studies do not all use the same data set or road safety outcome, so comparisons are difficult.

In the first stage of the analysis, the models that have been used to evaluate the New Zealand road safety advertising were replicated here using a single time series that encompassed the first three years of the campaign. The following evaluations of the New Zealand campaign were replicated:

- Macpherson & Lewis, 1998
- Cameron & Vulcan, 1998
- White, Walker, Glonek & Burn's, 2000A
- Tay, 1999
- Tay, 2001

These models were then extended across a series of road safety outcomes: Positive evidential breath tests (EBTs), Drink-Drive Convictions, Serious Crashes, Fatalities, and High-Alcohol Hour Serious Crashes, and, depending on the replicated model, different types of advertising variables. The models examined exhaust all the single equation approaches to the evaluation of the non-experimental road safety data. The estimated advertising effects from all the replications and extensions were then compared in an attempt to draw a conclusion as to which approach, if any, provided a consistent explanation of the effectiveness of the road safety advertising campaign.

In the second stage of the analysis, an alternative statistical modelling approach was undertaken to deal with a problem potentially shared by all of the original evaluations. All of the original approaches assume that the road safety system can be explained by a single equation model. In fact, there are a number of reasons to believe that the road safety system may include a series of two-way relationships that are best represented by a multiple equation model. For example, the presence of two-way relationships, or endogeneity, between the explanatory variables would render the use of single equation estimation inappropriate and result in biased estimates. A failure of the single-equation models to produce a consistent estimate of an advertising effect is indicative of a possible problem with endogeneity, and provides a basis for exploring the use of a multiple equation approach to the evaluation of road safety advertising.

Two stage least squares (2SLS) is a common method for estimating a system that contains two-way relationships and will produce the identical results to more complicated multiple equation methods when the system being analysed is identified. A series of models were developed using 2SLS that tested the generalisability of the estimated effects across seven road safety outcomes – EBTs, Drink-Drive Convictions, Serious Crashes, Fatalities, Alcohol-Related Fatalities, Serious Crashes, Alcohol-Related Serious Crashes, and High-Alcohol Hour Serious Crashes – and four types of advertising variables; All-Themes TARPs, All-Themes Adstock, Drink-Drive TARPs, and Drink-Drive Adstock. The 2SLS models examined the multiple equation approach to the evaluation of the non-experimental road safety data using a series of road safety outcomes. The advertising estimates were once again compared in an effort to identify a robust measure of the road safety advertising campaign's effectiveness.

6.2 Conclusions

In spite of the application of many expert's models and suggestions and the use of sophisticated statistical methods of evaluation, a robust measure of the effectiveness of road safety advertising has not been identified.

The replication and extension of previous models of evaluation using an up-to-date single set of road accident data and a range of road safety outcomes has produced a continuation of the conflicting and inconclusive results obtained in the original studies. None of the replicated measures produced a consistent estimate of the effect of the road safety advertising across the five outcomes. No consistency was found in terms of the direction and statistical significance of the estimated advertising effects for any of the replicated models. Among the significant advertising effects found in the single-equation models, 69% were positive thereby implying that the campaign was ineffective; however no regular pattern in the estimated direction of the relationship between the advertising and the road safety outcomes was identified for any of the replications so no conclusion about the campaign's effectiveness was able to be made.

Endogeneity in some of the key explanatory variables was the most likely reason for the inability of the single-equation models to produce a consistent advertising estimate of the road safety campaign's effectiveness. To address this issue, the data was re-examined using 2SLS. In line with the replications of previous single-equation models, the 2SLS procedure was undertaken using a series of road safety outcomes to test its ability to produce consistent advertising estimates. Despite speculation that some of the key explanatory variables have two-way relationships with the outcomes, the 2SLS procedure also failed to produce a robust measure of the effectiveness of the advertising.

Faced with this predicament, the typical response would be to simply choose the best model from the set of models and approaches undertaken. However, there is no objective way of knowing which model best reflects the true situation. Furthermore, the use of non-experimental data means there is no valid method to determine what the true position is, as there is no benchmark or test statistic that can be utilised to provide a measure of best fit against the actual effect. Moreover, no further refinements can be made to the evaluation models or estimation forms or functions that will enable us to make a conclusion about the true effectiveness of the road safety advertising.

Therefore, it is concluded that it is impossible to draw any robust and consistent conclusions of the effectiveness of road safety advertising using non-experimental data with econometric methods. One possible solution is to adopt an experimental approach constructed around a strictly controlled and measured outcome that is closely linked to the stated objectives of the road safety advertising campaign. The use of a well planned experiment based around a suitable outcome variable will enable researchers to discern the true effect of road safety advertising on human driving behaviour and ensure the appropriate use of limited road safety resources to maximise the safety of all drivers.

6.3 Research Limitations

The estimation procedures used in this research are based on approaches either previously utilised or proposed by road safety experts to evaluate the New Zealand advertising campaign. Suggestions and criticisms that were made by these previous researchers were incorporated into the research and then the evaluation models were tested further over a series of road safety outcomes and advertising variables. However, while all previous and proposed single and multiple equation approaches have been utilised in this research, thereby exhausting the current possibilities available to an analyst, it is not assumed that there are no further possible refinements. It is conceivable that another analyst could come up with a different approach to the estimation of the road safety advertising campaign although it is difficult to see what else might be done with non-experimental data.

One possibility is that a longer time series could have been used. This thesis was based on New Zealand road safety data from October 1993 though to December 1998. The analysis period encompassed the two years preceding and the three years following the implementation of the SRSP campaign with the analysis at the monthly level providing a total of 63 observations. A longer time series may improve the chance of identifying statistically significant advertising effects, however a larger number of observations is very unlikely to result in a change to the conclusions of the effect of the campaign on road safety outcomes drawn from those estimates. That is, further data may well improve the statistical sensitivity or power of the analysis, but it will not alter the nature of the estimated relationships.

Another limitation in this research, and all the previous evaluations, is that the data is restricted to the information that is recorded by the various Government agencies. The data will not include all the possible effects of advertising or changes to driver behaviour but is expected to capture and represent the majority of these effects. Likewise, the road safety data used here is not collected for the sole purpose of evaluating the advertising campaign's effectiveness. The collection of all the road safety outcomes used in the analysis of the advertising campaign predates the introduction of the SRSP campaign. Furthermore, there are known and acknowledged flaws in some of the statistics and, where possible, these have been accounted for in the models. However, as the data is non-experimental there is no way to correct all the known flaws in the data. An analyst of non-experimental data is at the mercy of the available data and any of its inherent qualities or weaknesses. Furthermore, the problems with the data have been recognised by all the previous researchers and this knowledge has not prohibited its use in the respective evaluations nor has it been used to qualify any of the resulting conclusions regarding the effectiveness of the advertising campaign.

6.4 Future Research

The use of non-experimental data will always be subject to the inescapable and intractable conclusion that there is no objective means to choose between competing measures of advertising effectiveness if there is no consistency in the results of the alternative models. One way to overcome this problem is to avoid the situation altogether by developing a true experiment to judge the effectiveness of the road safety advertising campaign. Through the use of a controlled field experiment, advertising exposure can be manipulated, extraneous factors controlled, and the effect of road safety advertising on driver behaviour measured. A test region can be compared to a control region and the data analysed using well grounded methods of analysis matched to the experimental design to uncover if a causal link exists between road safety advertising and driver behaviour.

The author accepts that there are considerable practical and technical issues that would need to be addressed before experimentation would be acceptable to policy makers and to the public. Identifying suitable test and control regions and controlling media programming for these, are two key issues that would need to be dealt with in the design of a road safety advertising experiment. Furthermore, the advertising campaign objectives would have to be carefully aligned with the choice of road safety outcome and whether the experiment is based on an existing road safety outcome or a new outcome is chosen, significant resources will need to be allocated to the development of processes that minimise, as much as is practically possible, any source of potential measurement error. Only through the application of experimentation will analysts, policy makers, and governments be able to discern the true effectiveness of road safety advertising and avoid the intractable difficulties posed by the econometric analysis of non-experimental data.

6.5 Contribution

The thesis has demonstrated that econometric models of non-experimental road safety data are over sensitive to subtle changes in form and estimation and are therefore unreliable for judging the effectiveness of the New Zealand road safety advertising campaign. This thesis has exhausted all available single and multiple equation approaches for the evaluation of non-experimental road safety data. The results here have demonstrated that a conclusion regarding the effectiveness of the road safety advertising campaign can not be drawn using an econometric model of non-experimental data. Road safety advertising researchers and policy makers can have no confidence in the estimates obtained from non-experimental data or in the ability of the available road safety statistics to measure the effectiveness of an advertising campaign.

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GLOSSARY OF TERMS

Adstock	A Koyck decay function of the accumulation of Target Audience Rating Points (TARPs) in the current week along with the decayed effects (applying a specific retention factor) of TARPs placed in the previous week or weeks. Therefore, Adstock is cumulative decayed ratings and represents the amount of advertising current at the time.
Alcohol-related fatalities	A road accident fatality that has been classified by the attending Police Officer as being the result of driving with excess alcohol. This can be a subjective assessment or the result of subsequent blood alcohol testing.
Alcohol-related serious crashes	A serious crash classified as being the result of driving with excess alcohol. Alcohol-related serious crashes are generally classified by the Police Officer attending the accident or the result of blood tests. The suspected cause of the accident is reported by the Police Officer in their subsequent traffic crash report (TCR).
All-theme advertisements	All advertising themes used for advertisements. All road safety advertising themes includes speeding, drink-drive and seat belt restraint advertisements. This distinction for road safety advertisements was used by Cameron et al (1993) in the evaluation of the Victorian TAC advertising campaign. See also drink-drive advertisements.
Autocorrelation	The problem of consecutive error terms in time series data being correlated. The consequences are similar to heteroscedasticity. One way to detect autocorrelation is through the use of the Durbin-Watson statistic (Lattin et al., 2003).
BAC	Blood alcohol test.
CBTs	Compulsory Breath Tests. CBTs were introduced in New Zealand in April 1993. Breath tests are largely random. The number of CBTs is recorded by the controlling Police Officer at each respective check point.
Countermeasures	A catch all term used in road safety literature to describe road safety initiatives designed to reduce road trauma.
Double-log	The transformation of both sides of the equation (dependent and independent variables) by the natural logarithm (e).

Drink-drive advertisements — Road safety advertisements focused on the reduction of drink-drive behaviour. This classification of road safety advertisements was used by (Cameron et al., 1993) - see also all-theme advertisements.

Drink-drive convictions — A conviction arising from being found to be driving with excess alcohol. The conviction is the result of a positive evidential breath test followed by a positive blood alcohol test. Drink-drive convictions are collated here from offences coded A101 through to A331. Conviction data is recorded for the date of the offence – not the date of the conviction which can occur up to six months after the offence.

EBTs — Positive evidential breath tests. EBTs are largely the result of CBTs but can also be generated from MBTs (Mobile Breath Tests).

Fatalities — A fatality is defined here as if as a result of a road accident a person is killed.

First-order autoregression — A simple linear regression model with the lagged dependent variable as one of the predictor variables.

High alcohol hour serious crashes — Serious crashes that occur during high alcohol hours. In New Zealand, high alcohol hours are defined as between 10pm and 4am, Monday to Thursday, and between 10pm and 6am Friday to Sunday.

M & L models — Macpherson and Lewis models as developed in Macpherson and Lewis (1996, 1998) to evaluate the effectiveness of the SRSP advertising.

Moderator effects — Effect in which a third independent variable (the moderator variable) causes the relationship between a dependent and independent variable pair to change, depending on the value of the moderator variable. Also known as an interaction effect (Hair et al., 1998).

Road safety outcomes — A term used here to describe the series of road safety statistics used as dependent variables in the evaluation models in Chapters 3 and 5.

Seasonal effects — Seasonal effects that may be present in the data due to factors such as holiday periods or increases in drink driving related to participation in winter sports. Seasonal effects are typically represented in road safety modelling by dummy variables for each month of the year. The dummy variables capture the seasonality in the data that is not explicitly represented by variables already in the model.

Serious casualty crashes — A serious casualty crash is typically defined as if as a result of the accident a person requires hospitalisation.

SRSP — Supplementary Road Safety Package. The SRSP was implemented in October 1995 and was based on the Victorian blue-print and involved the coordination of targeted enforcement and high profile road safety advertising.

Step function — The use of dummy variables to represent an event or change in the data or system.

TAC — Transport Accident Commission. The TAC funded the implementation of the Victorian road safety advertising and enforcement campaign that has since been adopted by countries such as New Zealand.

TARPs — Target audience rating points (TARPs) is a measure of audience reach. It is a summation of the rating points (the percentage of persons in the viewing area estimated to be watching the specific television channel at the time the advertisement is shown) for the particular target audience of the advertisement.

TCR — Traffic crash report. Completed by the attending Police Officer following a traffic accident.

Trend variable — A variable coded from 1 for the first observation through to *k* for the final observation. The trend variable is used to represent factors that are gradually increasing over time but which are not explicitly included in the model.

APPENDICES

APPENDIX 1. DATA CHARACTERISTICS OF QUANTITATIVE VARIABLES

Adstock

The level of advertising is commonly measured by the industry in terms of target audience rating points (TARPs). TARPs are an index of the intensity of advertising according to the following rule: 100 TARPs means that everyone in the target audience had the opportunity to see the advertisement once (Fry, 1996). However, television advertising placed in a certain week does not necessarily produce its full effects in that week (Broadbent, 1979). Studies of advertising effects based on awareness levels among the viewing public of the main messages of the advertising, have shown that there are indeed delayed effects (Delaney et al., 2004). The main objective in analysing awareness is to provide information on the response and decay of advertising effects.

The theory of decay has been formally defined by Broadbent (1979; 1984; 1988; 1990) who developed the concept of Adstock to describe the way that the audience's current levels of retained awareness are related to current and past levels of advertising. Formally, Adstock in the current week is the accumulation of Target Audience Rating Points (TARPs) in the current week with the decayed effects (applying a specific retention factor) of TARPs placed in the previous week. Therefore, Adstock is the cumulative decayed ratings and represents the amount of advertising current at the time. The calculation of Adstock needs three inputs: the TARPs schedule (weekly level), a parameter for the rate of fading of the effect (F), from which the half life (HL) can be calculated; and a starting value, the Adstock for the period before the data start, which is better understood by the term 'previous average rate of TARPs' or PT.

Calculation of Adstock

The calculation of Adstock (Broadbent 1990) is as follows: starting with the weekly TARPs schedule in a single column T, with rows 1 to n. Let $T(i)$ stand for the value in period i or row i. Let $A(i)$ hold the Adstocks, so $A(0) = PT$. PT is defined as the average TARPs for the previous 12 months. Two further columns are included to hold temporary calculated values, say P and Q. The constant is $C = (1-F) / (1+F)$. For a half-life of 5 weeks, F is set at 0.871 (see the discussion below about most common half-life for advertising).

Define $P(0) = C * PT$ and $Q(0) = 2 * F * PT / (1 + F)$.

Then subsequent values are found from:

$$P(i) = C * T(i),$$
$$Q(i) = 2 * (F * P(i - 1)) + F * Q(i - 1),$$
$$A(i) = P(i) + Q(i).$$

Half-Life for Advertising

The contribution of advertising to each period was previously thought to be a constant fraction of the amount of advertising in the previous period. However, Broadbent (1979) claimed that a single parameter cannot be used for all advertisements as there is evidence that the advertising for different brands decayed as different rates. Broadbent recommended that the concept of a half-life of the advertisement be used as a standard parameter. Broadbent (1979) claimed that a half-life of 5 weeks was shown to be most common estimate of the fading effect of advertising. Based on further studies of brand advertising, a half-life of five weeks was also assumed for the evaluation of the TAC advertising campaign (Cameron et al, 1993) and this value was also adopted by Macpherson and Lewis (1998): this corresponds to a retention factor of 87% per week ($F = .871$).

To consider the possibility that the impact of the TAC television advertising with drink-driving and speeding themes may not be as great near the end of the period to December 1993 as it was initially Fry (1996) extended the econometric models that had been developed by MUARC researchers such as that used by Cameron et al (1993). Using a series of models that included a quadratic version of the Adstock function, Fry found that there was some evidence of advertising wearout, but that the evidence was weak. He suggested that the large impact of the advertisements, as measured by awareness levels, coupled with a strategy of rotation of versions of the advertisements made it difficult to identify any statistically significant evidence of wearout.

Further research conducted by Shtifelman, Cameron and Diamantopoulou et al (1998) into the half life of TAC advertising for various campaigns and Victorian locations from 1987 to 1997 found that while the half life of the advertising varied between seven weeks and three weeks that a half-life of 5 weeks was typically an accurate measure of awareness levels. However, Shtifelman at al also found evidence of a decline in the half-life for each region of Victoria and that this is likely to be a result of the wearout first highlighted by Fry (1996). They concluded that there may be enough evidence to suggest the use of shorter half-lives of three to four weeks for the last 5 years of the study period but that the differences in the calculated coefficients were quite minimal. Therefore, a half life of 5 weeks was used in the calculation of adstock for the current study.

Base Level Awareness

Broadbent has also suggested the use of an awareness base level in the calculation of Adstock (1984) using a simple regression of the recorded awareness levels. Delaney et al (2004) found that the use of a base level provided a better fit to awareness levels and concluded from this that there was evidence that a base level of awareness was characteristic of the TAC campaign. However, the base level varied substantially between periods, themes and regions within Victoria. Furthermore, the viewing public's awareness levels across the study period are required to calculate the base Adstock level. Awareness data for the SRSP advertising campaign was not available for the current study.

All-Theme Road Safety Advertising

For the advertising component of the SRSP the LTSA ran graphic drink-drive advertisements alongside graphic television advertisements for other themes – speeding and the use of seat belts. It is possible that there is a cross-over effect from the use of fear appeals in all road safety advertisements on a person's decision to drink and then drive. For this reason, the Adstock was calculated for both drink-drive advertisements and for all road safety themes (all-theme). In this way both the specific effect of the drink-drive advertisements and the overall effect of the graphical road safety advertising campaign can be investigated.

The Adstock function not only lags the TARPs, but also has a smoothing effect on the data (see Figure 17 on the next page). If the Adstock data were to run out the lagged function of the previous monthly TARPs beyond the last month of December 1998, the total of the Adstock would equal that of the TARPs. It is also interesting to note that while there are a number of TARPs months with zero levels, there are no Adstock months with a zero level.

