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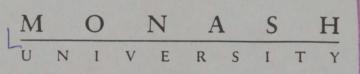
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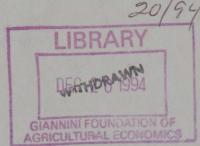
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Advertising wearout in the Fransport

A DIAGNOSTIC TEST FOR STRUCTURAL CHANGE

IN COINTEGRATED REGRESSION MODELS

accident commission road safety campaigns

Tim R.L. Fry

Working Paper No. 20/94

October 1994

DEPARTMENT OF ECONOMETRICS

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Advertising Wearout in the Transport Accident Commission Road Safety Campaigns.

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Abstract

This paper uses a varying coefficient regression model to investigate whether there is any significant advertising wearout in the Transport Accident Commission (TAC) road safety campaigns on Victorian television. The results suggest that there is some evidence that the effectiveness of the campaigns may be declining with increased exposure.

^{*}I wish to thank Simon Broadbent, Jane Fry and Brett Inder for useful comments on an earlier version. I am also grateful to the Monash University Accident Research Centre for supplying much of the data used. The views expressed in the paper are, however, solely those of the author.

1 Introduction.

The road safety advertising campaigns of the Transport Accident Commission (TAC), which commenced at the end of 1989, have been remarkably effective in reducing road trauma in Victoria (see Harper and L'Huiller (1992), Cameron and Newstead (1993a), (1993b) Cameron et al (1993)). Indeed, the campaign is viewed to have had such a large impact that modified versions of the television commercials are to be shown in other Australian states and in other countries. However, one debate that has arisen recently is whether the campaign is suffering from wearout. That is, has the effectiveness of the advertising been declining over time as exposure to it has increased? Using data covering the period 1983 - 1993, this paper investigates whether or not there is significant evidence of advertising wearout in the TAC road safety campaigns.

The plan of the paper is as follows: section 2 discusses the idea of advertising wearout and describes the statistical model to be used. Section 3 describes the data which is used to answer the question of whether the TAC road safety advertising does exhibit wearout. Section 4 contains the results of the analysis and finally section 5 contains some concluding remarks.

2 Varying Coefficient Models and Wearout.

The idea that advertising may suffer from wearout is not new (for a succinct summary of the literature see Kinnucan et al (1993) and references therein). The basic idea of wearout theory is that the response to an advertisement can be broken down into three stages. In the first stage an advertisement generates an increasing response as the audience absorbs its message. The second stage is where the response peaks and this is followed by the third stage - a decline (or wearout) as the audience becomes over-exposed to the advertisement and less likely to respond.

Although the theory is expressed in terms of a single advertisement, it is still likely to hold for an advertising campaign which might include several advertisements. However, in the case of applying the theory to a campaign, we should note the following two points. Firstly, the campaign needs to be thought of as a single advertisement. That is, the overall message remains unchanged throughout the campaign. The TAC campaigns have been devised to do just this. In other words, although the creative execution changes, the message remains the same. Indeed, there are only so many ways that the basic message: 'Speed Kills/Concentrate or Kill' or 'Drink then Drive: Bloody Idiot' can be communicated. Secondly, as Grass and Wallace (1969) point out, the use of more than one advertisement in a strategy of rotation can delay the onset of the third stage of wearout. As a

result we are likely to need a longer run of data than for a single advertisement to identify whether there is any evidence of wearout. Related to this point is the result of Appel (1971) who found that advertisements with a strong initial impact benefit from repeat exposure and thus wearout is likely to be delayed. Given the critical acclaim for the creative execution and impact of the TAC advertisements this again suggests that a long data series is likely to be needed.

Thus the theory implies that the response to advertising will vary over the duration of the campaign. Furthermore, it suggests that there is an initial 'growth' period, followed by a 'peak' and then a 'decline'. To investigate the issue of wearout we will use a simple varying coefficients regression model for the response variable y_t (see Kmenta (1986)). The model is given by:

$$y_t = \mathbf{x}_t' \boldsymbol{\beta} + \gamma_t A_t + u_t, \quad t = 1, ..., T$$
 (1)

where \mathbf{x}_t is a vector of explanatory variables and A_t is a measure of advertising. In this paper the response variable, y_t , will be defined as the logarithm of the number of serious casualty crashes in month t, where a serious casualty crash is defined as one which results in a death or admission to hospital.