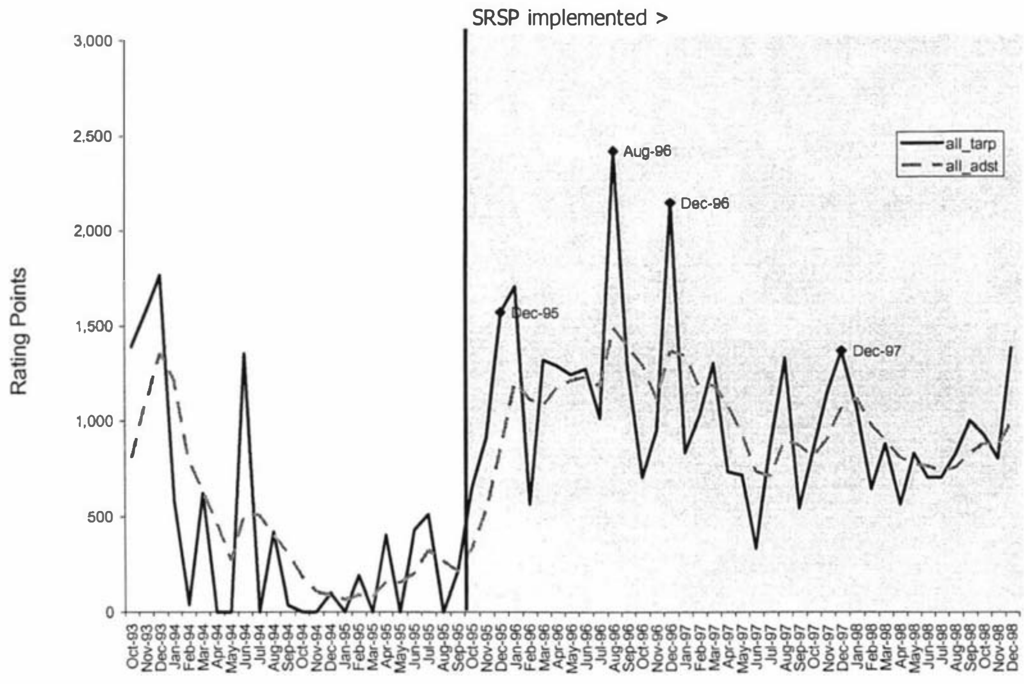

Figure 17. Monthly All-theme TARPs and Adstock – Oct 1993 to Dec 1998

Focusing on the levels of TARPs in Figure 17 we can see that the profile of the data is quite jagged with a series of peaks that are typically followed by troughs of noticeably lower levels of advertising. All-theme advertising was shown at its highest level during August 1996 followed by a similar level in December 1996 with levels noticeably decreasing after this point.

Switching our attention to the Adstock line in Figure 17 we can see the substantially greater levels of retained awareness following the introduction of the SRSP in October 1995.

Drink-Drive Road Safety Advertising

Focusing on the more specific drink-drive advertising may help isolate its effect on road safety outcomes.

In Figure 18 on the next page the level of drink-drive advertising TARPS have clearly increased with the introduction of the campaign in October 1995. Much like the All-theme advertising, after the implementation of the SRSP the data profile is characterised by large peaks followed by equally large reductions in advertising. Drink-drive TARPS were highest in August 1996 with almost quarterly peaks – the largest increases occurring in the months of December.

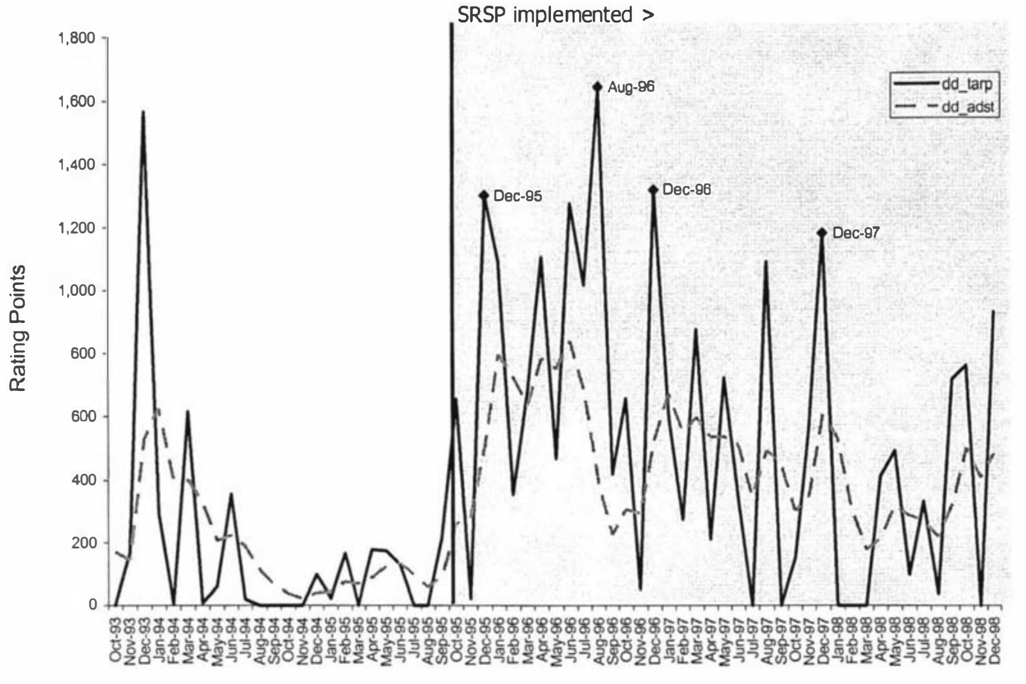

Figure 18. Monthly Drink-drive TARPs and Adstock – Oct 1993 to Dec 1998

There is also a noticeable change in the levels of adstock in Figure 18 for drink-drive advertisements following the introduction of the SRSP in October 1995. Levels range from a high of approximately 800 but never drop below 200.

Compulsory Breath Tests (CBTs)

Positive evidential breath tests (EBTs) are given to drivers from police operating either co-ordinated compulsory breath tests (CBTs) or independent mobile breath tests (MBTs). While data for EBTs is collected regularly from regional headquarters, MBTs, which represent a small proportion of total breath testing, are rarely recorded and therefore are not represented in the current study.

The operation of CBTs is generally confined to largely urban areas and evening (after 5pm) hours. The evening hours used for CBTs correspond roughly to the period used to classify high alcohol hour serious crashes. CBTs are used here, as they have been in previous studies (Cameron et al., 1993; Cameron & Vulcan, 1998; Macpherson & Lewis, 1998; Tay, 1999; White et al., 2000a), as a surrogate for enforcement. The New Zealand SRSP drink-drive road safety advertising campaign was run in conjunction with increased levels of CBT enforcement so it is important that this is accounted for in the modelling process. Unfortunately, individual CBTs are not traceable to specific documentation, but totals for each testing session are collected and reported. This practise may result in variation in the accuracy of CBT reporting. Smoothing the data is unlikely to be helpful in this respect as it may in turn dilute the estimated relationship between CBTs and road safety outcomes. Furthermore, it is not known with any certainty if some months are more affected than others. Another option is to represent the CBT effort with a dummy variable. Unfortunately, this option is not feasible here as the CBT campaign covered the complete analysis period. Therefore, where applicable, CBTs will be represented by monthly level data.

In Figure 19 below the level of CBTs follows a regular seasonal pattern of large peaks in the month of December followed by lower levels in January and February. This pattern is largely as a result of human resource allocation where police officers that are required for the annual CBT-Xmas period are given leave in the early New Year. The highest level of CBTs was in December 1995, with CBTs at their lowest numbers in July 1996. Somewhat surprisingly given the emphasis placed on breath testing in the SRSP drink-drive advertising, the number of CBTs appears to be reducing slightly across the time series.

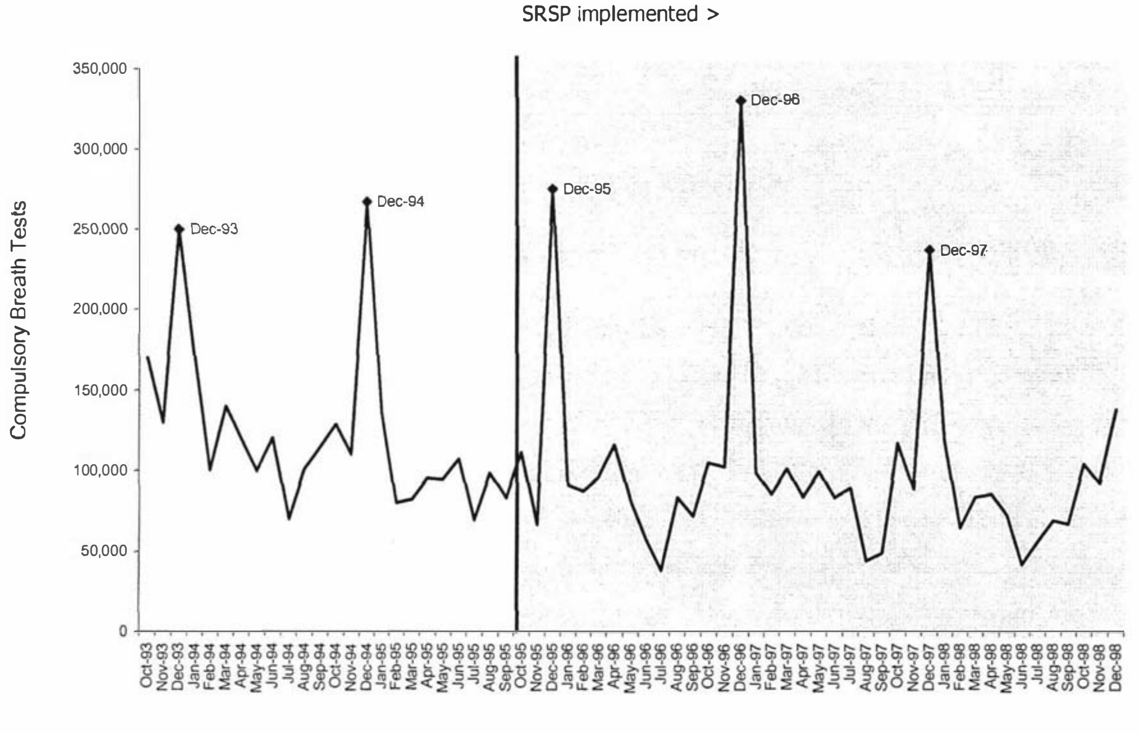

Figure 19. Monthly Compulsory Breath Tests (CBTs) – Oct 1993 to Dec 1998

Economic Indicators

In terms of explanatory variables used in road safety models, typically only one variable is included to describe the economic conditions and this is usually chosen to be some measure of unemployment (Hakim et al, 1991). While factors included in the long downward trend in road crashes tend to have a relatively small effect in the short term, economic activity has been shown to have a strong short term effect (Joksch, 1984). While economic indicators have been used as predictors of road accidents in road safety modeling for some time, their relationship was first estimated by Peltzman (1975) who developed a model of the demand for driving intensity that include an income effect. However, the role of economic factors was not widely accepted in the road safety area until the mid 1980's. In 1983, the Institute for Highway Safety published a graph of the relationship between the index of industrial production and traffic fatalities in the US (Wagenaar, 1984). This was validated by Joksch in 1984 when he found that industrial production provided the best fit among a series of economic indicators.

More recently a variety of other economic indicators have been used in the road safety literature including the employment rate (Partyka, 1984) leading index (White et al., 2000a) retail index (Tay, 2002) new car sales (Cameron et al., 1995a; Cameron & Vulcan, 1998; Guria & Leung, 2004) and the unemployment rate (Cameron & Newstead, 1993a; Cameron & Vulcan, 1998; Guria & Leung, 2004; Macpherson, 1996; Macpherson & Lewis, 1996, 1998; Tay, 2005b; White et al., 2000b).

Overall, the results strongly suggest that there is an inverse relationship between economic activity and road trauma. The negative sign of the unemployment rate coefficient in road safety models has been well discussed and documented in the literature (Brown, Jewel, & Richer, 1996; Harry, 1997; Kenkel, 1993; McCarthy, 1991, 1994; Peltzman, 1975; Saffer & Chaloupka, 1989; Thoresen et al., 1992; Zlatoper, 1987). One perspective of this relationship is that an increase in the level of economic activities will directly increase the amount of work-related travel thereby increasing the likelihood of a crash due to an increase in exposure. Since the level of economic activities is also a significant determinant of the level of income, it will have an indirect effect on the travel demands, especially discretionary driving, and more relevant to the current study, the demand for alcohol consumption (Tay, 2001). Furthermore, Evans and Graham (1988) claim that fatal crashes are very strongly affected in two ways by changes in the business cycle. Firstly, they are affected directly through changes in the total volume of travel, and secondly, indirectly through changes in levels of unemployment. It is likely that relatively small changes in unemployment produce relatively large changes in the numbers of marginally employable young males on the road, with corresponding changes in crash numbers (White & Walker, 2002).

The inclusion of an economic indicator in a road safety model is also consistent with the OECD (1997) principles as a representation of the socio-economic conditions factor.

However, the use of a common economic indicator, new car registrations may serve another purpose under the OECD model – a surrogate for transportation or exposure.

Unemployment

The most noticeable feature of the New Zealand unemployment data is the gradual decline towards the beginning of 1996 and the gradual increase since then. This pattern roughly coincides with the implantation of the SRSP advertising campaign.

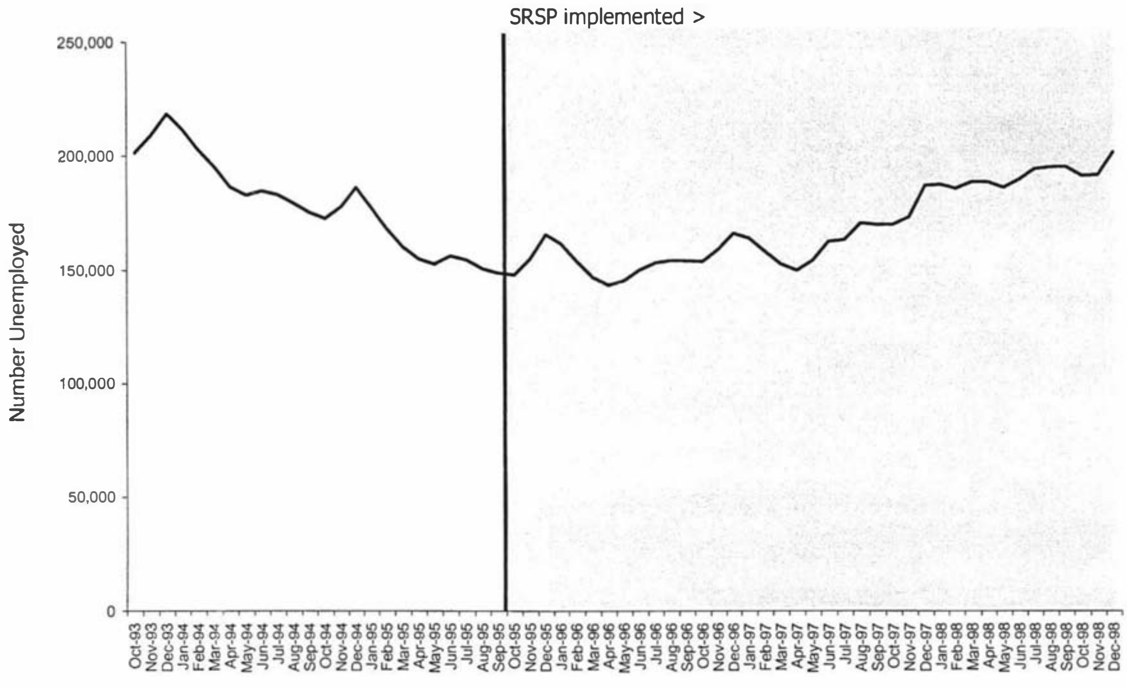

Figure 20. Monthly Level of Unemployment

New Car Registrations

While unemployment is expected to have an inverse relationship with most road safety outcomes, it is hypothesized that the relationship between new cars and the dependent variables will be positive (Cameron & Vulcan, 1998; White et al., 2000a). As the number of new car registrations increase there will be a corresponding increase in the population's propensity to drive. From a purely economic standpoint, greater levels of new car registrations will be an indication of better economic conditions. An improvement in economic conditions will produce an environment more favorable to greater levels of social drinking and consequently, greater levels of drink-driving. Furthermore, when considering the risk-exposure perspective the greater the number of vehicles and drivers on the road the greater the associated risk. This effect will be tempered in some situations as greater traffic congestion will restrict vehicle speed which is also a determinate of exposure (Hakim et al, 1991).

New car registrations gradually increased from the beginning of the series in October 1993 through to a peak in May 1996 (see Figure 21). Registrations then gradually decreased through to May 1998 where they then appear to be increasing once more through to the end of the series. There does not appear to be any noticeable seasonal pattern in the time series.

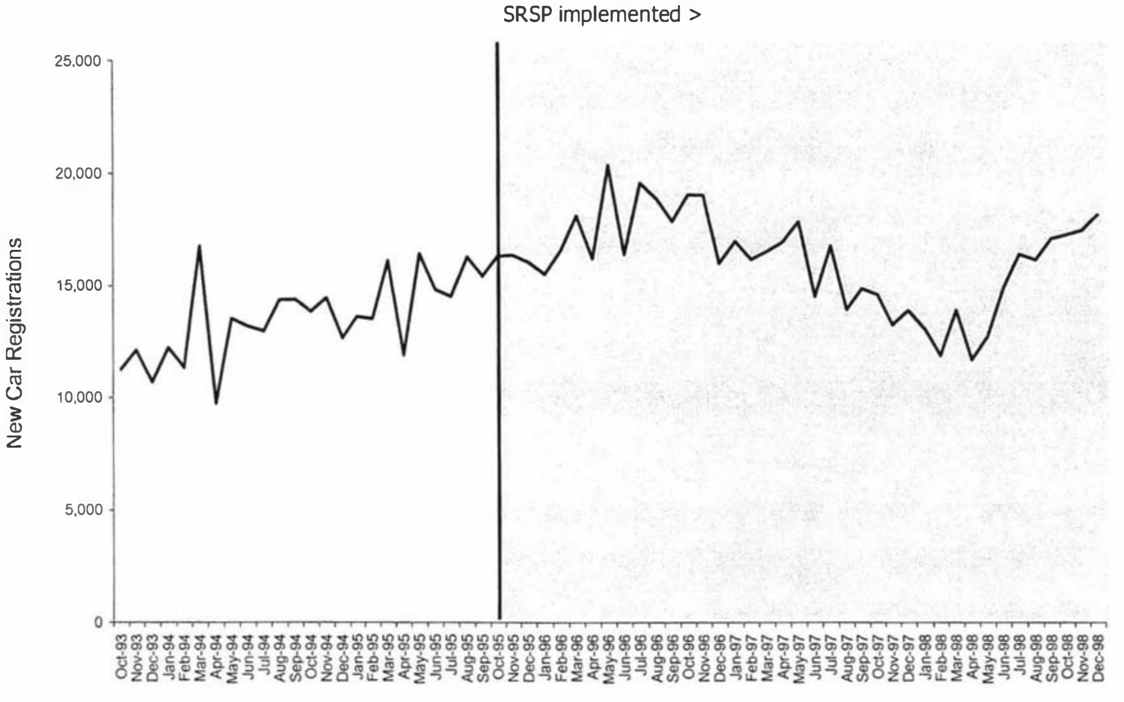

Figure 21. Monthly New Car Registrations

Unemployment and new car registrations are moderately and inversely correlated with one another (-.57). However, the implementation of the SRSP advertising campaign does not coincide with a change the pattern of new car registrations as it does with the number unemployed. Given the moderate strength of the relationship between new car registrations and unemployment, it is not likely that there will be any issues with collinearity if they were both placed into the same model.