A question that arises is the choice of advertising variable A_t to use in (1). This variable should reflect the build up of advertising exposure over time. Kinnucan et al (1993) use 'advertising goodwill', as defined by Nerlove and Waugh (1961),

which is an Almon Lag of advertising expenditures in previous time periods. The approach taken is this paper is to use an adstock variable (see Broadbent (1979)) as these variables are commonly used in market research models to evaluate the response to advertising. Further, as Cameron et al (1993) found that adstock variables with a five week 'half-life' were significant in their models for serious casualty crashes, we will also use adstock variables with five week 'half-lives' constructed from weekly Target Audience Rating Points (TARPs)¹.

Both advertising goodwill and adstock are based upon the notion that advertising has an impact which carries on through time. Thus after a burst of advertising, advertising awareness, and hence the response to advertising, can decay over time. To capture this mechanism an adstock variable for week w is defined as:

$$A_w = (1 - \lambda)[TARP_w + \lambda TARP_{w-1} + \lambda^2 TARP_{w-2} + \dots],$$

where $0 < \lambda < 1$ is a retention parameter. The retention parameter is related to another parameter of interest $\eta = \log(0.5)/\log(\lambda)$, the advertising half-life, the period by which half of the advertising response will be felt. It is a stylized fact in the market research literature that half-lives tend to be between four and six weeks.

¹TARPs are an index defined as follows: 100 TARPs means that everyone in the target audience (in this case persons aged 18-39 years) had the opportunity to see the advertisement once.

In other words, adstock in week w is a weighted sum of TARPs in the week and all previous weeks. The functional form of the relationship is a geometric lag with weights summing to one to ensure that adstock and TARPs will sum to the same number. Hence, guaranteeing that the total exposure generated via the adstock variable is the same as that implied by the TARPs. In practice w, weekly, differs from t, monthly. Thus adstock is calculated weekly and then cumulated to a monthly series for use in modeling.

We arout theory suggests that the coefficient on advertising varies according to the relationship:

$$\gamma_t = \gamma_0 + \gamma_1 i_t + \gamma_2 i_t^2, \quad i = 1, ..., T$$

and i_t is an indicator of the advertising presence (= 1 in the first period (t_1) of the advertising, = I in the last period (t_I) of the advertising). That is,

$$i_t = \begin{cases} 0 & 0 < t < t_1 \\ t - t_1 + 1 & t_1 \le t \le t_I \\ 0 & t > t_I. \end{cases}$$

It should be noted that the advertising index i_t does not run from 1 to T. This is to allow for the fact that the TAC advertising campaigns do not start at the beginning of the sample period (January 1983). In fact the $Drink\ Drive$ campaign

started in November 1989 and the Speed Kills/Concentrate or Kill campaign started in April 1990.

Advertising is hypothesized to reduce the number of serious casualty crashes. Hence, if we arout theory is correct, $\gamma_0 < 0, \gamma_1 < 0, \gamma_2 > 0$. That is, the time varying response to advertising is a "U" shaped quadratic with an initial response of $(\gamma_0 + \gamma_1 + \gamma_2)$, an end response of $(\gamma_0 + \gamma_1 I + \gamma_2 I^2)$, and a 'peak' response at $i^* = -\gamma_1/2\gamma_2$. The advantage of this specification for γ_t is that (1) can be estimated by least squares and the wearout hypothesis tested using an F test as follows:

$$H_0: \gamma_1 = \gamma_2 = 0$$

$$H_1 : \gamma_1, \gamma_2 \neq 0,$$

where rejection of the null hypothesis provides evidence of the wearout hypothesis.

3 Data.

The data set used is an extension of that of Cameron et al (1993) and includes 132 monthly observations for the period January 1983 to December 1993. The data comes from a variety of published (Australian Bureau of Statistics) and unpublished (Victorian Police, Vicroads) sources². In common with Cameron

²The data used is available on request from the author.

et al (1993) we partition the data set by region of the state and by time of day. That is, the data on serious casualty crashes (SCCs) in Victoria is partitioned into those occurring in the Melbourne statistical division (MSD) and those occurring in the rest of Victoria (ROV). A further partition is into those SCCs occurring in 'High Alcohol Hours' (HAH) and those occurring in 'Low Alcohol Hours' (LAH). The 'Low Alcohol Hours' are Monday-Thursday 6am to 6pm, Friday 6am to 4pm, Saturday 8am to 2pm and Sunday 10am to 4pm and are periods in which the percentage of drivers killed or admitted to hospital with a blood alcohol content exceeding 0.05% is below 4%. The 'High Alcohol Hours' are the converse of these times and are periods in which 38% of drivers killed or admitted to hospital have a blood alcohol content above 0.05%³.

This partitioning leads to four data sets for analysis: high alcohol hours in Melbourne, high alcohol hours in the rest of Victoria, low alcohol hours in Melbourne and low alcohol hours in the rest of Victoria (HAHMSD, HAHROV, LAHMSD, LAHROV). Advantages of this partitioning process are that it allows the identification of regional differences in results (e.g. differing impacts of random breath tests or unemployment) and it allows for a closer matching of TAC campaigns with the response variables. That is, the *Drink Drive* campaign is targeted at reducing serious casualty crashes which occur predominately in high

³The legal limit in Victoria is a blood alcohol content below 0.05%.

alcohol hours and the Speed Kills/Concentrate or Kill campaign is targeted at reducing serious casualty crashes which occur predominately in low alcohol hours.

In addition to data on SCCs we have data on unemployment rates and the number of random breath tests in the Melbourne statistical division and in the rest of Victoria. For the whole of the state we have data on the number of speed camera infringement notices issued; real alcohol sales (in 80/81 \$million); seasonal dummy variables; a time trend and weekly TARPs for the TAC campaigns. In the modeling, the state wide variables are used in each of the partitions (HAHMSD, HAHROV, LAHMSD, LAHROV). This is justified since the Victorian police confirm that the pattern of speed camera activity is comparable in both regions of the state and also because media buying strategies were such that TARPs were planned and bought at the same levels in both the Melbourne and country television areas. We do, however, have to assume that the pattern of real alcohol sales in country Victoria is the same as that for Melbourne. Thus, although reflecting the level in the whole of the state, these variables are used to represent the pattern of activity in each region of the state.

4 Results.

In this section we present the results of our analyses for four models: high alcohol hours in Melbourne, high alcohol hours in the rest of Victoria, low alcohol hours

in Melbourne and low alcohol hours in the rest of Victoria for the period January 1983 to December 1993. Our model specifications are based upon those for the period January 1983 to December 1992 previously reported in the comprehensive modeling exercise carried out by Cameron et al (1993). In particular, we utilize a double-log (or constant elasticity) formulation. This formulation is consistent with the 'road trauma chain' of Cameron (1990), which has a multiplicative structure, and also with that adopted for modelling fatalities in Fry (1993) and Thoresen et al (1992). It also reflects the arguments made in Andreasson (1991) in favor of modeling numbers and not rates. However, it should be noted that our results are not directly comparable to those in Cameron et al (1993) as we have dropped the random breath test variable from the high alcohol hours, rest of Victoria model as it was always statistically insignificant with the wrong sign⁴.

Estimation of the models was carried out in LIMDEP (Greene (1991)) using ordinary least squares (OLS). Tables 1 to 4 contain the results of fitting the varying coefficient models to each of the data sets. Both OLS and robust (White (1980)) standard errors are presented along with summary diagnostics - R^2 , DW, and BP (the Breusch-Pagan test for heteroskedasticity, see Breusch and Pagan (1979)) - and the F test for the null hypothesis of a constant coefficient model. Also presented are the estimated start, peak and end advertising elasticities for

⁴We have also corrected an error in their construction of the adstock variables.

each model.