APPENDIX 2. OUTPUT FOR CHAPTER 3

Model 1(a). Macpherson & Lewis Replication – EBTs & All-Theme Adstock

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.857	.735	.657	.22423

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6.684	14	.477	9.496	.000
	Residual	2.413	48	.050		
	Total	9.098	62			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.441	1.766		.250	.804
	Ln of all themes adstock	-.007	.039	-.015	-.173	.863
	Ln of cbts	.535	.148	.595	3.617	.001
	trend factors	.020	.002	.939	9.102	.000
	Ln of Feb dummy	.249	.152	.177	1.642	.107
	Ln of March dummy	.270	.144	.192	1.871	.067
	Ln of April dummy	.296	.144	.211	2.055	.045
	Ln of May dummy	.383	.148	.272	2.589	.013
	Ln of June dummy	.332	.155	.236	2.149	.037
	Ln of July dummy	.537	.168	.382	3.198	.002
	Ln of August dummy	.391	.154	.278	2.539	.014
	Ln of September dummy	.405	.155	.288	2.607	.012
	Ln of October dummy	.387	.136	.299	2.846	.006
	Ln of November dummy	.340	.139	.263	2.453	.018
	Ln of December dummy	.081	.175	.063	.463	.645

a. Dependent Variable: Ln of monthly EBTs

Model 1(b). Macpherson & Lewis Replication – EBTs & Drink-Drive Adstock

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.859	.738	.662	.22285

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6.714	14	.480	9.657	.000
	Residual	2.384	48	.050		
	Total	9.098	62			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.654	1.776		.368	.714
	Ln of drink-drive adstock	-.030	.038	-.069	-.792	.432
	Ln of cbts	.527	.147	.587	3.589	.001
	trend factors	.020	.002	.960	9.568	.000
	Ln of Feb dummy	.242	.151	.172	1.601	.116
	Ln of March dummy	.260	.144	.185	1.806	.077
	Ln of April dummy	.288	.144	.205	2.002	.051
	Ln of May dummy	.375	.147	.267	2.554	.014
	Ln of June dummy	.323	.154	.230	2.095	.042
	Ln of July dummy	.519	.169	.369	3.074	.003
	Ln of August dummy	.364	.157	.259	2.322	.025
	Ln of September dummy	.376	.159	.267	2.369	.022
	Ln of October dummy	.369	.137	.285	2.682	.010
	Ln of November dummy	.315	.142	.243	2.225	.031
	Ln of December dummy	.081	.173	.062	.465	.644

a. Dependent Variable: Ln of monthly EBTs

Model 2(a). Macpherson & Lewis Replication – Drink-Drive Convictions & All-Theme Adstock

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.815	.664	.566	.08888

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.748	14	.053	6.766	.000
	Residual	.379	48	.008		
	Total	1.128	62			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	7.098	.700		10.138	.000
	Ln of all themes adstock	.038	.015	.232	2.454	.018
	Ln of Feb dummy	-.026	.060	-.053	-.434	.667
	Ln of March dummy	.130	.057	.262	2.264	.028
	Ln of April dummy	.167	.057	.337	2.921	.005
	Ln of May dummy	.238	.059	.482	4.070	.000
	Ln of June dummy	.150	.061	.304	2.455	.018
	Ln of July dummy	.221	.067	.447	3.321	.002
	Ln of August dummy	.249	.061	.502	4.070	.000
	Ln of September dummy	.228	.062	.460	3.699	.001
	Ln of October dummy	.229	.054	.503	4.248	.000
	Ln of November dummy	.139	.055	.305	2.528	.015
	Ln of December dummy	.294	.069	.646	4.251	.000
	trend factors	.002	.001	.215	1.855	.070
	Ln of cbts	.009	.059	.029	.158	.875

a. Dependent Variable: Ln of D-drive convictions

Model 2(b). Macpherson & Lewis Replication – Drink-Drive Convictions & Drink-Drive Adstock

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.809	.655	.554	.09003

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.738	14	.053	6.507	.000
	Residual	.389	48	.008		
	Total	1.128	62			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	6.958	.718		9.697	.000
	Ln of drink-drive adstock	.033	.015	.216	2.156	.036
	Ln of cbts	.025	.059	.079	.420	.677
	trend factors	.002	.001	.242	2.104	.041
	Ln of Feb dummy	-.019	.061	-.038	-.308	.759
	Ln of March dummy	.135	.058	.273	2.325	.024
	Ln of April dummy	.172	.058	.347	2.959	.005
	Ln of May dummy	.238	.059	.480	4.003	.000
	Ln of June dummy	.157	.062	.316	2.515	.015
	Ln of July dummy	.240	.068	.486	3.526	.001
	Ln of August dummy	.275	.063	.555	4.335	.000
	Ln of September dummy	.253	.064	.512	3.950	.000
	Ln of October dummy	.244	.056	.536	4.394	.000
	Ln of November dummy	.163	.057	.357	2.843	.007
	Ln of December dummy	.288	.070	.633	4.116	.000

a. Dependent Variable: Ln of D-drive convictions

Model 3(a). Macpherson & Lewis Replication – Serious Casualties & All-Theme Adstock

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.841	.707	.622	.09520

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.050	14	.075	8.279	.000
	Residual	.435	48	.009		
	Total	1.485	62			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	6.297	.750		8.397	.000
	Ln of all themes adstock	-.006	.016	-.031	-.347	.730
	Ln of cbts	-.038	.063	-.105	-.607	.547
	trend factors	-.006	.001	-.696	-6.424	.000
	Ln of Feb dummy	-.046	.064	-.080	-.710	.481
	Ln of March dummy	.127	.061	.224	2.078	.043
	Ln of April dummy	-.007	.061	-.013	-.119	.906
	Ln of May dummy	.064	.063	.112	1.012	.316
	Ln of June dummy	-.011	.066	-.019	-.162	.872
	Ln of July dummy	-.088	.071	-.154	-1.228	.225
	Ln of August dummy	-.086	.065	-.151	-1.311	.196
	Ln of September dummy	-.089	.066	-.157	-1.357	.181
	Ln of October dummy	.044	.058	.084	.756	.453
	Ln of November dummy	-.013	.059	-.026	-.228	.821
	Ln of December dummy	.184	.074	.351	2.477	.017

a. Dependent Variable: Ln of serious casualties

Model 3(b). Macpherson & Lewis Replication – Serious Casualties & Drink-Drive Adstock

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.841	.707	.621	.09527

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.050	14	.075	8.262	.000
	Residual	.436	48	.009		
	Total	1.485	62			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	6.251	.759		8.233	.000
	Ln of drink-drive adstock	.004	.016	.021	.224	.823
	Ln of cbts	-.039	.063	-.107	-.616	.540
	trend factors	-.006	.001	-.720	-6.783	.000
	Ln of Feb dummy	-.045	.065	-.079	-.691	.493
	Ln of March dummy	.130	.062	.228	2.107	.040
	Ln of April dummy	-.005	.061	-.009	-.085	.932
	Ln of May dummy	.066	.063	.117	1.057	.296
	Ln of June dummy	-.009	.066	-.015	-.130	.897
	Ln of July dummy	-.085	.072	-.150	-1.179	.244
	Ln of August dummy	-.082	.067	-.144	-1.220	.228
	Ln of September dummy	-.085	.068	-.149	-1.248	.218
	Ln of October dummy	.047	.059	.090	.804	.425
	Ln of November dummy	-.010	.061	-.018	-.157	.876
	Ln of December dummy	.185	.074	.354	2.496	.016

a. Dependent Variable: Ln of serious casualties

Model 4(a). Macpherson & Lewis Replication – Fatalities & All-Theme Adstock

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.674	.454	.295	.17022

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.158	14	.083	2.853	.003
	Residual	1.391	48	.029		
	Total	2.548	62			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.691	1.341		2.007	.050
	Ln of all themes adstock	-.022	.029	-.090	-.749	.457
	Ln of cbts	.104	.112	.219	.926	.359
	trend factors	-.002	.002	-.150	-1.011	.317
	Ln of Feb dummy	.024	.115	.032	.207	.837
	Ln of March dummy	.298	.110	.400	2.713	.009
	Ln of April dummy	-.004	.109	-.005	-.033	.974
	Ln of May dummy	.100	.112	.135	.893	.376
	Ln of June dummy	.053	.117	.071	.450	.655
	Ln of July dummy	.174	.128	.233	1.361	.180
	Ln of August dummy	.055	.117	.074	.472	.639
	Ln of September dummy	.003	.118	.004	.023	.982
	Ln of October dummy	.114	.103	.167	1.105	.275
	Ln of November dummy	.241	.105	.351	2.285	.027
	Ln of December dummy	.255	.133	.373	1.926	.060

a. Dependent Variable: Ln of Fatalities

Model 4(b). Macpherson & Lewis Replication – Fatalities & Drink-Drive Adstock

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.675	.455	.296	.17009

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.160	14	.083	2.863	.003
	Residual	1.389	48	.029		
	Total	2.548	62			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.802	1.356		2.067	.044
	Ln of drink-drive adstock	-.023	.029	-.100	-.796	.430
	Ln of cbts	.094	.112	.198	.839	.406
	trend factors	-.002	.002	-.153	-1.059	.295
	Ln of Feb dummy	.019	.115	.025	.162	.872
	Ln of March dummy	.293	.110	.394	2.662	.011
	Ln of April dummy	-.008	.110	-.010	-.069	.945
	Ln of May dummy	.100	.112	.134	.888	.379
	Ln of June dummy	.048	.118	.064	.407	.685
	Ln of July dummy	.160	.129	.215	1.243	.220
	Ln of August dummy	.036	.120	.049	.304	.762
	Ln of September dummy	-.016	.121	-.022	-.132	.895
	Ln of October dummy	.103	.105	.150	.982	.331
	Ln of November dummy	.224	.108	.326	2.068	.044
	Ln of December dummy	.259	.132	.378	1.954	.057

a. Dependent Variable: Ln of Fatalities

Model 5(a). Macpherson & Lewis Replication – High Alcohol Hour Serious Crashes & All-Theme Adstock

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.732	.535	.400	.22268

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.744	14	.196	3.952	.000
	Residual	2.380	48	.050		
	Total	5.124	62			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	6.788	1.754		3.870	.000
	Ln of all themes adstock	-.040	.038	-.115	-1.030	.308
	Ln of cbts	-.222	.147	-.330	-1.515	.136
	trend factors	-.011	.002	-.700	-5.128	.000
	Ln of Feb dummy	.125	.151	.118	.830	.410
	Ln of March dummy	.273	.143	.259	1.905	.063
	Ln of April dummy	.079	.143	.074	.548	.586
	Ln of May dummy	.119	.147	.113	.813	.420
	Ln of June dummy	.079	.154	.075	.512	.611
	Ln of July dummy	-.067	.167	-.063	-.401	.690
	Ln of August dummy	.167	.153	.158	1.093	.280
	Ln of September dummy	.001	.154	.001	.005	.996
	Ln of October dummy	.166	.135	.171	1.226	.226
	Ln of November dummy	.103	.138	.106	.745	.460
	Ln of December dummy	.480	.174	.495	2.769	.008

a. Dependent Variable: Ln of High Alcohol Serious Injuries

Model 5(b). Macpherson & Lewis Replication – High Alcohol Hour Serious Crashes & Drink-Drive Adstock

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.734	.539	.404	.22188

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.761	14	.197	4.006	.000
	Residual	2.363	48	.049		
	Total	5.124	62			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	7.015	1.768		3.967	.000
	Ln of drink-drive adstock	-.045	.038	-.138	-1.190	.240
	Ln of cbts	-.241	.146	-.357	-1.648	.106
	trend factors	-.011	.002	-.700	-5.260	.000
	Ln of Feb dummy	.115	.150	.109	.764	.449
	Ln of March dummy	.263	.143	.250	1.836	.073
	Ln of April dummy	.070	.143	.066	.490	.626
	Ln of May dummy	.117	.146	.111	.799	.428
	Ln of June dummy	.069	.153	.065	.448	.656
	Ln of July dummy	-.094	.168	-.089	-.557	.580
	Ln of August dummy	.130	.156	.123	.834	.409
	Ln of September dummy	-.036	.158	-.035	-.230	.819
	Ln of October dummy	.143	.137	.147	1.047	.300
	Ln of November dummy	.069	.141	.071	.489	.627
	Ln of December dummy	.486	.173	.500	2.815	.007

a. Dependent Variable: Ln of High Alcohol Serious Injuries

Model 6(a). Replication of Cameron & Vulcan (1998) – Serious Crashes & New Cars

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.834	.695	.589	.09918

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	7.961	1.509		5.274	.000
	SRSP for Sept 95 to Sept 96	.134	.042	.342	3.164	.003
	SRSP for Sept 96 to Sept 97	-.037	.041	-.095	-.920	.362
	SRSP for Sept 97 to Sept 98	.170	.039	.434	4.310	.000
	Ln of Feb dummy	-.008	.067	-.015	-.123	.903
	Ln of March dummy	.196	.065	.345	3.008	.004
	Ln of April dummy	-.028	.065	-.049	-.427	.672
	Ln of May dummy	.129	.066	.228	1.965	.055
	Ln of June dummy	.042	.068	.073	.609	.546
	Ln of July dummy	.017	.074	.029	.225	.823
	Ln of August dummy	-.018	.069	-.032	-.267	.791
	Ln of September dummy	-.023	.069	-.040	-.329	.744
	Ln of October dummy	.049	.061	.093	.799	.428
	Ln of November dummy	.021	.062	.040	.335	.740
	Ln of December dummy	.053	.074	.102	.723	.473
	Ln of cbts	.109	.062	.300	1.757	.086
	Ln of new car registrations	-.373	.120	-.385	-3.120	.003

a. Dependent Variable: Ln of serious casualties

Model 6(b). Replication of Cameron & Vulcan (1998) – Serious Crashes & Unemployment

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.799	.638	.513	.10806

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	6.231	2.609		2.388	.021
	SRSP for Sept 95 to Sept 96	.034	.053	.087	.638	.527
	SRSP for Sept 96 to Sept 97	-.125	.047	-.319	-2.675	.010
	SRSP for Sept 97 to Sept 98	.148	.043	.378	3.467	.001
	Ln of Feb dummy	.015	.073	.027	.208	.836
	Ln of March dummy	.142	.071	.250	1.998	.052
	Ln of April dummy	-.004	.072	-.008	-.062	.951
	Ln of May dummy	.083	.074	.145	1.122	.268
	Ln of June dummy	.038	.076	.066	.497	.622
	Ln of July dummy	-.004	.082	-.007	-.048	.962
	Ln of August dummy	-.047	.076	-.083	-.628	.533
	Ln of September dummy	-.053	.076	-.094	-.698	.489
	Ln of October dummy	.008	.066	.016	.125	.901
	Ln of November dummy	-.004	.068	-.008	-.061	.952
	Ln of December dummy	.014	.079	.027	.176	.861
	Ln of cbts	.161	.065	.444	2.483	.017
	Ln of total registered unemployed	-.200	.205	-.142	-.976	.334

a. Dependent Variable: Ln of serious casualties

Model 6(c). Replication of White et al (2000a) – Serious Crashes, New Cars & Trend

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.874	.764	.674	.08834

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	6.300	1.421		4.432	.000
	SRSP for Sept 95 to Sept 96	.102	.039	.260	2.630	.012
	SRSP for Sept 96 to Sept 97	.002	.038	.005	.050	.960
	SRSP for Sept 97 to Sept 98	-.033	.052	-.084	-.632	.531
	Ln of Feb dummy	-.029	.060	-.051	-.485	.630
	Ln of March dummy	.146	.060	.257	2.454	.018
	Ln of April dummy	-.006	.058	-.011	-.103	.919
	Ln of May dummy	.085	.060	.149	1.416	.164
	Ln of June dummy	.011	.061	.019	.180	.858
	Ln of July dummy	-.051	.069	-.090	-.749	.458
	Ln of August dummy	-.061	.062	-.108	-.985	.330
	Ln of September dummy	-.064	.063	-.113	-1.024	.311
	Ln of October dummy	.048	.054	.092	.885	.381
	Ln of November dummy	.002	.056	.004	.033	.974
	Ln of December dummy	.145	.071	.277	2.050	.046
	Ln of cbts	.014	.061	.039	.229	.820
	Ln of new car registrations	-.073	.135	-.075	-.536	.594
	trend factors	-.005	.001	-.567	-3.603	.001

Model 6(d). Replication of White et al (2000a) – Serious Crashes, Unemployment & Trend

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.877	.769	.682	.08734

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	7.972	2.137		3.731	.001
	SRSP for Sept 95 to Sept 96	.058	.043	.148	1.335	.189
	SRSP for Sept 96 to Sept 97	-.027	.042	-.068	-.630	.532
	SRSP for Sept 97 to Sept 98	-.014	.043	-.036	-.328	.744
	Ln of Feb dummy	-.035	.060	-.061	-.580	.565
	Ln of March dummy	.124	.057	.218	2.151	.037
	Ln of April dummy	-.017	.058	-.030	-.288	.775
	Ln of May dummy	.059	.060	.105	.995	.325
	Ln of June dummy	-.003	.062	-.006	-.056	.956
	Ln of July dummy	-.070	.067	-.124	-1.045	.301
	Ln of August dummy	-.079	.061	-.139	-1.284	.206
	Ln of September dummy	-.083	.062	-.146	-1.337	.188
	Ln of October dummy	.034	.054	.065	.633	.530
	Ln of November dummy	-.007	.055	-.014	-.133	.895
	Ln of December dummy	.153	.070	.292	2.195	.033
	Ln of cbts	.012	.060	.032	.194	.847
	Ln of total registered unemployed	-.191	.166	-.136	-1.156	.254
	trend factors	-.005	.001	-.617	-5.042	.000

Model 7(a). Replication of Cameron & Vulcan (1998) – EBTs & New Cars

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.884	.782	.706	.20764

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7.114	16	.445	10.313	.000
	Residual	1.983	46	.043		
	Total	9.098	62			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.177	3.160		.056	.956
	Ln of cbts	.059	.130	.066	.459	.649
	SRSP for Sept 95 to Sept 96	-.245	.088	-.253	-2.766	.008
	SRSP for Sept 96 to Sept 97	.417	.085	.431	4.913	.000
	SRSP for Sept 97 to Sept 98	.617	.082	.638	7.497	.000
	Ln of Feb dummy	.113	.141	.081	.805	.425
	Ln of March dummy	.131	.136	.093	.960	.342
	Ln of April dummy	.320	.136	.227	2.344	.023
	Ln of May dummy	.245	.138	.174	1.777	.082
	Ln of June dummy	.191	.143	.136	1.337	.188
	Ln of July dummy	.270	.155	.192	1.742	.088
	Ln of August dummy	.240	.144	.171	1.674	.101
	Ln of September dummy	.261	.145	.186	1.802	.078
	Ln of October dummy	.433	.127	.335	3.401	.001
	Ln of November dummy	.294	.130	.227	2.264	.028
	Ln of December dummy	.529	.155	.409	3.420	.001
	Ln of new car registrations	.645	.251	.269	2.576	.013

a. Dependent Variable: Ln of monthly EBTs

Model 7(b). Replication of Cameron & Vulcan (1998) – EBTs & Unemployment

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.868	.753	.667	.22105

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6.850	16	.428	8.762	.000
	Residual	2.248	46	.049		
	Total	9.098	62			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.976	5.337		.745	.460
	Ln of cbts	-.031	.133	-.035	-.234	.816
	SRSP for Sept 95 to Sept 96	-.084	.109	-.087	-.768	.446
	SRSP for Sept 96 to Sept 97	.559	.095	.578	5.869	.000
	SRSP for Sept 97 to Sept 98	.581	.087	.601	6.664	.000
	Ln of Feb dummy	.070	.149	.050	.471	.640
	Ln of March dummy	.220	.145	.156	1.513	.137
	Ln of April dummy	.273	.147	.194	1.853	.070
	Ln of May dummy	.319	.151	.227	2.120	.039
	Ln of June dummy	.194	.155	.138	1.251	.217
	Ln of July dummy	.301	.167	.214	1.806	.077
	Ln of August dummy	.287	.154	.204	1.856	.070
	Ln of September dummy	.309	.156	.220	1.979	.054
	Ln of October dummy	.500	.136	.386	3.679	.001
	Ln of November dummy	.336	.138	.259	2.430	.019
	Ln of December dummy	.600	.162	.463	3.701	.001
	Ln of total registered unemployed	.279	.419	.080	.666	.509

a. Dependent Variable: Ln of monthly EBTs

Model 7(c). Replication of White et al (2000a) – EBTs, New Cars & Trend

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.938	.879	.834	.15625

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7.999	17	.471	19.273	.000
	Residual	1.099	45	.024		
	Total	9.098	62			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	5.086	2.514		2.023	.049
	Ln of cbts	.340	.108	.378	3.142	.003
	SRSP for Sept 95 to Sept 96	-.150	.068	-.155	-2.194	.033
	SRSP for Sept 96 to Sept 97	.301	.067	.311	4.517	.000
	SRSP for Sept 97 to Sept 98	.213	.091	.220	2.329	.024
	Ln of Feb dummy	.175	.106	.125	1.646	.107
	Ln of March dummy	.277	.105	.197	2.631	.012
	Ln of April dummy	.255	.103	.182	2.474	.017
	Ln of May dummy	.376	.106	.268	3.551	.001
	Ln of June dummy	.282	.109	.200	2.589	.013
	Ln of July dummy	.471	.121	.335	3.883	.000
	Ln of August dummy	.367	.110	.261	3.337	.002
	Ln of September dummy	.383	.111	.273	3.457	.001
	Ln of October dummy	.435	.096	.336	4.540	.000
	Ln of November dummy	.350	.098	.271	3.565	.001
	Ln of December dummy	.260	.125	.201	2.083	.043
	Ln of new car registrations	-.243	.239	-.101	-1.016	.315
	trend factors	.014	.002	.677	6.019	.000

a. Dependent Variable: Ln of monthly EBTs

Model 7(d). Replication of White et al (2000a) – EBTs, Unemployment & Trend

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.937	.879	.833	.15672

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7.992	17	.470	19.142	.000
	Residual	1.105	45	.025		
	Total	9.098	62			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.250	3.835		-.065	.948
	Ln of cbts	.332	.108	.369	3.067	.004
	SRSP for Sept 95 to Sept 96	-.142	.078	-.146	-1.821	.075
	SRSP for Sept 96 to Sept 97	.322	.076	.332	4.230	.000
	SRSP for Sept 97 to Sept 98	.257	.078	.266	3.296	.002
	Ln of Feb dummy	.191	.107	.136	1.784	.081
	Ln of March dummy	.264	.103	.188	2.557	.014
	Ln of April dummy	.303	.105	.216	2.898	.006
	Ln of May dummy	.376	.107	.267	3.508	.001
	Ln of June dummy	.293	.111	.209	2.649	.011
	Ln of July dummy	.462	.121	.329	3.833	.000
	Ln of August dummy	.363	.110	.258	3.295	.002
	Ln of September dummy	.381	.111	.271	3.423	.001
	Ln of October dummy	.437	.097	.338	4.517	.000
	Ln of November dummy	.343	.098	.265	3.505	.001
	Ln of December dummy	.262	.125	.203	2.097	.042
	Ln of total registered unemployed	.259	.297	.074	.871	.389
	trend factors	.013	.002	.605	6.820	.000

a. Dependent Variable: Ln of monthly EBTs

Model 8(a). Replication of Cameron & Vulcan (1998) - Drink-Drive Convictions & New Cars