If the coefficients on Adstock, $i \times \text{Adstock}$ and $i^2 \times \text{Adstock}$ in the varying coefficient model are negative, negative and positive respectively, then there is evidence of advertising wearout. Furthermore, if the F test rejects the null (p < 0.05), then the presence of advertising wearout is statistically significant. In all four models we find that the pattern of coefficients indicates the presence of advertising wearout⁵. However, this wearout is only statistically significant in the model for serious casualty crashes in low alcohol hours in country Victoria $(LAHROV)^6$. Given the arguments in section 2 concerning the delaying of wearout in advertising campaigns it is probable that the lack of statistical significance is caused by the shortness of the data period. This is partly confirmed by the fact that the peak responses are estimated to occur near the end of the sample. Thus with extra data it might be possible to find statistical significance in the other models.

In interpreting our other results we should note that in all models there is no evidence of serial correlation as indicated by the Durbin-Watson statistics. There is, however, evidence of heteroskedasticity in three of the four models. Thus, the

⁵The constant and time-varying advertising elasticities for all four datasets are plotted in the Appendix.

⁶The same inferences are obtained if Bonferroni t tests are used.

White standard errors should be preferred in interpretation. In all models we see that the signs are consistent with expectations (and previous results - Cameron et al (1993)) and all variables have acceptable levels of statistical significance. The models fit well and appear well specified.

Finally, note that for completeness, tables 5 to 8 contain the results for the constant coefficient models. Interpretation of these results is similar to that for the varying coefficient models. It is interesting to note that in moving from a constant elasticity specification to a varying elasticity specification the statistical significance of the unemployment rate variable falls dramatically in all models. This may be due to a collinearity problem between the variables.

5 Conclusions.

This paper has taken data on the TAC television road safety campaigns and using a varying coefficient regression model has investigated the issue of advertising wearout. Some, albeit weak, evidence of advertising wearout has been found. That is, the impact of the TAC advertising in reducing the number of serious casualty crashes may be diminishing over time. If this is true it would have significant implications for future road safety advertising. However, it should be noted that the statistical significance of these results is weak. It is likely that the large impact that the individual advertisements have, coupled with the

strategy of rotating different creative executions, has made it difficult to identify strong statistical evidence of wearout. This suggests that a similar study might be made when more data is available. However, as the TAC has launched a new Drink/Drive campaign in September 1994 with the message: "Should you be driving home tonight?" and is to introduce a new Speeding campaign early in 1995, very little extra data will be available for such a study. Furthermore, since the campaigns continue to introduce different creative executions, the prospect for conclusively finding a case for or against advertising wearout is likely to be low.

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Table 1: High Alcohol Hours, Melbourne.

Variable	Coefficient	Std. Error	White Std. Error
Constant	1.47810	0.84860	0.76330
Trend	0.00377	0.00092	0.00083
February	0.17889	0.04530	0.05907
March	0.22910	0.04249	0.03633
April	0.17442	0.04549	0.04179
May	0.32243	0.04696	0.04476
June	0.22865	0.04931	0.04940
July	0.20699	0.04792	0.04439
August	0.19057	0.04617	0.04625
September	0.21224	0.04403	0.04933
October	0.20076	0.04354	0.04139
November	0.17283	0.04305	0.04824
December	0.05895	0.06170	0.04602
Unemployment	-0.30862	0.07714	0.07131
Alcohol Sales	0.58980	0.17040	0.15390
Random Breath Tests	-0.01198	0.00412	0.00347
Adstock	-0.02580	0.00955	0.00938
$i \times Adstock$	-0.00125	0.00123	0.00124
$i^2 \times Adstock$	0.00003	0.00002	0.00002

R^2	0.8575	
DW	1.9153	
BP(18)	33.1024	p = 0.0162
F(2,113)	2.2204	p = 0.1133

	Elasticity	White Std. Error	Date
Start	-0.02702	0.00121	November 1989
Peak	-0.04007	0.01974	September 1991
End	-0.01989	0.02272	December 1993

Table 2: High Alcohol Hours, Rest of Victoria.

Variable	Coefficient	Std. Error	White Std. Error
Constant	2.23680	1.17600	1.16660
Trend	0.00255	0.00100	0.00081
February	-0.08056	0.06318	0.05605
March	0.00892	0.06036	0.04766
April	-0.09204	0.06459	0.05861
May	-0.13348	0.06677	0.06250
June	-0.17542	0.07040	0.07090
July	-0.233221	0.06872	0.07919
August	-0.21977	0.06573	0.05714
September	-0.26541	0.06287	0.07510
October	-0.07250	0.06203	0.05746
November	-0.06877	0.06033	0.07102
December	-0.10973	0.08736	0.08243
Unemployment	-0.02863	0.12240	0.11500
Alcohol Sales	0.51956	0.23920	0.23480
Adstock	-0.02181	0.01579	0.01362
$i \times Adstock$	-0.001964	0.00162	0.00153
$i^2 \times Adstock$	0.00002.	0.00002	0.00002

\mathbb{R}^2	0.6868	•
DW	1.8318	
BP(17)	30.1579	p = 0.0252
F(2,114)	0.9828	p = 0.3774

	Elasticity	White Std. Error	Date
Start	-0.02375	0.00149	November 1989
Peak	-0.06410	0.03018	May 1993
End	-0.06301	0.03000	December 1993

Table 3: Low Alcohol Hours, Melbourne.

Variable	Coefficient	Std. Error	White Std. Error
Constant	4.9120	0.25980	0.21150
Trend	0.00389	0.00113	0.00095
February	0.16637	0.04512	0.03590
March	0.27621	0.04401	0.04984
April	0.22465	0.04398	0.03381
May	0.30203	0.04415	0.04105
June	0.29959	0.04503	0.04449
July	0.22796	0.04558	0.04183
August	0.18589	0.04640	0.04257
September	0.15752	0.04535	0.03676
October	0.25537	0.04636	0.04229
November	0.18220	0.04663	0.04222
December	0.15813	0.04429	0.04086
Unemployment	-0.03537	0.10980	0.09014
Speed Cameras	-0.02418	0.00504	0.00520
Adstock	-0.03735	0.01077	0.01054
$i \times Adstock$	-0.00086	0.00127	0.00109
$i^2 \times Adstock$	0.000001	0.00002	0.00002

\mathbb{R}^2	0.7994	
DW	1.7617	
BP(17)	13.1526	p = 0.7259
F(2,114)	1.6765	p = 0.1916

	Elasticity	White Std. Error	Date
Start	-0.03820	0.00105	April 1990
Peak	-0.27945	8.46000	****
End	-0.07446	0.01959	December 1993

Table 4: Low Alcohol Hours, Rest of Victoria.

Variable	Coefficient	Std. Error	White Std. Error
Constant	4.66550	0.24440	0.21800
Trend	0.00276	0.00070	0.00062
February	-0.20585	0.05154	0.05510
March	0.02635	0.05150	0.04931
April	-0.00567	0.05174	0.04768
May	-0.13183	0.05186 .	0.05084
June	-0.16952	0.05178	0.04877
July	-0.20430	0.05225	0.04365
August	-0.29865	0.05225	0.06271
September	-0.30795	0.05234	0.04570
October	-0.12047	0.05227	0.04333
November	-0.10794	0.05221	0.03821
December	0.03309	0.05209	0.04774
Unemployment	0.00970	0.09909	0.08723
Speed Cameras	-0.00902	0.00607	0.00560
Adstock	-0.01773	0.01193	0.00992
$i \times Adstock$	-0.002737	0.00124	0.00117
.i ² ×Adstock	0.00003	0.00002	0.00002

\mathbb{R}^2	0.7097	
DW	1.7257	
BP(17)	27.9913	p = 0.0450
F(2,114)	4.3589	p = 0.0150

	Elasticity	White Std. Error	Date
Start	-0.02044	0.00113	April 1990
Peak	-0.07286	0.01632	July 1993
\mathbf{End}	-0.07210	0.01638	December 1993

Table 5: Constant Elasticity - High Alcohol Hours, Melbourne.