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.823	.677	.565	.08899

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.763	16	.048	6.023	.000
	Residual	.364	46	.008		
	Total	1.128	62			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	8.067	1.354		5.956	.000
	SRSP for Sept 95 to Sept 96	.107	.038	.315	2.827	.007
	SRSP for Sept 96 to Sept 97	-.126	.036	-.369	-3.461	.001
	SRSP for Sept 97 to Sept 98	.077	.035	.225	2.175	.035
	Ln of Feb dummy	-.040	.060	-.081	-.666	.509
	Ln of March dummy	.126	.058	.254	2.157	.036
	Ln of April dummy	.157	.058	.318	2.693	.010
	Ln of May dummy	.230	.059	.465	3.896	.000
	Ln of June dummy	.141	.061	.286	2.307	.026
	Ln of July dummy	.213	.066	.431	3.215	.002
	Ln of August dummy	.249	.062	.502	4.039	.000
	Ln of September dummy	.226	.062	.456	3.637	.001
	Ln of October dummy	.243	.055	.533	4.445	.000
	Ln of November dummy	.149	.056	.326	2.670	.010
	Ln of December dummy	.337	.066	.739	5.079	.000
	Ln of cbts	-.021	.056	-.065	-.369	.714
	Ln of new car registrations	-.041	.107	-.049	-.383	.703

a. Dependent Variable: Ln of D-drive convictions

Model 8(b). Replication of Cameron & Vulcan (1998) - Drink-Drive Convictions & Unemployment

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.825	.680	.569	.08850

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.767	16	.048	6.123	.000
	Residual	.360	46	.008		
	Total	1.128	62			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	5.944	2.137		2.782	.008
	SRSP for Sept 95 to Sept 96	.124	.044	.363	2.828	.007
	SRSP for Sept 96 to Sept 97	.137	.038	.401	3.578	.001
	SRSP for Sept 97 to Sept 98	.076	.035	.223	2.171	.035
	Ln of Feb dummy	-.031	.060	-.064	-.527	.601
	Ln of March dummy	.131	.058	.265	2.255	.029
	Ln of April dummy	.175	.059	.353	2.963	.005
	Ln of May dummy	.240	.060	.485	3.979	.000
	Ln of June dummy	.152	.062	.307	2.449	.018
	Ln of July dummy	.221	.067	.446	3.309	.002
	Ln of August dummy	.255	.062	.515	4.123	.000
	Ln of September dummy	.233	.063	.471	3.726	.001
	Ln of October dummy	.247	.054	.541	4.538	.000
	Ln of November dummy	.150	.055	.329	2.715	.009
	Ln of December dummy	.328	.065	.719	5.053	.000
	Ln of cbts	-.015	.053	-.046	-.273	.786
	Ln of total registered unemployed	.137	.168	.111	.815	.419

a. Dependent Variable: Ln of D-drive convictions

Model 8(c). Replication of White et al (2000a) – Drink-Drive Convictions, New Cars & Trend

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.851	.725	.621	.08307

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.817	17	.048	6.966	.000
	Residual	.310	45	.007		
	Total	1.128	62			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	9.278	1.336		6.942	.000
	SRSP for Sept 95 to Sept 96	.130	.036	.383	3.589	.001
	SRSP for Sept 96 to Sept 97	.097	.035	.286	2.745	.009
	SRSP for Sept 97 to Sept 98	-.023	.049	-.067	-.473	.638
	Ln of Feb dummy	-.025	.057	-.050	-.440	.662
	Ln of March dummy	.162	.056	.327	2.892	.006
	Ln of April dummy	.142	.055	.286	2.580	.013
	Ln of May dummy	.263	.056	.531	4.660	.000
	Ln of June dummy	.164	.058	.331	2.833	.007
	Ln of July dummy	.263	.064	.531	4.080	.000
	Ln of August dummy	.280	.059	.566	4.782	.000
	Ln of September dummy	.256	.059	.517	4.342	.000
	Ln of October dummy	.243	.051	.534	4.771	.000
	Ln of November dummy	.163	.052	.357	3.111	.003
	Ln of December dummy	.270	.066	.593	4.077	.000
	Ln of cbts	.049	.057	.154	.845	.402
	Ln of new car registrations	-.260	.127	-.308	-2.045	.047
	trend factors	.003	.001	.474	2.792	.008

a. Dependent Variable: Ln of D-drive convictions

Model 8(d). Replication of White et al (2000a) – Drink-Drive Convictions, Unemployment & Trend

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.839	.703	.591	.08620

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.793	17	.047	6.279	.000
	Residual	.334	45	.007		
	Total	1.128	62			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	5.308	2.109		2.517	.015
	SRSP for Sept 95 to Sept 96	.115	.043	.337	2.683	.010
	SRSP for Sept 96 to Sept 97	.101	.042	.296	2.409	.020
	SRSP for Sept 97 to Sept 98	.027	.043	.079	.630	.532
	Ln of Feb dummy	-.013	.059	-.027	-.225	.823
	Ln of March dummy	.138	.057	.278	2.427	.019
	Ln of April dummy	.179	.058	.362	3.117	.003
	Ln of May dummy	.248	.059	.502	4.217	.000
	Ln of June dummy	.167	.061	.337	2.738	.009
	Ln of July dummy	.245	.066	.495	3.697	.001
	Ln of August dummy	.266	.061	.538	4.400	.000
	Ln of September dummy	.244	.061	.493	3.985	.000
	Ln of October dummy	.237	.053	.521	4.460	.000
	Ln of November dummy	.151	.054	.332	2.809	.007
	Ln of December dummy	.277	.069	.608	4.027	.000
	Ln of cbts	.040	.059	.127	.674	.504
	Ln of total registered unemployed	.134	.163	.109	.818	.418
	trend factors	.002	.001	.259	1.866	.069

a. Dependent Variable: Ln of D-drive convictions

Model 9(a). Replication of Cameron & Vulcan (1998) – Fatalities & New Cars

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.672	.452	.262	.17420

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.003	2.651		1.133	.263
	Ln of cbts	.116	.109	.245	1.070	.290
	SRSP for Sept 95 to Sept 96	-.026	.074	-.051	-.353	.726
	SRSP for Sept 96 to Sept 97	-.039	.071	-.076	-.546	.588
	SRSP for Sept 97 to Sept 98	-.104	.069	-.202	-1.500	.140
	Ln of new car registrations	-.064	.210	-.050	-.305	.762
	Ln of Feb dummy	.027	.118	.036	.226	.822
	Ln of March dummy	.309	.114	.415	2.704	.010
	Ln of April dummy	-.009	.114	-.012	-.076	.940
	Ln of May dummy	.111	.116	.149	.960	.342
	Ln of June dummy	.056	.120	.075	.463	.646
	Ln of July dummy	.181	.130	.243	1.391	.171
	Ln of August dummy	.057	.121	.077	.477	.636
	Ln of September dummy	.006	.121	.008	.046	.964
	Ln of October dummy	.111	.107	.161	1.035	.306
	Ln of November dummy	.238	.109	.347	2.181	.034
	Ln of December dummy	.232	.130	.339	1.787	.080

a. Dependent Variable: Ln of Fatalities

Model 9(b). Replication of Cameron & Vulcan (1998) – Fatalities & Unemployment

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.674	.454	.265	.17384

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	4.433	4.198		1.056	.296
	Ln of cbts	.125	.104	.263	1.198	.237
	SRSP for Sept 95 to Sept 96	-.068	.086	-.132	-.790	.434
	SRSP for Sept 96 to Sept 97	-.072	.075	-.141	-.961	.342
	SRSP for Sept 97 to Sept 98	-.097	.069	-.189	-1.413	.164
	Ln of Feb dummy	.025	.117	.034	.215	.830
	Ln of March dummy	.290	.114	.390	2.541	.014
	Ln of April dummy	-.018	.116	-.024	-.155	.878
	Ln of May dummy	.090	.118	.120	.756	.453
	Ln of June dummy	.045	.122	.061	.372	.712
	Ln of July dummy	.168	.131	.226	1.284	.206
	Ln of August dummy	.044	.121	.059	.362	.719
	Ln of September dummy	-.009	.123	-.012	-.076	.940
	Ln of October dummy	.096	.107	.140	.900	.373
	Ln of November dummy	.230	.109	.336	2.116	.040
	Ln of December dummy	.230	.127	.335	1.802	.078
	Ln of total registered unemployed	-.176	.330	-.095	-.535	.595

a. Dependent Variable: Ln of Fatalities

Model 9(c). Replication of White et al (2000a) – Fatalities, New Cars & Trend

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.675	.456	.250	.17553

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.496	2.824		.884	.382
	Ln of cbts	.087	.121	.184	.720	.476
	SRSP for Sept 95 to Sept 96	-.036	.077	-.070	-.468	.642
	SRSP for Sept 96 to Sept 97	-.027	.075	-.053	-.359	.721
	SRSP for Sept 97 to Sept 98	-.062	.103	-.121	-.602	.550
	Ln of Feb dummy	.020	.120	.027	.170	.866
	Ln of March dummy	.294	.118	.395	2.484	.017
	Ln of April dummy	-.002	.116	-.003	-.018	.986
	Ln of May dummy	.097	.119	.131	.818	.418
	Ln of June dummy	.046	.122	.062	.379	.707
	Ln of July dummy	.160	.136	.215	1.175	.246
	Ln of August dummy	.044	.124	.060	.359	.722
	Ln of September dummy	-.007	.125	-.009	-.057	.955
	Ln of October dummy	.110	.108	.161	1.025	.311
	Ln of November dummy	.232	.110	.339	2.102	.041
	Ln of December dummy	.260	.140	.379	1.854	.070
	trend factors	-.001	.003	-.132	-.554	.583
	Ln of new car registrations	.028	.269	.022	.103	.918

a. Dependent Variable: Ln of Fatalities

Model 9(d). Replication of White et al (2000a) – Fatalities, Unemployment & Trend

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.678	.459	.255	.17502

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	4.861	4.282		1.135	.262
	Ln of cbts	.088	.121	.186	.731	.468
	SRSP for Sept 95 to Sept 96	-.062	.087	-.121	-.712	.480
	SRSP for Sept 96 to Sept 97	-.048	.085	-.094	-.564	.575
	SRSP for Sept 97 to Sept 98	-.064	.087	-.125	-.735	.466
	Ln of Feb dummy	.013	.120	.017	.109	.914
	Ln of March dummy	.286	.115	.384	2.480	.017
	Ln of April dummy	-.021	.117	-.028	-.180	.858
	Ln of May dummy	.084	.120	.113	.701	.487
	Ln of June dummy	.035	.124	.047	.284	.777
	Ln of July dummy	.152	.135	.204	1.129	.265
	Ln of August dummy	.036	.123	.049	.295	.769
	Ln of September dummy	-.017	.124	-.022	-.133	.895
	Ln of October dummy	.103	.108	.150	.949	.348
	Ln of November dummy	.229	.109	.334	2.095	.042
	Ln of December dummy	.264	.140	.385	1.889	.065
	trend factors	-.001	.002	-.116	-.619	.539
	Ln of total registered unemployed	-.174	.332	-.094	-.525	.602

a. Dependent Variable: Ln of Fatalities

Model 10(a). Replication of Cameron & Vulcan (1998) – High Alcohol Hour Serious Crashes & New Cars

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.715	.511	.340	.23349

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	9.616	3.553		2.706	.010
	Ln of cbts	.037	.146	.055	.253	.802
	SRSP for Sept 95 to Sept 96	.218	.099	.300	2.192	.033
	SRSP for Sept 96 to Sept 97	-.089	.095	-.123	-.934	.355
	SRSP for Sept 97 to Sept 98	-.373	.093	-.514	-4.033	.000
	Ln of Feb dummy	.193	.158	.183	1.218	.229
	Ln of March dummy	.399	.153	.378	2.603	.012
	Ln of April dummy	.044	.153	.041	.285	.777
	Ln of May dummy	.242	.155	.230	1.563	.125
	Ln of June dummy	.172	.161	.163	1.069	.291
	Ln of July dummy	.116	.174	.110	.668	.507
	Ln of August dummy	.284	.162	.270	1.761	.085
	Ln of September dummy	.118	.163	.112	.727	.471
	Ln of October dummy	.173	.143	.178	1.208	.233
	Ln of November dummy	.160	.146	.165	1.095	.279
	Ln of December dummy	.242	.174	.249	1.389	.172
	Ln of new car registrations	-.667	.282	-.370	-2.367	.022

a. Dependent Variable: Nat log of HAH Serious injuries

Model 10(b). Replication of Cameron & Vulcan (1998) – High Alcohol Hour Serious Crashes & Unemployment

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.674	.454	.264	.24668

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	4.921	5.956		.826	.413
	Ln of cbts	.131	.148	.194	.881	.383
	SRSP for Sept 95 to Sept 96	.063	.122	.086	.515	.609
	SRSP for Sept 96 to Sept 97	-.228	.106	-.314	-2.146	.037
	SRSP for Sept 97 to Sept 98	.337	.097	.465	3.467	.001
	Ln of Feb dummy	.240	.166	.227	1.441	.156
	Ln of March dummy	.312	.162	.295	1.924	.061
	Ln of April dummy	.098	.165	.093	.594	.555
	Ln of May dummy	.171	.168	.162	1.018	.314
	Ln of June dummy	.174	.173	.165	1.006	.320
	Ln of July dummy	.088	.186	.083	.471	.640
	Ln of August dummy	.240	.172	.228	1.395	.170
	Ln of September dummy	.073	.174	.069	.416	.679
	Ln of October dummy	.108	.152	.111	.712	.480
	Ln of November dummy	.119	.154	.123	.772	.444
	Ln of December dummy	.167	.181	.172	.925	.360
	Ln of total registered unemployed	-.225	.468	-.086	-.481	.632

a. Dependent Variable: Nat log of HAH Serious injuries

Model 10(c). Replication of White et al (2000a) – High Alcohol Hour Serious Crashes, New Cars & Trend

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.763	.583	.425	.21798

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	6.443	3.507		1.837	.073
	Ln of cbts	-.144	.151	-.214	-.956	.344
	SRSP for Sept 95 to Sept 96	.157	.095	.216	1.645	.107
	SRSP for Sept 96 to Sept 97	-.014	.093	-.020	-.153	.879
	SRSP for Sept 97 to Sept 98	.112	.128	.154	.879	.384
	Ln of Feb dummy	.153	.148	.145	1.029	.309
	Ln of March dummy	.304	.147	.288	2.070	.044
	Ln of April dummy	.085	.144	.081	.593	.556
	Ln of May dummy	.157	.148	.149	1.063	.293
	Ln of June dummy	.114	.152	.108	.750	.457
	Ln of July dummy	-.013	.169	-.013	-.080	.937
	Ln of August dummy	.202	.154	.192	1.317	.194
	Ln of September dummy	.039	.155	.037	.254	.801
	Ln of October dummy	.172	.134	.177	1.284	.206
	Ln of November dummy	.124	.137	.128	.904	.371
	Ln of December dummy	.416	.174	.428	2.389	.021
	Ln of new car registrations	-.092	.334	-.051	-.277	.783
	trend factors	-.009	.003	-.583	-2.788	.008

a. Dependent Variable: Nat log of HAH Serious injuries

Model 10(d). Replication of White et al (2000a) – High Alcohol Hour Serious Crashes, Unemployment & Trend

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.764	.584	.427	.21755

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	8.156	5.323		1.532	.132
	Ln of cbts	-.147	.150	-.218	-.980	.332
	SRSP for Sept 95 to Sept 96	.107	.108	.147	.991	.327
	SRSP for Sept 96 to Sept 97	-.046	.106	-.064	-.438	.663
	SRSP for Sept 97 to Sept 98	.089	.108	.123	.825	.414
	Ln of Feb dummy	.147	.149	.139	.989	.328
	Ln of March dummy	.278	.143	.263	1.941	.059
	Ln of April dummy	.075	.145	.071	.515	.609
	Ln of May dummy	.128	.149	.121	.861	.394
	Ln of June dummy	.098	.154	.092	.635	.529
	Ln of July dummy	-.035	.167	-.034	-.212	.833
	Ln of August dummy	.182	.153	.173	1.192	.239
	Ln of September dummy	.018	.155	.017	.114	.909
	Ln of October dummy	.156	.134	.161	1.162	.252
	Ln of November dummy	.113	.136	.117	.833	.409
	Ln of December dummy	.425	.174	.438	2.451	.018
	Ln of total registered unemployed	-.210	.412	-.080	-.508	.614
	trend factors	-.010	.003	-.617	-3.761	.000

a. Dependent Variable: Nat log of HAH Serious injuries

Model 11(a) – (12a). Replication of Tay (1999) – EBTs (Double-Log)