Variable	Coefficient	Std. Error	White Std. Error
Constant	1.73220	0.69010	0.67220
Trend	0.00369	0.00081	0.00076
February	0.17453	0.04373	0.05846
March	0.22729	0.04247	0.03689
April	0.16863	0.04481	0.04002
May	0.31483	0.04619	0.04512
June	0.21903	0.04759	0.04873
July	0.19912	0.04759	0.04446
August	0.18324	0.04652	0.04703
September	0.20740	0.04441	0.05009
October	0.19756	0.04382	0.04306
November	0.17570	0.04299	0.04448
December	0.08124	0.05773	0.04748
Unemployment	-0.31826	0.03585	0.03622
Alcohol Sales	0.52924	0.15400	0.14770
Random Breath Tests	-0.01294	0.00411	0.00349
Adstock	-0.03429	0.00774	0.00660

R² 0.8519 DW 1.8346

BP(16) 26.9463 p = 0.0421

Table 6: Constant Elasticity - High Alcohol Hours, Rest of Victoria.

Variable	Coefficient	Std. Error	White Std. Error
Constant	1.34590	0.96790	0.90570
Trend	0.00243	0.00099	0.000829
February	-0.06691	0.06228	0.05584
March	0.01088	0.06030	0.04811
April	-0.08431	0.06413	0.05846
May	-0.12206	0.06594	0.06097
June	-0.16139	0.06925	0.06958
July	-0.22579	0.06817	0.07808
August	-0.21250	0.06531	0.05725
September	-0.26033	0.06267	0.07606
October	-0.07771	0.06187	0.05719
November	-0.07254	0.06020	0.07348
December	-0.14497	0.08175	0.07346
Unemployment	-0.17359	0.06504	0.05881
Alcohol Sales	0.63506	0.21930	0.20870
Adstock	-0.03807	0.00846	0.00791

R² 0.6814 DW 1.8282

BP(15) 30.4215 p = 0.0105

Table 7: Constant Elasticity - Low Alcohol Hours, Melbourne.

Variable	Coefficient	Std. Error	White Std. Error
Constant	4.57110	0.11470	0.10660
Trend	0.00235	0.00057	0.00051
February	0.18128	0.04426	0.03712
March	0.28181	0.04410	0.05140
April	0.22316	0.04418	0.03709
May	0.29857	0.04436	0.04389
June	0.28562	0.04453	0.04607
July	0.21070	0.04465	0.04122
August	0.16665	0.04511	0.04312
September	0.14410	0.04494	0.03890
October	0.23442	0.04484	0.04331
November	0.15953	0.04485	0.04075
December	0.15301	0.04443	0.04145
Unemployment	-0.18467	0.04408	0.04027
Speed Cameras	-0.02299	0.00502	0.00513
Adstock	-0.03038	0.00959	0.00972

R² 0.7935 DW 1.7057

BP(15) 11.2911 p = 0.7317

Table 8: Constant Elasticity - Low Alcohol Hours, Rest of Victoria.

Variable	Coefficient	Std. Error	White Std. Error
Constant	4.10680	0.15770	0.13870
Trend	0.00174	0.00062	0.00053
February	-0.19958	0.05297	0.05729
March	0.02266	0.05295	0.05113
April	-0.00665	0.05316	0.04751
May	-0.13015	0.05329	0.05338
June	-0.17157	0.5321	0.04936
July	-0.21826	0.05350	0.04748
August	-0.30250	0.05370	0.06583
September	-0.30963	0.05378	0.04648
October	-0.13297	0.5354	0.04702
November	-0.11957	0.05348	0.04050
December	0.02668	0.05344	0.05087
Unemployment	-0.22577	0.06022	0.05434
Speed Cameras	-0.01092	0.00617	0.00613
Adstock	-0.03154	0.00983	0.01031

R² 0.6875 DW 1.5794

BP(15) 25.5836 p = 0.0426

Appendix.