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.808	.653	.629	.23334

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5.940	4	1.485	27.272	.000
	Residual	3.158	58	.054		
	Total	9.098	62			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.911	1.330		2.188	.033
	Ln of December dummy	-.064	.152	-.050	-.423	.674
	trend factors	.019	.002	.898	8.936	.000
	Ln of cbts	.353	.113	.393	3.115	.003
	Ln of all themes adstock	-.014	.040	-.031	-.358	.722

a. Dependent Variable: Ln of monthly EBTs

Model 11(b). Replication of Tay (1999) – EBTs (Linear-Log)

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.821	.674	.652	429.094

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	22093696	4	5523424.091	29.999	.000
	Residual	10679068	58	184121.871		
	Total	32772765	62			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-6839.384	2445.824		-2.796	.007
	Ln of December dummy	-83.019	278.706	-.034	-.298	.767
	trend factors	35.461	3.863	.894	9.179	.000
	Ln of cbts	662.990	208.642	.389	3.178	.002
	Ln of all themes adstock	-1.757	73.479	-.002	-.024	.981

a. Dependent Variable: Positive evidential breath tests

Model 11(c). Replication of Tay (1999) – EBTs (Log-Linear)

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.825	.680	.658	.22401

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6.187	4	1.547	30.826	.000
	Residual	2.910	58	.050		
	Total	9.098	62			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	6.534	.143		45.584	.000
	December dummy	-.313	.193	-.242	-1.625	.109
	trend factors	.020	.002	.970	10.055	.000
	national compulsory breath tests	3.992E-06	.000	.584	3.726	.000
	ADSTOCK for all themes	.000	.000	-.150	-1.812	.075

a. Dependent Variable: Ln of monthly EBTs

Model 11(d). Replication of Tay (1999) – EBTs (Linear)

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.839	.705	.684	408.461

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	23096045	4	5774011.217	34.608	.000
	Residual	9676720	58	166840.000		
	Total	32772765	62			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	13.560	261.350		.052	.959
	December dummy	-630.143	351.214	-.256	-1.794	.078
	trend factors	38.640	3.677	.974	10.509	.000
	national compulsory breath tests	.008	.002	.613	4.069	.000
	ADSTOCK for all themes	-.196	.139	-.112	-1.406	.165

a. Dependent Variable: Positive evidential breath tests

Model 12(b). Replication of Tay (1999) – Drink-Drive Convictions

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.530	.281	.231	.11823

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.317	4	.079	5.667	.001
	Residual	.811	58	.014		
	Total	1.128	62			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	7.874	.674		11.684	.000
	Ln of December dummy	.188	.077	.412	2.445	.018
	trend factors	.002	.001	.237	1.638	.107
	Ln of cbts	-.041	.057	-.129	-.709	.481
	Ln of all themes adstock	.029	.020	.182	1.450	.152

a. Dependent Variable: Ln of D-drive convictions

Model 12(c). Replication of Tay (1999) – Serious Crashes

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.760	.578	.549	.10396

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.859	4	.215	19.860	.000
	Residual	.627	58	.011		
	Total	1.485	62			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	5.140	.593		8.674	.000
	Ln of December dummy	.092	.068	.176	1.362	.178
	trend factors	-.005	.001	-.609	-5.491	.000
	Ln of cbts	.063	.051	.173	1.241	.220
	Ln of all themes adstock	-.009	.018	-.051	-.533	.596

a. Dependent Variable: Ln of serious casualties

Model 12(d). Replication of Tay (1999) – Fatalities

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.491	.241	.189	.18258

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.615	4	.154	4.612	.003
	Residual	1.933	58	.033		
	Total	2.548	62			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.680	1.041		2.575	.013
	Ln of all themes adstock	-.024	.031	-.100	-.781	.438
	Ln of cbts	.115	.089	.241	1.291	.202
	trend factors	-.002	.002	-.139	-.933	.355
	Ln of December dummy	.146	.119	.213	1.232	.223

a. Dependent Variable: Ln of Fatalities

Model 12(e). Replication of Tay (1999) – High Alcohol Hour Serious Crashes

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.674	.455	.417	.21945

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.331	4	.583	12.099	.000
	Residual	2.793	58	.048		
	Total	5.124	62			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	5.895	1.251		4.713	.000
	Ln of all themes adstock	-.044	.038	-.127	-1.165	.249
	Ln of cbts	-.135	.107	-.200	-1.266	.210
	trend factors	-.010	.002	-.655	-5.196	.000
	Ln of December dummy	.297	.143	.306	2.086	.041

a. Dependent Variable: Nat log of HAH Serious injuries

Model 13(a). Replication of Tay (1999) – Autoregressive Model (EBTs)

FINAL PARAMETERS:

Estimate of Autocorrelation Coefficient

Rho	.63134704
Standard Error of Rho	.10271754

Cochrane-Orcutt Estimates

Multiple R	.72501452
R-Squared	.52564605
Adjusted R-Squared	.48329302
Standard Error	.1823479
Durbin-Watson	2.0031308

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	4	2.0633858	.51584646
Residuals	56	1.8620424	.03325076

Variables in the Equation:

	B	SEB	BETA	T	SIG T
December	.1592313	.0973222	.22535546	1.6361244	.10742228
Trend	.0194175	.0039290	.50910651	4.9421370	.00000737
CBTs	.2323763	.0817062	.39181398	2.8440485	.00620824
Adstock	-.0709193	.0692708	-.10469158	-1.0237977	.31033321
CONSTANT	4.5975580	1.0383603	.	4.4277099	.00004463

Model 13(b). Replication of Tay (1999) – Autoregressive Model (Drink-Drive Convictions)

FINAL PARAMETERS:

Estimate of Autocorrelation Coefficient

Rho	.52536597
Standard Error of Rho	.11270133

Cochrane-Orcutt Estimates

Multiple R	.63450285
R-Squared	.40259387
Adjusted R-Squared	.34925403
Standard Error	.10258193
Durbin-Watson	1.8886669

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	4	.39712501	.09928125
Residuals	56	.58929094	.01052305

Variables in the Equation:

	B	SEB	BETA	T	SIG T
December	.1946400	.05734144	.52573090	3.394404	.00126974
Trend	.0029785	.00175886	.20056959	1.693423	.09593120
CBTs	.0252039	.04778010	.08225456	.527497	.59993235
Adstock	.0108965	.03333664	.03794147	.326862	.74499103
CONSTANT	7.1846799	.58995596	.	12.178333	.00000000

Model 13(c). Replication of Tay (1999) – Autoregressive Model (Serious Crashes)

FINAL PARAMETERS:

Estimate of Autocorrelation Coefficient

Rho	.13543777
Standard Error of Rho	.13123279

Cochrane-Orcutt Estimates

Multiple R	.72121303
R-Squared	.52014823
Adjusted R-Squared	.47730432
Standard Error	.10478273
Durbin-Watson	2.0376259

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	4	.66648050	.16662013
Residuals	56	.61484752	.01097942

Variables in the Equation:

	B	SEB	BETA	T	SIG T
December	.0931207	.06715124	.19527796	1.3867311	.17101949
Trend	-.0051909	.00107225	-.55866605	-4.8411771	.00001055
CBTS	.0655980	.05220679	.18560495	1.2565034	.21414979
Adstock	-.0087757	.02079684	-.04439011	-.4219716	.67466138
CONSTANT	5.1038149	.61676655	.	8.2751163	.00000000

Model 13(d). Replication of Tay (1999) – Autoregressive Model (Fatalities)

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FINAL PARAMETERS:

Estimate of Autocorrelation Coefficient

Rho                       -.18517972
Standard Error of Rho     .13016241

Cochrane-Orcutt Estimates

Multiple R                .5314786
R-Squared                 .2824695
Adjusted R-Squared        .21840428
Standard Error            .18138167
Durbin-Watson             2.0228

            Analysis of Variance:

               DF   Sum of Squares      Mean Square

Regression      4          .7252805       .18132013
Residuals      56         1.8423614       .03289931

           Variables in the Equation:

                    B          SEB          BETA            T        SIG T

ln_all     -.0288751    .0267002   -.13921231   -1.0814568   .28412918
ln_cbts     .1115329    .0864188    .24702117    1.2906088   .20214258
trend      -.0012197    .0014406   -.12712073    -.8466615   .40078754
ln_dec      .1656809    .1211898    .24022201    1.3671194   .17705083
CONSTANT   2.7306808   1.0112987    .             2.7001722   .00914871
```

Model 13(e). Replication of Tay (1999) – Autoregressive Model (High Alcohol Hour Serious Crashes)

FINAL PARAMETERS:

Estimate of Autocorrelation Coefficient

Rho	.10915734
Standard Error of Rho	.13166176

Cochrane-Orcutt Estimates

Multiple R	.63362743
R-Squared	.40148371
Adjusted R-Squared	.34804476
Standard Error	.22161541
Durbin-Watson	2.0271706

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	4	1.8449301	.46123251
Residuals	56	2.7503499	.04911339

Variables in the Equation:

	B	SEB	BETA	T	SIG T
ln_all	-.0469858	.0427868	-.12903568	-1.0981378	.27684355
ln_cbts	-.1363995	.1103750	-.20483449	-1.2357821	.22169849
trend	-.0100398	.0022135	-.58791184	-4.5357905	.00003075
ln_dec	.3122044	.1429228	.34402574	2.1844277	.03313365
CONSTANT	5.9194559	1.3023626	.	4.5451672	.00002977

Model 14(a). Replication of Tay (1999) – Structural Change Model (EBTs)

FINAL PARAMETERS:

Estimate of Autocorrelation Coefficient

Rho	.59239732
Standard Error of Rho	.10863328

Cochrane-Orcutt Estimates

Multiple R	.76824975
R-Squared	.59020768
Adjusted R-Squared	.53708646
Standard Error	.17504601
Durbin-Watson	2.0180666

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	6	2.3830835	.39718058
Residuals	54	1.6546198	.03064111

Variables in the Equation:

	B	SEB	BETA	T	SIG T
DSRSP	2.3335279	.8813361	1.9690006	2.6477162	.01060024
Trend	.0238889	.0049130	.6828199	4.8623573	.00001041
December	.1480050	.0950719	.2031337	1.5567690	.12536731
CBTs	.2498716	.0798618	.4103696	3.1288006	.00282869
Adstock	.0722942	.0847571	.1120166	.8529584	.39744998
Sadstock	-.3920224	.1475258	-2.1844071	-2.6573138	.01033761
CONSTANT	3.5619724	1.0705945	.	3.3270976	.00158405

Model 14(b). Replication of Tay (1999) – Structural Change Model (Drink-Drive Convictions)

FINAL PARAMETERS:

Estimate of Autocorrelation Coefficient

Rho	.50263941
Standard Error of Rho	.11656864

Cochrane-Orcutt Estimates

Multiple R	.66789553
R-Squared	.44608444
Adjusted R-Squared	.37428057
Standard Error	.10023569
Durbin-Watson	1.8828274

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	6	.43693017	.07282169
Residuals	54	.54254844	.01004719

Variables in the Equation:

	B	SEB	BETA	T	SIG T
DSRSP	.8749436	.47114771	1.7541463	1.857047	.06876193
Trend	.0020979	.00241925	.1485619	.867187	.38967703
December	.1947073	.05657996	.5230058	3.441277	.00112474
CBTs	.0298413	.04715639	.0972319	.632815	.52952493
Adstock	.0336495	.04336363	.1217157	.775985	.44114313
Sadstock	-.1248663	.07724807	-1.6785270	-1.616432	.11182871
CONSTANT	7.0014871	.61102213	.	11.458647	.00000000

Model 14(c). Replication of Tay (1999) – Structural Change Model (Serious Crashes)

FINAL PARAMETERS:

Estimate of Autocorrelation Coefficient

Rho	-.00105781
Standard Error of Rho	.1348399

Cochrane-Orcutt Estimates

Multiple R	.80141225
R-Squared	.6422616
Adjusted R-Squared	.5958881
Standard Error	.09836673
Durbin-Watson	1.9987966

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	6	.93807303	.15634550
Residuals	54	.52250477	.00967601

Variables in the Equation:

	B	SEB	BETA	T	SIG T
DSRSP	-.2335493	.31863032	-.7288018	-.7329789	.46674135
Trend	-.0084503	.00135097	-.9863029	-6.2549869	.00000000
December	.0826973	.06482957	.1592802	1.2756106	.20755342
CBTs	.0723914	.04871464	.1984163	1.4860294	.14308674
Adstock	-.0617869	.02430166	-.3358628	-2.5424974	.01390641
Sadstock	.0636597	.04904424	1.3638855	1.2980061	.19980217
CONSTANT	5.3429885	.57919824	.	9.2248009	.00000000

Model 14(d). Replication of Tay (1999) – Structural Change Model (Fatalities)

FINAL PARAMETERS:

Estimate of Autocorrelation Coefficient

Rho	-.18465197
Standard Error of Rho	.13252126

Cochrane-Orcutt Estimates

Multiple R	.53144883
R-Squared	.28243786
Adjusted R-Squared	.18942055
Standard Error	.18469736
Durbin-Watson	2.0218908

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	6	.7250676	.12084460
Residuals	54	1.8421081	.03411311

Variables in the Equation:

	B	SEB	BETA	T	SIG T
DSRSP	.0041258	.1275672	.01145739	.0323421	.97431845
trend	-.0011770	.0021659	-.12262021	-.5434000	.58909073
ln_dec	.1660451	.1235592	.24076323	1.3438497	.18461644
ln_cbts	.1115101	.0883350	.24693690	1.2623544	.21224594
ln_all	-.0269384	.0375685	-.12983115	-.7170479	.47643475
Sadstock	-.0000084	.0001026	-.02546256	-.0819295	.93500573
CONSTANT	2.7197588	1.0378495	.	2.6205715	.01137639

Model 14(e). Replication of Tay (1999) – Structural Change Model (High Alcohol Hour Serious Crashes)

FINAL PARAMETERS:

Estimate of Autocorrelation Coefficient

Rho	-.01658701
Standard Error of Rho	.13482142

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Cochrane-Orcutt Estimates

Multiple R	.71527932
R-Squared	.5116245
Adjusted R-Squared	.44831657
Standard Error	.21496427
Durbin-Watson	1.9881069

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	6	2.6141097	.43568495
Residuals	54	2.4953205	.04620964

Variables in the Equation:

	B	SEB	BETA	T	SIG T
DSRSP	.3588722	.6885736	.60781364	.5211821	.60437082
trend	-.0154720	.0029139	-.98049476	-5.3096351	.00000212
ln_dec	.2982543	.1420031	.30674747	2.1003362	.04038473
ln_cbts	-.1267525	.1062491	-.18665643	-1.1929750	.23809460
ln_all	-.1122868	.0523559	-.33114912	-2.1446819	.03649511
Ln_Sadst	-.0067915	.1058974	-.07898815	-.0641330	.94910113
CONSTANT	6.2044175	1.2619238	.	4.9166339	.00000860

Model 15(a). Replication of Tay (2001) Model (EBTs)

FINAL PARAMETERS:

Estimate of Autocorrelation Coefficient

Rho	.59048201
Standard Error of Rho	.11191781

Cochrane-Orcutt Estimates

Multiple R	.74089549
R-Squared	.54892613
Adjusted R-Squared	.46048027
Standard Error	.18912116
Durbin-Watson	2.0505981

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	9	2.2198144	.24664605
Residuals	51	1.8241076	.03576681

Variables in the Equation:

	B	SEB	BETA	T	SIG T
ln_jul	.1622846	.0899060	.20850908	1.8050475	.07697232
ln_aug	.0339119	.0994650	.04357124	.3409430	.73454710
ln_sept	.0050360	.0890651	.00647039	.0565425	.95513056
ln_ncars	.0313481	.1976823	.01570728	.1585783	.87462741
trend	.0239259	.0487318	.68656403	.4909718	.62555249
ln_cbts	.3877992	.1439155	.63603965	2.6946319	.00951763
CBT_Trend	-.0012011	.0038937	-.39719492	-.3084810	.75897287
Advert	-.1976015	.3791118	-.16719060	-.5212222	.60446807
Advert_T	.0102723	.0174127	.39048368	.5899279	.55784376
CONSTANT	2.2033153	2.5889136	.	.8510579	.39871556

Model 15(b). Replication of Tay (2001) Model (Drink-Drive Convictions)

```
FINAL PARAMETERS:

Estimate of Autocorrelation Coefficient

Rho                      .36959965
Standard Error of Rho    .12885562

Cochrane-Orcutt Estimates

Multiple R               .66712596
R-Squared                .44505704
Adjusted R-Squared       .3362447
Standard Error           .1023094
Durbin-Watson           1.8789151
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Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	9	.42812300	.04756922
Residuals	51	.53382784	.01046721

Variables in the Equation:

	B	SEB	BETA	T	SIG T
ln_jul	.1502787	.0507976	.3600807	2.9583808	.00467905
ln_aug	.1367691	.0535196	.3277103	2.5554932	.01362828
ln_sept	.0869295	.0498519	.2082905	1.7437534	.08722760
ln_ncars	-.0447646	.1130438	-.0471912	-.3959939	.69376138
trend	.0527961	.0270234	4.7817009	1.9537200	.05622971
ln_cbts	.3005123	.0829159	.9689222	3.6243035	.00066808
CBT_Tren	-.0038432	.0021954	-3.9577651	-1.7505535	.08603653
Advert	.3170438	.1410539	.7878585	2.2476787	.02894980
Advert_T	-.0088346	.0064231	-1.0313977	-1.3754407	.17500647
CONSTANT	4.3660095	1.5013412	.	2.9080728	.00537314

Model 15(c). Replication of Tay (2001) Model (Serious Crashes)

FINAL PARAMETERS:

Estimate of Autocorrelation Coefficient

Rho	.02331424
Standard Error of Rho	.13863736

Cochrane-Orcutt Estimates

Multiple R	.82103055
R-Squared	.67409116
Adjusted R-Squared	.61018747
Standard Error	.09854288
Durbin-Watson	2.0020369

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	9	1.0243378	.11381531
Residuals	51	.4952457	.00971070

Variables in the Equation:

	B	SEB	BETA	T	SIG T
ln_jul	-.0958813	.0509580	-.1671484	-1.8815772	.06560674
ln_aug	-.1162626	.0492519	-.2026788	-2.3605711	.02210833
ln_sept	-.0950507	.0485527	-.1657004	-1.9576815	.05574986
ln_ncars	.0244543	.1096905	.0239364	.2229388	.82447361
trend	-.0106091	.0254417	-1.1844411	-.4169983	.67842973
ln_cbts	-.0001324	.0818265	-.0003531	-.0016177	.99871560
CBT_Tren	.0008158	.0020758	1.0295792	.3930179	.69594433
Advert	.2287960	.0999426	.6833671	2.2892733	.02623648
Advert_T	-.0081045	.0043660	-1.1524774	-1.8562808	.06919501
CONSTANT	5.1388853	1.4981828	.	3.4300789	.00120345

Model 15(d). Replication of Tay (2001) Model (Fatalities)

FINAL PARAMETERS:

Estimate of Autocorrelation Coefficient

Rho	-.1443049
Standard Error of Rho	.13342864

Cochrane-Orcutt Estimates

Multiple R	.52408246
R-Squared	.27466242
Adjusted R-Squared	.18063718
Standard Error	.18455469
Durbin-Watson	2.0205823

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	6	.6964710	.11607849
Residuals	54	1.8392635	.03406043

Variables in the Equation:

	B	SEB	BETA	T	SIG T
ln_ncars	.26524756	.1940072	.2219726	1.3672047	.17722564
trend	-.02327410	.0450758	-2.3566940	-.5163322	.60773049
ln_cbts	.13982826	.1459151	.3063223	.9582853	.34218991
CBT_Tren	.00186388	.0036769	2.1310366	.5069219	.61427349
Advert	-.15733745	.1669176	-.4248491	-.9426053	.35008099
Advert_T	.00268357	.0072266	.3453133	.3713430	.71183510
CONSTANT	-.26325924	2.7202901	.	-.0967762	.92326244

Model 15(e). Replication of Tay (2001) Model (High Alcohol Hour Serious Crashes)

FINAL PARAMETERS:

Estimate of Autocorrelation Coefficient

Rho	-.1332072
Standard Error of Rho	.13743921

Cochrane-Orcutt Estimates

Multiple R	.75497555
R-Squared	.56998809
Adjusted R-Squared	.48567203
Standard Error	.21981518
Durbin-Watson	1.981097

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	9	3.2664110	.36293455
Residuals	51	2.4642544	.04831871

Variables in the Equation:

	B	SEB	BETA	T	SIG T
ln_jul	-.11688750	.1151732	-.1043920	-1.0148845	.31495161
ln_aug	.04373678	.1086492	.0390612	.4025504	.68896137
ln_sept	-.12034026	.1082271	-.1074756	-1.1119230	.27138548
ln_ncars	.14884938	.2371624	.0823015	.6276265	.53304891
trend	.09292475	.0544914	6.1983860	1.7053118	.09422095
ln_cbts	.27654002	.1783973	.4011767	1.5501360	.12729277
CBT_Tren	.00738903	.0044469	-5.5654808	-1.6616267	.10272339
Advert	.53880618	.2019804	.9585482	2.6676158	.01021357
Advert_T	-.02410266	.0086904	-2.0433181	-2.7734732	.00772807
CONSTANT	-.78968078	3.2755161	.	-.2410859	.81045516

APPENDIX 3. OUTPUT FOR CHAPTER 5 – THE 2SLS MODELLING PROCESS

2SLS Model Specifications

Table 37. 2SLS Model Specifications –Model 16 Series

	Model Number			
	16(a)	16(b)	16(c)	16(d)
Endogenous Variables				
Dependent				
EBTs (Y_{1a})	x	x	x	x
Drink-drive Convictions(Y_{1b})				
Serious Crashes (Y_{1c})				
Fatalities (Y_{1d})				
High Alcohol Hour Serious Crashes (Y_{1e})				
Alcohol-related Serious Crashes (Y_{1f})				
Alcohol-related Fatalities (Y_{1g})				
Explanatory				
All-theme TARPs (Y_{2a})	x			
Drink-drive TARPs (Y_{2b})			x	
All-theme Adstock (Y_{2c})		x		x
Drink-drive Adstock(Y_{2d})				
Compulsory Breath Tests (Y_3)	x	x	x	x
Exogenous Variables				
Explanatory				
Unemployment (x_4)	x	x	x	x
Trend (x_6)	x	x	x	x
Seasonal Dummy Variables (x_{7-17})	x	x	x	x
Instrumental Only				
12 mth lag All-theme TARPs (z_{18})	x	x		
12 mth lag Drink-drive TARPs (z_{19})			x	x
12 mth lag Drink-drive Convictions (z_{20})	x	x	x	x
12 mth lag Fatalities (z_{21})	x	x	x	x
1 mth lag Fatalities (z_{22})	x	x	x	x
12 mth lag Alcohol-related Crashes (z_{23})	x	x	x	x
12 mth lag Alcohol-related Fatalities (z_{24})	x	x	x	x
12 mth lag Road Injuries (z_{25})	x	x	x	x
12 mth lag CBTs (z_{26})	x	x	x	x
1 mth lag CBTs (z_{27})	x	x	x	x
1 mth lag EBTs (z_{28})				
12 mth lag Serious Crashes (z_{29})	x	x	x	x
12 mth lag HAH* Serious Crashes (z_{30})	x	x	x	x

*HAH = High Alcohol Hour. **X** denotes presence in model

Table 38. 2SLS Model Specifications –Model 17 Series

	Model Number			
	17(a)	**17(b)**	**17(c)**	**17(d)**
Endogenous Variables				
Dependent				
EBTs (Y_{1a})				
Drink-drive Convictions(Y_{1b})	x	x	x	x
Serious Crashes (Y_{1c})				
Fatalities (Y_{1d})				
High Alcohol Hour Serious Crashes (Y_{1e})				
Alcohol-related Serious Crashes (Y_{1f})				
Alcohol-related Fatalities (Y_{1g})				
Explanatory				
All-theme TARPs (Y_{2a})		x		
Drink-drive TARPs (Y_{2b})				x
All-theme Adstock (Y_{2c})	x			
Drink-drive Adstock(Y_{2d})			x	
Compulsory Breath Tests (Y_3)	x	x	x	x
Exogenous Variables				
Explanatory				
Unemployment (x_4)	x	x	x	x
Trend (x_6)	x	x	x	x
Seasonal Dummy Variables (x_{7-17})	x	x	x	x
Instrumental Only				
12 mth lag All-theme TARPs (z_{18})	x	x		
12 mth lag Drink-drive TARPs (z_{19})			x	x
12 mth lag Drink-drive Convictions (z_{20})				
12 mth lag Fatalities (z_{21})	x	x	x	x
1 mth lag Fatalities (z_{22})	x	x	x	x
12 mth lag Alcohol-related Crashes (z_{23})	x	x	x	x
12 mth lag Alcohol-related Fatalities (z_{24})	x	x	x	x
12 mth lag Road Injuries (z_{25})	x	x	x	x
12 mth lag CBTs (z_{26})	x	x	x	x
1 mth lag CBTs (z_{27})	x	x	x	x
1 mth lag EBTs (z_{28})	x	x	x	x
12 mth lag Serious Crashes (z_{29})	x	x	x	x
12 mth lag HAH* Serious Crashes (z_{30})	x	x	x	x

*HAH = High Alcohol Hour. **X** denotes presence in model

Table 39. 2SLS Model Specifications –Model 18 Series

	Model Number			
	18(a)	18(b)	18(c)	18(d)
Endogenous Variables				
Dependent				
EBTs (Y_{1a})				
Drink-drive Convictions(Y_{1b})				
Serious Crashes (Y_{1c})	x	x	x	x
Fatalities (Y_{1d})				
High Alcohol Hour Serious Crashes (Y_{1e})				
Alcohol-related Serious Crashes (Y_{1f})				
Alcohol-related Fatalities (Y_{1g})				
Explanatory				
All-theme TARPs (Y_{2a})		x		
Drink-drive TARPs (Y_{2b})				x
All-theme Adstock (Y_{2c})	x			
Drink-drive Adstock(Y_{2d})			x	
Compulsory Breath Tests (Y_3)	x	x	x	x
Exogenous Variables				
Explanatory				
Unemployment (x_4)	x	x	x	x
New Car Registrations (x_5)	x	x	x	x
Trend (x_6)	x	x	x	x
Seasonal Dummy Variables (x_{7-17})	x	x	x	x
Instrumental Only				
12 mth lag All-theme TARPs (z_{18})	x	x		
12 mth lag Drink-drive TARPs (z_{19})			x	x
12 mth lag Drink-drive Convictions (z_{20})	x	x	x	x
12 mth lag Fatalities (z_{21})	x	x	x	x
1 mth lag Fatalities (z_{22})	x	x	x	x
12 mth lag Alcohol-related Crashes (z_{23})	x	x	x	x
12 mth lag Alcohol-related Fatalities (z_{24})	x	x	x	x
12 mth lag Road Injuries (z_{25})	x	x	x	x
12 mth lag CBTs (z_{26})	x	x	x	x
1 mth lag CBTs (z_{27})	x	x	x	x
1 mth lag EBTs (z_{28})	x	x	x	x
12 mth lag Serious Crashes (z_{29})				
12 mth lag HAH* Serious Crashes (z_{30})	x	x	x	x

*HAH = High Alcohol Hour. **X** denotes presence in model

Table 40. 2SLS Model Specifications –Model 19 Series

	Model Number			
	19(a)	**19(b)**	**19(c)**	**19(d)**
Endogenous Variables				
Dependent				
EBTs (Y_{1a})				
Drink-drive Convictions(Y_{1b})				
Serious Crashes (Y_{1c})				
Fatalities (Y_{1d})	**x**	**x**	**x**	**x**
High Alcohol Hour Serious Crashes (Y_{1e})				
Alcohol-related Serious Crashes (Y_{1f})				
Alcohol-related Fatalities (Y_{1g})				
Explanatory				
All-theme TARPs (Y_{2a})	**x**	**x**	**x**	**x**
Drink-drive TARPs (Y_{2b})	**x**	**x**	**x**	**x**
All-theme Adstock (Y_{2c})	**x**	**x**	**x**	**x**
Drink-drive Adstock(Y_{2d})	**x**	**x**	**x**	**x**
Compulsory Breath Tests (Y_3)	**x**	**x**	**x**	**x**
Exogenous Variables				
Explanatory				
Unemployment (x_4)	**x**	**x**	**x**	**x**
New Car Registrations (x_5)	**x**	**x**	**x**	**x**
Trend (x_6)	**x**	**x**	**x**	**x**
Seasonal Dummy Variables (x_{7-17})	**x**	**x**	**x**	**x**
Instrumental Only				
12 mth lag All-theme TARPs (z_{18})	**x**	**x**		
12 mth lag Drink-drive TARPs (z_{19})			**x**	**x**
12 mth lag Drink-drive Convictions (z_{20})	**x**	**x**	**x**	**x**
12 mth lag Fatalities (z_{21})	**x**	**x**	**x**	**x**
1 mth lag Fatalities (z_{22})	**x**	**x**	**x**	**x**
12 mth lag Alcohol-related Crashes (z_{23})	**x**	**x**	**x**	**x**
12 mth lag Alcohol-related Fatalities (z_{24})	**x**	**x**	**x**	**x**
12 mth lag Road Injuries (z_{25})	**x**	**x**	**x**	**x**
12 mth lag CBTs (z_{26})	**x**	**x**	**x**	**x**
1 mth lag CBTs (z_{27})	**x**	**x**	**x**	**x**
1 mth lag EBTs (z_{28})	**x**	**x**	**x**	**x**
12 mth lag Serious Crashes (z_{29})	**x**	**x**	**x**	**x**
12 mth lag HAH* Serious Crashes (z_{30})	**x**	**x**	**x**	**x**

*HAH = High Alcohol Hour. **X** denotes presence in model

Table 41. 2SLS Model Specifications – Model 20 Series

	Model Number			
	22(a)	20(b)	20(c)	20(d)
Endogenous Variables				
Dependent				
EBTs (Y_{1a})				
Drink-drive Convictions(Y_{1b})				
Serious Crashes (Y_{1c})				
Fatalities (Y_{1d})				
High Alcohol Hour Serious Crashes (Y_{1e})	x	x	x	x
Alcohol-related Serious Crashes (Y_{1f})				
Alcohol-related Fatalities (Y_{1g})				
Explanatory				
All-theme TARPs (Y_{2a})	x			
Drink-drive TARPs (Y_{2b})			x	
All-theme Adstock (Y_{2c})		x		
Drink-drive Adstock(Y_{2d})				x
Compulsory Breath Tests (Y_3)	x	x	x	x
Exogenous Variables				
Explanatory				
Unemployment (x_4)	x	x	x	x
New Car Registrations (x_5)	x	x	x	x
Trend (x_6)	x	x	x	x
Seasonal Dummy Variables (x_{7-17})	x	x	x	x
Instrumental Only				
12 mth lag All-theme TARPs (z_{18})	x	x		
12 mth lag Drink-drive TARPs (z_{19})			x	x
12 mth lag Drink-drive Convictions (z_{20})	x	x	x	x
12 mth lag Fatalities (z_{21})	x	x	x	x
1 mth lag Fatalities (z_{22})	x	x	x	x
12 mth lag Alcohol-related Crashes (z_{23})	x	x	x	x
12 mth lag Alcohol-related Fatalities (z_{24})	x	x	x	x
12 mth lag Road Injuries (z_{25})	x	x	x	x
12 mth lag CBTs (z_{26})	x	x	x	x
1 mth lag CBTs (z_{27})	x	x	x	x
1 mth lag EBTs (z_{28})	x	x	x	x
12 mth lag Serious Crashes (z_{29})	x	x	x	x
12 mth lag HAH* Serious Crashes (z_{30})				

*HAH = High Alcohol Hour. **X** denotes presence in model

Table 42. 2SLS Model Specifications –Model 21 Series

	Model Number			
	21(a)	21(b)	21(c)	21(d)
Endogenous Variables				
Dependent				
EBTs (Y_{1a})				
Drink-drive Convictions(Y_{1b})				
Serious Crashes (Y_{1c})				
Fatalities (Y_{1d})				
High Alcohol Hour Serious Crashes (Y_{1e})				
Alcohol-related Serious Crashes (Y_{1f})	x	x	x	x
Alcohol-related Fatalities (Y_{1g})				
Explanatory				
All-theme TARPs (Y_{2a})		x		
Drink-drive TARPs (Y_{2b})				x
All-theme Adstock (Y_{2c})	x			
Drink-drive Adstock(Y_{2d})			x	
Compulsory Breath Tests (Y_3)	x	x	x	x
Exogenous Variables				
Explanatory				
Unemployment (x_4)	x	x	x	x
New Car Registrations (x_5)	x	x	x	x
Trend (x_6)	x	x	x	x
Seasonal Dummy Variables (x_{7-17})	x	x	x	x
Instrumental Only				
12 mth lag All-theme TARPs (z_{18})	x	x		
12 mth lag Drink-drive TARPs (z_{19})			x	x
12 mth lag Drink-drive Convictions (z_{20})	x	x	x	x
12 mth lag Fatalities (z_{21})	x	x	x	x
1 mth lag Fatalities (z_{22})	x	x	x	x
12 mth lag Alcohol-related Crashes (z_{23})				
12 mth lag Alcohol-related Fatalities (z_{24})	x	x	x	x
12 mth lag Road Injuries (z_{25})	x	x	x	x
12 mth lag CBTs (z_{26})	x	x	x	x
1 mth lag CBTs (z_{27})	x	x	x	x
1 mth lag EBTs (z_{28})	x	x	x	x
12 mth lag Serious Crashes (z_{29})	x	x	x	x
12 mth lag HAH* Serious Crashes (z_{30})	x	x	x	x

*HAH = High Alcohol Hour. **X** denotes presence in model

Table 43. 2SLS Model Specifications –Model 22 Series

	Model Number			
	22(a)	22(b)	22(c)	22(d)
Endogenous Variables				
Dependent				
EBTs (Y_{1a})				
Drink-drive Convictions(Y_{1b})				
Serious Crashes (Y_{1c})				
Fatalities (Y_{1d})				
High Alcohol Hour Serious Crashes (Y_{1e})				
Alcohol-related Serious Crashes (Y_{1f})				
Alcohol-related Fatalities (Y_{1g})	x	x	x	x
Explanatory				
All-theme TARPs (Y_{2a})	x			
Drink-drive TARPs (Y_{2b})			x	
All-theme Adstock (Y_{2c})		x		
Drink-drive Adstock(Y_{2d})				x
Compulsory Breath Tests (Y_3)	x	x	x	x
Exogenous Variables				
Explanatory				
Unemployment (x_4)	x	x	x	x
New Car Registrations (x_5)	x	x	x	x
Trend (x_6)	x	x	x	x
Seasonal Dummy Variables (x_{7-17})	x	x	x	x
Instrumental Only				
12 mth lag All-theme TARPs (z_{18})	x	x		
12 mth lag Drink-drive TARPs (z_{19})			x	x
12 mth lag Drink-drive Convictions (z_{20})	x	x	x	x
12 mth lag Fatalities (z_{21})	x	x	x	x
1 mth lag Fatalities (z_{22})	x	x	x	x
12 mth lag Alcohol-related Crashes (z_{23})	x	x	x	x
12 mth lag Alcohol-related Fatalities (z_{24})				
12 mth lag Road Injuries (z_{25})	x	x	x	x
12 mth lag CBTs (z_{26})	x	x	x	x
1 mth lag CBTs (z_{27})	x	x	x	x
1 mth lag EBTs (z_{28})	x	x	x	x
12 mth lag Serious Crashes (z_{29})	x	x	x	x
12 mth lag HAH* Serious Crashes (z_{30})	x	x	x	x

*HAH = High Alcohol Hour. **X** denotes presence in model

2SLS Model Output

Model 16(a). 2SLS – EBTs by All-Theme TARPs

```
Dependent variable.. Y1a_ebts

Listwise Deletion of Missing Data

Multiple R           .84687
R Square             .71719
Adjusted R Square    .62693
Standard Error       .23347

            Analysis of Variance:

               DF   Sum of Squares      Mean Square

Regression     15        6.4967953        .43311969
Residuals      47        2.5618812        .05450811

F =       7.94597       Signif F =  .0000

------------------ Variables in the Equation ------------------

Variable              B          SE B        Beta          T  Sig T

Y2a_all_      -.000128       .019689   -.000819      -.006  .9949
Y3_cbts        .868049       .401762    .966239      2.161  .0359
x4_unem        .411995       .299813    .118035      1.374  .1759
x6_trend       .022256       .004003   1.064995      5.560  .0000
x7_feb         .386036       .206022    .274595      1.874  .0672
x8_mar         .359641       .163155    .255820      2.204  .0324
x9_apr         .391760       .161735    .278666      2.422  .0193
x10_may        .512549       .181174    .364586      2.829  .0068
x11_jun        .498715       .221386    .354745      2.253  .0290
x12_jul        .765871       .280809    .544779      2.727  .0089
x13_aug        .549984       .215399    .391214      2.553  .0140
x14_sept       .572331       .220155    .407110      2.600  .0124
x15_oct        .395442       .143018    .305465      2.765  .0081
x16_nov        .410031       .159614    .316734      2.569  .0134
x17_dec       -.182013       .324779   -.140598      -.560  .5779
(Constant)   -8.558408      5.224819                -1.638  .1081
```

Model 16(b). 2SLS –EBTs by All-Theme Adstock

Dependent variable.. Y1a_ebts

Listwise Deletion of Missing Data

Multiple R	.84943
R Square	.72153
Adjusted R Square	.63265
Standard Error	.23106

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	15	6.5018360	.43345573
Residuals	47	2.5093674	.05339080

F = 8.11855 Signif F = .0000

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
Y2c_all_	.014854	.048333	.032349	.307	.7599
Y3_cbts	.818873	.422706	.911500	1.937	.0587
x4_unem	.414929	.293581	.118875	1.413	.1641
x6_trend	.021542	.004225	1.030820	5.099	.0000
x7_feb	.369963	.208721	.263162	1.773	.0828
x8_mar	.354294	.162247	.252016	2.184	.0340
x9_apr	.386726	.160898	.275086	2.404	.0202
x10_may	.505251	.179982	.359394	2.807	.0073
x11_jun	.482063	.222020	.342900	2.171	.0350
x12_jul	.739088	.289812	.525727	2.550	.0141
x13_aug	.533450	.219123	.379453	2.434	.0188
x14_sept	.556490	.222664	.395842	2.499	.0160
x15_oct	.399994	.142217	.308981	2.813	.0072
x16_nov	.403541	.158825	.311721	2.541	.0144
x17_dec	-.145380	.341579	-.112301	-.426	.6723
(Constant)	-8.096427	5.380111		-1.505	.1390

Model 16(c). 2SLS – EBTs by Drink-Drive TARPs

Dependent variable.. Y1a_ebts

Listwise Deletion of Missing Data

Multiple R	.85623
R Square	.73313
Adjusted R Square	.64796
Standard Error	.22191

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	15	6.3580023	.42386682
Residuals	47	2.3144065	.04924269

F = 8.60771 Signif F = .0000

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
Y2b_dd_T	-.004613	.020260	-.032337	-.228	.8209
Y3_cbts	.679854	.449177	.756756	1.514	.1368
x4_unem	.417275	.305607	.119547	1.365	.1786
x6_trend	.020852	.003909	.997833	5.334	.0000
x7_feb	.313769	.216706	.223190	1.448	.1543
x8_mar	.323807	.162766	.230330	1.989	.0525
x9_apr	.363478	.158105	.258549	2.299	.0260
x10_may	.467846	.181397	.332788	2.579	.0131
x11_jun	.426327	.227965	.303254	1.870	.0677
x12_jul	.645108	.310334	.458878	2.079	.0431
x13_aug	.470213	.230293	.334472	2.042	.0468
x14_sept	.489522	.235824	.348206	2.076	.0434
x15_oct	.400004	.136646	.308989	2.927	.0053
x16_nov	.368382	.163201	.284562	2.257	.0287
x17_dec	-.033052	.366039	-.025531	-.090	.9284
(Constant)	-6.362523	5.901254		-1.078	.2865

Model 16(d). 2SLS – EBTs by Drink-Drive Adstock

Dependent variable.. Y1a_ebts

Listwise Deletion of Missing Data

Multiple R	.85553
R Square	.73193
Adjusted R Square	.64637
Standard Error	.22270

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	15	6.3643722	.42429148
Residuals	47	2.3309668	.04959504

F = 8.55512 Signif F = .0000

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
Y2d_dd_a	.021534	.050768	.049556	.424	.6734
Y3_cbts	.583420	.517531	.649414	1.127	.2653
x4_unem	.477051	.297239	.136673	1.605	.1152
x6_trend	.019490	.005065	.932656	3.848	.0004
x7_feb	.289140	.228061	.205671	1.268	.2111
x8_mar	.320416	.162287	.227918	1.974	.0542
x9_apr	.356230	.159922	.253394	2.228	.0307
x10_may	.448225	.188563	.318831	2.377	.0216
x11_jun	.391146	.245415	.278230	1.594	.1177
x12_jul	.607860	.328197	.432383	1.852	.0703
x13_aug	.457666	.232217	.325546	1.971	.0546
x14_sept	.477974	.236898	.339992	2.018	.0494
x15_oct	.422298	.144397	.326210	2.925	.0053
x16_nov	.375923	.157945	.290387	2.380	.0214
x17_dec	.030725	.407951	.023734	.075	.9403
(Constant)	-6.068278	5.806649		-1.045	.3013

Model 17(a). 2SLS – Drink-Drive Convictions by All-Theme Adstock

Dependent variable.. Y1b_conv

Listwise Deletion of Missing Data

Multiple R	.81580
R Square	.66553
Adjusted R Square	.55879
Standard Error	.08886

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	15	.73838104	.04922540
Residuals	47	.37107589	.00789523

F = 6.23483 Signif F = .0000

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
Y2c_all_	.020326	.017995	.125734	1.129	.2644
Y3_cbts	-.049862	.114369	-.157655	-.436	.6648
x4_unem	.204333	.111618	.166286	1.831	.0735
x6_trend	.001431	.001207	.194476	1.185	.2419
x7_feb	-.057114	.069401	-.115400	-.823	.4147
x8_mar	.101266	.059813	.204609	1.693	.0971
x9_apr	.134702	.059694	.272167	2.257	.0287
x10_may	.197318	.063967	.398685	3.085	.0034
x11_jun	.108480	.072780	.219185	1.491	.1428
x12_jul	.169743	.088556	.342968	1.917	.0614
x13_aug	.209601	.072036	.423503	2.910	.0055
x14_sept	.184453	.073112	.372691	2.523	.0151
x15_oct	.219177	.054364	.480919	4.032	.0002
x16_nov	.121805	.057774	.267265	2.108	.0404
x17_dec	.345693	.099981	.758521	3.458	.0012
(Constant)	10.378255	1.737274		5.974	.0000

Model 17(b). 2SLS – Drink-Drive Convictions by All-Theme TARPs

```
Dependent variable.. Y1b_conv

Listwise Deletion of Missing Data

Multiple R           .83207
R Square             .69235
Adjusted R Square    .59416
Standard Error       .08590

            Analysis of Variance:

               DF   Sum of Squares      Mean Square

Regression     15        .78051358        .05203424
Residuals      47        .34683069        .00737938

F =       7.05131       Signif F =  .0000
```

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
Y2a_all_	.019937	.007496	.363274	2.660	.0107
Y3_cbts	-.045063	.109915	-.142480	-.410	.6837
x4_unem	.164285	.108589	.133695	1.513	.1370
x6_trend	.000657	.001180	.089300	.557	.5802
x7_feb	-.059600	.067072	-.120423	-.889	.3787
x8_mar	.102689	.057823	.207486	1.776	.0822
x9_apr	.144614	.057850	.292194	2.500	.0160
x10_may	.228180	.063083	.461041	3.617	.0007
x11_jun	.093425	.070627	.188768	1.323	.1923
x12_jul	.182654	.085538	.369055	2.135	.0380
x13_aug	.217599	.069653	.439662	3.124	.0031
x14_sept	.185923	.070683	.375661	2.630	.0115
x15_oct	.217857	.052453	.478022	4.153	.0001
x16_nov	.118820	.055857	.260716	2.127	.0387
x17_dec	.317826	.096331	.697375	3.299	.0019
(Constant)	9.882058	1.682322		5.874	.0000

Model 17(c). 2SLS – Drink-Drive Convictions by Drink-Drive Adstock

```
Dependent variable.. Y1b_conv

Listwise Deletion of Missing Data

Multiple R           .81260
R Square             .66032
Adjusted R Square    .55192
Standard Error       .08973

            Analysis of Variance:

               DF   Sum of Squares      Mean Square

Regression     15        .73560144        .04904010
Residuals      47        .37839952        .00805105

F =       6.09114       Signif F =  .0000

------------------ Variables in the Equation ------------------

Variable               B          SE B         Beta          T  Sig T

Y2d_dd_a         .018424       .018487      .120434       .997  .3241
Y3_cbts         -.024700       .118837     -.078096      -.208  .8362
x4_unem          .187792       .113781      .152825      1.650  .1055
x6_trend         .001664       .001251      .226235      1.330  .1899
x7_feb          -.046421       .070694     -.093794      -.657  .5146
x8_mar           .108644       .060725      .219517      1.789  .0800
x9_apr           .141812       .060560      .286533      2.342  .0235
x10_may          .203022       .064934      .410209      3.127  .0030
x11_jun          .119918       .074273      .242297      1.615  .1131
x12_jul          .191514       .090744      .386957      2.110  .0402
x13_aug          .231892       .074176      .468542      3.126  .0030
x14_sept         .206839       .075530      .417921      2.738  .0087
x15_oct          .227697       .056468      .499612      4.032  .0002
x16_nov          .138395       .059909      .303667      2.310  .0253
x17_dec          .329574       .103363      .723152      3.189  .0025
(Constant)      9.900489      1.774072                   5.581  .0000
```

Model 17(d). 2SLS – Drink-Drive Convictions by Drink-Drive TARPs

Dependent variable.. Y1b_conv

Listwise Deletion of Missing Data

Multiple R	.82419
R Square	.67928
Adjusted R Square	.57693
Standard Error	.08713

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	15	.75573853	.05038257
Residuals	47	.35681228	.00759175

F = 6.63649 Signif F = .0000

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
Y2b_dd_T	.015782	.008198	.314241	1.925	.0603
Y3_cbts	.048227	.118331	.152484	.408	.6855
x4_unem	.118222	.118038	.096209	1.002	.3217
x6_trend	.002220	.001107	.301803	2.006	.0506
x7_feb	-.005932	.071530	-.011986	-.083	.9343
x8_mar	.129015	.060208	.260677	2.143	.0373
x9_apr	.145641	.058813	.294271	2.476	.0169
x10_may	.207224	.063106	.418699	3.284	.0019
x11_jun	.132793	.072412	.268310	1.834	.0730
x12_jul	.253855	.094080	.512917	2.698	.0097
x13_aug	.266106	.074976	.537671	3.549	.0009
x14_sept	.241736	.076387	.488431	3.165	.0027
x15_oct	.222481	.053382	.488168	4.168	.0001
x16_nov	.160858	.059708	.352954	2.694	.0098
x17_dec	.235533	.107665	.516807	2.188	.0337
(Constant)	8.229783	1.951740		4.217	.0001

Model 18(a). 2SLS – Serious Crashes by All-Theme Adstock

Dependent variable.. Y1c_serious_crash

Listwise Deletion of Missing Data

Multiple R	.86645
R Square	.75073
Adjusted R Square	.66403
Standard Error	.09558

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	16	1.2655752	.07909845
Residuals	46	.4202180	.00913517

F = 8.65867 Signif F = .0000

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
Y2c_all_	-.015092	.019163	-.077160	-.788	.4350
Y3_cbts	-.126241	.120016	-.329898	-1.052	.2984
x4_unem	-.340436	.169590	-.228977	-2.007	.0506
x5_ncars	.024343	.131802	.023799	.185	.8543
x6_trend	-.006892	.001331	-.774242	-5.178	.0000
x7_feb	-.095549	.074337	-.159562	-1.285	.2051
x8_mar	.063331	.064961	.105760	.975	.3347
x9_apr	-.054297	.067762	-.090674	-.801	.4271
x10_may	.009453	.068543	.015786	.138	.8909
x11_jun	-.073018	.077465	-.121937	-.943	.3508
x12_jul	-.193307	.094138	-.322814	-2.053	.0457
x13_aug	-.153390	.076981	-.256154	-1.993	.0523
x14_sept	-.154006	.078010	-.257183	-1.974	.0544
x15_oct	.017360	.058563	.031482	.296	.7682
x16_nov	-.078561	.062360	-.142470	-1.260	.2141
x17_dec	.230977	.105703	.418877	2.185	.0340
(Constant)	11.609184	3.213412		3.613	.0007

Model 18(b). 2SLS – Serious Crashes by All-Theme TARPs

Dependent variable.. Y1c_serious_crash

Listwise Deletion of Missing Data

Multiple R	.86528
R Square	.74871
Adjusted R Square	.66130
Standard Error	.09607

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	16	1.2650406	.07906504
Residuals	46	.4245934	.00923029

F = 8.56582 Signif F = .0000

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
Y2a_all_	-.006065	.008134	-.091334	-.746	.4597
Y3_cbts	-.134410	.119599	-.351245	-1.124	.2669
x4_unem	-.361559	.167177	-.243185	-2.163	.0358
x5_ncars	.031742	.130662	.031032	.243	.8091
x6_trend	-.006873	.001354	-.772070	-5.074	.0000
x7_feb	-.096827	.074614	-.161696	-1.298	.2009
x8_mar	.063973	.065270	.106831	.980	.3322
x9_apr	-.058236	.067893	-.097251	-.858	.3955
x10_may	.001430	.070154	.002389	.020	.9838
x11_jun	-.069520	.078282	-.116095	-.888	.3791
x12_jul	-.199438	.094472	-.333053	-2.111	.0402
x13_aug	-.156623	.077372	-.261553	-2.024	.0488
x14_sept	-.154553	.078410	-.258096	-1.971	.0547
x15_oct	.019700	.058709	.035726	.336	.7387
x16_nov	-.077026	.062663	-.139688	-1.229	.2252
x17_dec	.245011	.105282	.444328	2.327	.0244
(Constant)	11.965430	3.147462		3.802	.0004

Model 18(c). 2SLS – Serious Crashes by Drink-Drive Adstock

```
Dependent variable.. Y1c_serious_crash

Listwise Deletion of Missing Data

Multiple R           .86551
R Square             .74911
Adjusted R Square    .66184
Standard Error       .09590

            Analysis of Variance:

               DF   Sum of Squares      Mean Square

Regression     16        1.2631426        .07894642
Residuals      46         .4230500        .00919674

F =       8.58418       Signif F =  .0000
```

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
Y2d_dd_a	-.008045	.019502	-.043468	-.413	.6819
Y3_cbts	-.145137	.122742	-.379279	-1.182	.2431
x4_unem	-.356325	.167931	-.239664	-2.122	.0393
x5_ncars	.032864	.134235	.032129	.245	.8077
x6_trend	-.007160	.001346	-.804368	-5.319	.0000
x7_feb	-.103014	.074933	-.172029	-1.375	.1759
x8_mar	.060546	.065668	.101109	.922	.3613
x9_apr	-.059134	.067909	-.098751	-.871	.3884
x10_may	.007173	.069070	.011978	.104	.9177
x11_jun	-.080187	.078251	-.133908	-1.025	.3108
x12_jul	-.206141	.095447	-.344246	-2.160	.0360
x13_aug	-.164825	.078715	-.275250	-2.094	.0418
x14_sept	-.165061	.079996	-.275644	-2.063	.0447
x15_oct	.015192	.060537	.027550	.251	.8030
x16_nov	-.085804	.064529	-.155606	-1.330	.1902
x17_dec	.244369	.107868	.443164	2.265	.0282
(Constant)	12.060716	3.204062		3.764	.0005

Model 18(d). 2SLS – Serious Crashes by Drink-Drive TARPs

Dependent variable.. Y1c_serious_crash

Listwise Deletion of Missing Data

Multiple R	.87609
R Square	.76753
Adjusted R Square	.68667
Standard Error	.09138

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	16	1.2682340	.07926463
Residuals	46	.3841199	.00835043

F = 9.49228 Signif F = .0000

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
Y2b_dd_T	.008443	.009456	.138938	.893	.3766
Y3_cbts	-.127721	.119031	-.333767	-1.073	.2889
x4_unem	-.376427	.159519	-.253185	-2.360	.0226
x5_ncars	.115524	.142641	.112941	.810	.4222
x6_trend	-.007156	.001235	-.803886	-5.795	.0000
x7_feb	-.091078	.072936	-.152096	-1.249	.2181
x8_mar	.080241	.064902	.133999	1.236	.2226
x9_apr	-.068745	.065345	-.114802	-1.052	.2983
x10_may	.011519	.065842	.019236	.175	.8619
x11_jun	-.079550	.074555	-.132844	-1.067	.2915
x12_jul	-.172409	.097998	-.287914	-1.759	.0852
x13_aug	-.136489	.078633	-.227931	-1.736	.0893
x14_sept	-.135599	.079842	-.226444	-1.698	.0962
x15_oct	.027590	.056240	.050034	.491	.6261
x16_nov	-.058919	.064066	-.106851	-.920	.3625
x17_dec	.215702	.109079	.391176	1.977	.0540
(Constant)	12.805060	3.020033		4.240	.0001

Model 19(a). 2SLS – Fatalities by All-Theme TARPs

Dependent variable.. Y1d_fatals

Listwise Deletion of Missing Data

Multiple R	.66804
R Square	.44628
Adjusted R Square	.25368
Standard Error	.17490

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	16	1.1341428	.07088392
Residuals	46	1.4071968	.03059124

F = 2.31713 Signif F = .0134

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
Y2a_all_	.001694	.015236	.020534	.111	.9119
Y3_cbts	.145529	.232850	.306073	.625	.5351
x4_unem	-.057459	.304853	-.031104	-.188	.8513
x5_ncars	.019016	.238035	.014962	.080	.9367
x6_trend	-.001950	.002597	-.176284	-.751	.4566
x7_feb	.039489	.139038	.053073	.284	.7777
x8_mar	.303529	.119562	.407943	2.539	.0146
x9_apr	.004990	.124115	.006707	.040	.9681
x10_may	.114830	.128906	.154332	.891	.3777
x11_jun	.069711	.146654	.093692	.475	.6368
x12_jul	.198902	.178504	.267324	1.114	.2710
x13_aug	.071851	.144258	.096568	.498	.6208
x14_sept	.021345	.146465	.028688	.146	.8848
x15_oct	.113375	.106943	.165475	1.060	.2946
x16_nov	.250131	.115078	.365074	2.174	.0349
x17_dec	.225659	.200279	.329356	1.127	.2657
(Constant)	2.573846	5.783215		.445	.6584

Model 19(b). 2SLS – Fatalities by All-Theme Adstock

```
Dependent variable.. Yld_fatals

Listwise Deletion of Missing Data

Multiple R           .66820
R Square             .44649
Adjusted R Square    .25397
Standard Error       .17481

            Analysis of Variance:

               DF   Sum of Squares      Mean Square

Regression     16       1.1338866         .07086791
Residuals      46       1.4056522         .03055766

F =      2.31915       Signif F =  .0133
```

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
Y2c_all_	-.002211	.034975	-.009097	-.063	.9499
Y3_cbts	.150287	.233427	.316079	.644	.5229
x4_unem	-.052243	.310770	-.028280	-.168	.8672
x5_ncars	.027959	.241112	.021998	.116	.9082
x6_trend	-.001789	.002521	-.161727	-.710	.4815
x7_feb	.041769	.138777	.056137	.301	.7648
x8_mar	.302919	.119602	.407124	2.533	.0148
x9_apr	.005899	.124417	.007929	.047	.9624
x10_may	.112040	.126977	.150582	.882	.3822
x11_jun	.072562	.145174	.097523	.500	.6196
x12_jul	.199858	.178672	.268610	1.119	.2691
x13_aug	.072185	.144228	.097017	.500	.6191
x14_sept	.021994	.146304	.029560	.150	.8812
x15_oct	.112426	.107152	.164089	1.049	.2996
x16_nov	.250248	.115021	.365245	2.176	.0348
x17_dec	.223776	.201870	.326608	1.109	.2734
(Constant)	2.388849	5.912149		.404	.6880

Model 19(c). 2SLS – Fatalities by Drink-Drive TARPs

Dependent variable.. Y1d_fatals

Listwise Deletion of Missing Data

Multiple R	.66771
R Square	.44584
Adjusted R Square	.25309
Standard Error	.17505

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	16	1.1340912	.07088070
Residuals	46	1.4096301	.03064413

F = 2.31303 Signif F = .0136

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
Y2b_dd_T	-.000898	.019450	-.011898	-.046	.9634
Y3_cbts	.151369	.237392	.318355	.638	.5269
x4_unem	-.056245	.305795	-.030446	-.184	.8549
x5_ncars	.030745	.277692	.024190	.111	.9123
x6_trend	-.001811	.002432	-.163707	-.744	.4604
x7_feb	.041517	.141024	.055798	.294	.7698
x8_mar	.302466	.124420	.406514	2.431	.0190
x9_apr	.006951	.126559	.009343	.055	.9564
x10_may	.113437	.127561	.152460	.889	.3785
x11_jun	.074177	.146497	.099693	.506	.6150
x12_jul	.199114	.189603	.267609	1.050	.2991
x13_aug	.071658	.151492	.096309	.473	.6384
x14_sept	.021634	.153867	.029076	.141	.8888
x15_oct	.112088	.108061	.163597	1.037	.3050
x16_nov	.249296	.122857	.363855	2.029	.0483
x17_dec	.225110	.211914	.328555	1.062	.2937
(Constant)	2.388165	5.883626		.406	.6867

Model 19(d). 2SLS – Fatalities by Drink-Drive Adstock

```
Dependent variable.. Y1d_fatals

Listwise Deletion of Missing Data

Multiple R           .66819
R Square             .44647
Adjusted R Square    .25394
Standard Error       .17484

            Analysis of Variance:

                DF   Sum of Squares     Mean Square

Regression      16        1.1341787       .07088617
Residuals       46        1.4061378       .03056821

F =       2.31895       Signif F =  .0134

------------------ Variables in the Equation ------------------

Variable              B          SE B         Beta          T  Sig T

Y2d_dd_a        -.002553      .036099    -.011100       -.071  .9439
Y3_cbts          .155686      .239640     .327434        .650  .5191
x4_unem         -.054889      .306465    -.029712       -.179  .8586
x5_ncars         .029036      .244842     .022846        .119  .9061
x6_trend        -.001740      .002581    -.157336       -.674  .5036
x7_feb           .043462      .139809     .058413        .311  .7573
x8_mar           .303192      .120285     .407490       2.521  .0152
x9_apr           .006359      .124392     .008547        .051  .9594
x10_may          .113264      .127423     .152227        .889  .3787
x11_jun          .074451      .146378     .100062        .509  .6134
x12_jul          .202002      .180420     .271491       1.120  .2687
x13_aug          .072422      .146233     .097335        .495  .6228
x14_sept         .022291      .148659     .029959        .150  .8815
x15_oct          .110757      .110655     .161654       1.001  .3221
x16_nov          .249424      .118115     .364043       2.112  .0402
x17_dec          .219422      .206886     .320253       1.061  .2944
(Constant)      2.346806     5.908739                    .397  .6931
```

Model 20(a). 2SLS – High Alcohol Hour Serious Crashes by All-Theme TARPs

Dependent variable.. Y1e_HAH_serious_crash

Listwise Deletion of Missing Data

Multiple R	.74525
R Square	.55540
Adjusted R Square	.40076
Standard Error	.22283

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	16	2.8532394	.17832746
Residuals	46	2.2840175	.04965255

F = 3.59151 Signif F = .0003

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
Y2a_all_	-.018306	.018898	-.156473	-.969	.3378
Y3_cbts	-.273312	.287616	-.405381	-.950	.3469
x4_unem	-.375796	.388253	-.143461	-.968	.3381
x5_ncars	.158447	.303207	.087920	.523	.6038
x6_trend	-.011656	.003190	-.743205	-3.654	.0007
x7_feb	.105319	.175020	.099824	.602	.5503
x8_mar	.224481	.152001	.212769	1.477	.1465
x9_apr	.049364	.157824	.046788	.313	.7559
x10_may	.037989	.164181	.036007	.231	.8180
x11_jun	.052366	.183886	.049634	.285	.7771
x12_jul	-.138435	.224056	-.131212	-.618	.5397
x13_aug	.111800	.182065	.105967	.614	.5422
x14_sept	-.049797	.184549	-.047199	-.270	.7885
x15_oct	.148397	.136193	.152745	1.090	.2816
x16_nov	.085508	.146046	.088014	.585	.5611
x17_dec	.554974	.250800	.571236	2.213	.0319
(Constant)	10.278178	7.322324		1.404	.1671

Model 20(b). 2SLS – High Alcohol Hour Serious Crashes by All-Theme TARPs

Dependent variable.. Y1e_HAH_serious_crash

Listwise Deletion of Missing Data

Multiple R	.75362
R Square	.56794
Adjusted R Square	.41765
Standard Error	.22321

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	16	3.0125085	.18828178
Residuals	46	2.2918030	.04982181

F = 3.77910 Signif F = .0002

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
Y2c_all_	-.091229	.044880	-.264730	-2.033	.0479
Y3_cbts	-.184361	.292042	-.273447	-.631	.5310
x4_unem	-.236457	.396129	-.090268	-.597	.5535
x5_ncars	.257967	.307755	.143142	.838	.4062
x6_trend	-.010490	.003198	-.668855	-3.280	.0020
x7_feb	.132914	.175989	.125980	.755	.4540
x8_mar	.219390	.152228	.207943	1.441	.1563
x9_apr	.077510	.158713	.073466	.488	.6276
x10_may	.061915	.161194	.058684	.384	.7027
x11_jun	.060801	.183711	.057629	.331	.7422
x12_jul	-.092393	.225044	-.087572	-.411	.6833
x13_aug	.135958	.182448	.128865	.745	.4599
x14_sept	-.036654	.184937	-.034741	-.198	.8438
x15_oct	.129378	.136829	.133169	.946	.3493
x16_nov	.081325	.146311	.083708	.556	.5810
x17_dec	.460925	.254172	.474431	1.813	.0763
(Constant)	7.062353	7.551318		.935	.3545

Model 20(c). 2SLS – High Alcohol Hour Serious Crashes by All-Theme TARPs

Dependent variable.. Y1e_HAH_serious_crash

Listwise Deletion of Missing Data

Multiple R	.74397
R Square	.55349
Adjusted R Square	.39818
Standard Error	.22255

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	16	2.8241407	.17650879
Residuals	46	2.2783161	.04952861

F = 3.56377 Signif F = .0004

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
Y2b_dd_T	.003930	.022927	.036709	.171	.8646
Y3_cbts	-.318805	.292890	-.472856	-1.088	.2821
x4_unem	-.388878	.388509	-.148455	-1.001	.3221
x5_ncars	.074350	.346610	.041256	.215	.8311
x6_trend	-.012996	.003029	-.828683	-4.291	.0001
x7_feb	.085897	.177916	.081416	.483	.6315
x8_mar	.230462	.157797	.218438	1.460	.1510
x9_apr	.038701	.159521	.036682	.243	.8094
x10_may	.059562	.160840	.056455	.370	.7128
x11_jun	.016685	.182841	.015814	.091	.9277
x12_jul	-.142566	.238605	-.135127	-.597	.5531
x13_aug	.111295	.191340	.105488	.582	.5636
x14_sept	-.055460	.194288	-.052566	-.285	.7766
x15_oct	.156780	.137026	.161374	1.144	.2585
x16_nov	.086802	.155602	.089345	.558	.5797
x17_dec	.560251	.265933	.576668	2.107	.0406
(Constant)	11.691641	7.382864		1.584	.1201

Model 20(d). 2SLS – High Alcohol Hour Serious Crashes by All-Theme TARPs

```
Dependent variable.. Y1e_HAH_serious_crash

Listwise Deletion of Missing Data

Multiple R           .76203
R Square             .58069
Adjusted R Square    .43485
Standard Error       .21818

            Analysis of Variance:

               DF   Sum of Squares      Mean Square

Regression     16        3.0324152        .18952595
Residuals      46        2.1896425        .04760092

F =       3.98156       Signif F =  .0001

------------------ Variables in the Equation ------------------

Variable              B          SE B         Beta          T  Sig T

Y2d_dd_a       -.093152       .044378     -.285648     -2.099  .0413
Y3_cbts        -.247428       .284549     -.366989      -.870  .3891
x4_unem        -.291435       .382242     -.111256      -.762  .4497
x5_ncars        .297608       .305399      .165138       .974  .3349
x6_trend       -.011039       .003098     -.703864     -3.563  .0009
x7_feb          .103256       .171545      .097869       .602  .5502
x8_mar          .187930       .149664      .178125      1.256  .2156
x9_apr          .056527       .154684      .053578       .365  .7165
x10_may         .044634       .157715      .042305       .283  .7784
x11_jun         .027722       .179325      .026276       .155  .8778
x12_jul        -.167731       .219526     -.158980      -.764  .4487
x13_aug         .044889       .180264      .042547       .249  .8045
x14_sept       -.128130       .183234     -.121445      -.699  .4879
x15_oct         .080916       .137754      .083286       .587  .5598
x16_nov         .005400       .147103      .005558       .037  .9709
x17_dec         .493540       .248686      .508001      1.985  .0532
(Constant)     8.059673      7.305268                   1.103  .2756
```

Model 21(a). 2SLS – Alcohol-Related Serious Crashes by All-Theme Adstock

```
Dependent variable.. Y1f_alc_crash

Listwise Deletion of Missing Data

Multiple R           .91425
R Square             .83585
Adjusted R Square    .77875
Standard Error       .10136

            Analysis of Variance:

               DF   Sum of Squares      Mean Square

Regression     16        2.4066056        .15041285
Residuals      46         .4726360        .01027469

F =      14.63915       Signif F =  .0000

------------------ Variables in the Equation ------------------
```

Variable	B	SE B	Beta	T	Sig T
Y2c_all_	-.058614	.020234	-.228237	-2.897	.0058
Y3_cbts	-.044771	.129390	-.089107	-.346	.7309
x4_unem	-.326141	.179952	-.167071	-1.812	.0765
x5_ncars	.062041	.139767	.046195	.444	.6592
x6_trend	-.008719	.001423	-.745969	-6.127	.0000
x7_feb	.064246	.079256	.081712	.811	.4218
x8_mar	.151862	.069021	.193149	2.200	.0329
x9_apr	-.006811	.071931	-.008663	-.095	.9250
x10_may	.101133	.072949	.128627	1.386	.1723
x11_jun	.135889	.082687	.172832	1.643	.1071
x12_jul	.151215	.100834	.192325	1.500	.1405
x13_aug	.150571	.082171	.191506	1.832	.0734
x14_sept	.154377	.083298	.196347	1.853	.0703
x15_oct	.198904	.062112	.274726	3.202	.0025
x16_nov	.232757	.066288	.321483	3.511	.0010
x17_dec	.333342	.113377	.460411	2.940	.0051
(Constant)	10.576737	3.411205		3.101	.0033

Model 21(b). 2SLS – Alcohol-Related Serious Crashes by All-Theme TARPs

```
Dependent variable.. Y1f_alc_crash

Listwise Deletion of Missing Data

Multiple R           .89826
R Square             .80688
Adjusted R Square    .73970
Standard Error       .11062

            Analysis of Variance:

               DF   Sum of Squares      Mean Square

Regression     16        2.3518663        .14699164
Residuals      46         .5629130        .01223724

F =      12.01183       Signif F =  .0000

------------------ Variables in the Equation ------------------

Variable              B          SE B        Beta         T  Sig T

Y2a_all_       -.015028      .009369   -.172368    -1.604  .1156
Y3_cbts        -.084528      .140071   -.168236     -.603  .5492
x4_unem        -.416085      .192610   -.213145    -2.160  .0360
x5_ncars        .116998      .150483    .087115      .777  .4409
x6_trend       -.009153      .001570   -.783174    -5.830  .0000
x7_feb          .053681      .086361    .068275      .622  .5373
x8_mar          .156696      .075296    .199297     2.081  .0430
x9_apr         -.022688      .078255   -.028856     -.290  .7732
x10_may         .084006      .081121    .106844     1.036  .3058
x11_jun         .139854      .090664    .177876     1.543  .1298
x12_jul         .129444      .109922    .164636     1.178  .2450
x13_aug         .139938      .089692    .177983     1.560  .1256
x14_sept        .151890      .090903    .193184     1.671  .1015
x15_oct         .209849      .067605    .289843     3.104  .0033
x16_nov         .238282      .072315    .329114     3.295  .0019
x17_dec         .384550      .122758    .531139     3.133  .0030
(Constant)    12.367858     3.629011                3.408  .0014
```

Model 21(c). 2SLS – Alcohol-Related Serious Crashes by Drink-Drive Adstock

Dependent variable.. Y1f_alc_crash

Listwise Deletion of Missing Data

Multiple R	.91428
R Square	.83592
Adjusted R Square	.77884
Standard Error	.10117

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	16	2.3984308	.14990193
Residuals	46	.4707968	.01023471

F = 14.64642 Signif F = .0000

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
Y2d_dd_a	-.057025	.020577	-.234648	-2.771	.0080
Y3_cbts	-.046143	.131655	-.091838	-.350	.7276
x4_unem	-.374278	.177265	-.191729	-2.111	.0402
x5_ncars	.045495	.141633	.033875	.321	.7495
x6_trend	-.008787	.001433	-.751821	-6.132	.0000
x7_feb	.059069	.079490	.075128	.743	.4612
x8_mar	.139863	.069410	.177886	2.015	.0498
x9_apr	-.014938	.071714	-.018999	-.208	.8359
x10_may	.100975	.073125	.128427	1.381	.1740
x11_jun	.130861	.083102	.166438	1.575	.1222
x12_jul	.128114	.101738	.162944	1.259	.2143
x13_aug	.110112	.083611	.140047	1.317	.1944
x14_sept	.114396	.084994	.145496	1.346	.1849
x15_oct	.168340	.063865	.232511	2.636	.0114
x16_nov	.193926	.068245	.267850	2.842	.0067
x17_dec	.326324	.115104	.450717	2.835	.0068
(Constant)	10.975305	3.385084		3.242	.0022

Model 21(d). 2SLS – Alcohol-Related Serious Crashes by Drink-Drive TARPs

Dependent variable.. Y1f_alc_crash

Listwise Deletion of Missing Data

Multiple R	.89825
R Square	.80685
Adjusted R Square	.73967
Standard Error	.10989

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	16	2.3206306	.14503941
Residuals	46	.5555231	.01207659

F = 12.00997 Signif F = .0000

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
Y2b_dd_T	-.002935	.011379	-.036788	-.258	.7976
Y3_cbts	-.101982	.146239	-.202974	-.697	.4891
x4_unem	-.427045	.192004	-.218760	-2.224	.0311
x5_ncars	.140645	.171695	.104722	.819	.4169
x6_trend	-.010071	.001505	-.861715	-6.692	.0000
x7_feb	.040778	.088424	.051864	.461	.6469
x8_mar	.155923	.078334	.198313	1.990	.0525
x9_apr	-.020059	.078610	-.025512	-.255	.7997
x10_may	.108958	.079503	.138580	1.370	.1772
x11_jun	.124409	.090302	.158232	1.378	.1750
x12_jul	.124759	.119589	.158676	1.043	.3023
x13_aug	.137202	.095528	.174502	1.436	.1577
x14_sept	.144982	.097029	.184397	1.494	.1420
x15_oct	.210795	.067628	.291150	3.117	.0031
x16_nov	.231306	.077410	.319479	2.988	.0045
x17_dec	.387367	.133399	.535030	2.904	.0056
(Constant)	12.886615	3.634398		3.546	.0009

Model 22(a). 2SLS – Alcohol-Related Fatalities by All-Theme TARPs

Dependent variable.. Y1g_alc_fatal

Listwise Deletion of Missing Data

Multiple R	.64266
R Square	.41302
Adjusted R Square	.20885
Standard Error	.35250

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	16	4.0218388	.25136492
Residuals	46	5.7158624	.12425788

F = 2.02293 Signif F = .0319

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
Y2a_all_	-.002039	.029873	-.013081	-.068	.9459
Y3_cbts	-.572626	.438637	-.637346	-1.305	.1982
x4_unem	-.078940	.613375	-.022614	-.129	.8982
x5_ncars	.459951	.479422	.191520	.959	.3424
x6_trend	-.012816	.004969	-.613236	-2.579	.0132
x7_feb	-.294887	.273727	-.209742	-1.077	.2870
x8_mar	.124923	.239470	.088853	.522	.6044
x9_apr	-.188305	.249096	-.133934	-.756	.4535
x10_may	-.343693	.257389	-.244456	-1.335	.1883
x11_jun	-.219486	.287181	-.156112	-.764	.4486
x12_jul	-.196105	.346542	-.139482	-.566	.5742
x13_aug	-.070809	.283838	-.050364	-.249	.8041
x14_sept	-.037878	.287647	-.026941	-.132	.8958
x15_oct	.323258	.215406	.249685	1.501	.1403
x16_nov	.306800	.229904	.236972	1.334	.1886
x17_dec	.671543	.386175	.518700	1.739	.0887
(Constant)	14.787623	11.547906		1.281	.2068

Model 22(b). 2SLS – Alcohol-Related Fatalities by All-Theme Adstock

Dependent variable.. Y1g_alc_fatal

Listwise Deletion of Missing Data

Multiple R	.64251
R Square	.41282
Adjusted R Square	.20858
Standard Error	.35267

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	16	4.0224271	.25140170
Residuals	46	5.7214442	.12437922

F = 2.02125 Signif F = .0321

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
Y2c_all_	.006885	.071069	.014994	.097	.9232
Y3_cbts	-.580393	.442256	-.645991	-1.312	.1959
x4_unem	-.093151	.626048	-.026685	-.149	.8824
x5_ncars	.478143	.486552	.199095	.983	.3309
x6_trend	-.013091	.004904	-.626373	-2.669	.0105
x7_feb	-.298458	.274174	-.212281	-1.089	.2820
x8_mar	.126620	.239720	.090060	.528	.5999
x9_apr	-.190361	.250003	-.135396	-.761	.4503
x10_may	-.339320	.252929	-.241345	-1.342	.1863
x11_jun	-.223119	.285732	-.158696	-.781	.4389
x12_jul	-.197459	.347170	-.140445	-.569	.5723
x13_aug	-.071009	.283975	-.050506	-.250	.8037
x14_sept	-.038135	.287793	-.027124	-.133	.8952
x15_oct	.325352	.216089	.251302	1.506	.1390
x16_nov	.307347	.230106	.237395	1.336	.1882
x17_dec	.675729	.389640	.521934	1.734	.0896
(Constant)	15.175838	11.853800		1.280	.2069

Model 22(c). 2SLS – Alcohol-Related Fatalities by Drink-Drive TARPs

Dependent variable.. Y1g_alc_fatal

Listwise Deletion of Missing Data

Multiple R	.64465
R Square	.41557
Adjusted R Square	.21229
Standard Error	.36420

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	16	4.3386458	.27116536
Residuals	46	6.1016511	.13264459

F = 2.04430 Signif F = .0300

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
Y2b_dd_T	.049418	.037268	.346376	1.326	.1914
Y3_cbts	-.555270	.472523	-.618029	-1.175	.2460
x4_unem	-.122114	.635610	-.034982	-.192	.8485
x5_ncars	.843511	.566648	.351232	1.489	.1434
x6_trend	-.012916	.004910	-.618011	-2.631	.0116
x7_feb	-.257940	.290103	-.183462	-.889	.3786
x8_mar	.201794	.258197	.143528	.782	.4385
x9_apr	-.254939	.260437	-.181328	-.979	.3328
x10_may	-.353193	.262278	-.251212	-1.347	.1847
x11_jun	-.261661	.296935	-.186109	-.881	.3828
x12_jul	-.077900	.388761	-.055407	-.200	.8421
x13_aug	.018543	.312315	.013189	.059	.9529
x14_sept	.052826	.317086	.037573	.167	.8684
x15_oct	.364258	.224131	.281353	1.625	.1110
x16_nov	.404536	.254651	.312464	1.589	.1190
x17_dec	.551968	.432603	.426341	1.276	.2084
(Constant)	18.545730	12.036646		1.541	.1302

Model 22(d). 2SLS –Alcohol-Related Fatalities by Drink-Drive Adstock

```
Dependent variable.. Y1g_alc_fatal

Listwise Deletion of Missing Data

Multiple R           .63333
R Square             .40111
Adjusted R Square    .19280
Standard Error       .36675

            Analysis of Variance:

               DF   Sum of Squares      Mean Square

Regression     16       4.1439582         .25899738
Residuals      46       6.1873612         .13450785

F =       1.92552       Signif F =  .0424
```

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
Y2d_dd_a	.039946	.074622	.091921	.535	.5950
Y3_cbts	-.725380	.468765	-.807366	-1.547	.1286
x4_unem	-.092420	.642188	-.026476	-.144	.8862
x5_ncars	.540243	.513372	.224953	1.052	.2981
x6_trend	-.014772	.005145	-.706829	-2.871	.0062
x7_feb	-.346888	.286437	-.246728	-1.211	.2321
x8_mar	.120573	.251092	.085759	.480	.6334
x9_apr	-.210401	.259686	-.149650	-.810	.4220
x10_may	-.363740	.264060	-.258714	-1.377	.1750
x11_jun	-.272758	.299085	-.194002	-.912	.3665
x12_jul	-.260608	.364683	-.185360	-.715	.4785
x13_aug	-.091891	.300838	-.065359	-.305	.7614
x14_sept	-.058489	.305723	-.041601	-.191	.8491
x15_oct	.359562	.231525	.277726	1.553	.1273
x16_nov	.315953	.246718	.244042	1.281	.2067
x17_dec	.790960	.412149	.610938	1.919	.0612
(Constant)	17.310833	12.252751		1.413	.1644