DEPARTMENT OF MARKETING

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FACULTY OF APPLIED ECONOMICS

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Abstract

The authors investigate the impact of direct-response commercials on incoming calls at a national call center. To this end, the authors analyze the data of a fast service for repairs of (parts of) a durable consumption good in Flanders, Belgium. The authors have access to data at the 15 minute interval covering 30 months in which 5172 radio commercials were broadcasted on six radio stations at various times of the day and at with differing commercial lengths. Their model is a two-level model, where the first-level estimates of the short-run and long-run effects are correlated with various aspects of the commercial in the second level. Their main conclusion is that GRPs are the key drivers of the effectiveness of commercials.

Keywords: advertising effectiveness, two-level model, advertising response, long-run elasticity, short-run effects

Empirical research into the effectiveness of advertising goes back a long way. Marketers have spent high amounts of money on advertising, which motivates the need for a careful assessment of the effectiveness, careful media planning both in terms of timing and medium selection, and ultimately for a sufficient return on the investment in advertising.

The empirical estimation of advertising effectiveness is not easy, see for example Tellis (2004). First, consumers may have various reasons to make purchases, and advertising may be just one of the many triggers. Second, advertisements for one particular brand may take place in various media making it hard to disentangle the different media effects. Third, advertising might not only have immediate effects but also long-term effects. Next, advertising may have time-varying effects during a campaign period. Also, sequential commercials can have overlapping effects and overlapping decays. Advertising response may differ across target segments and individuals, and wear-in and wear-out effects can further complicate the analysis.

The objective of the present study is to investigate the mediating role of three core aspects of commercials, and these are the channels (in our case radio and TV), the time of broadcasting (like the hour of the week) and the length of the commercial (15 seconds, 30 seconds etc.). We believe we can add to the relevant literature on advertising effectiveness as we have access to a very large and very detailed dataset concerning direct-response radio commercials. Recently, there have appeared various studies that relied on highly disaggregated or high frequency data, and we aim to provide new and additional empirical results to this growing body of literature. We measure the impact of direct-response commercials by the number of incoming calls at a national call center. The firm's advertising outings are mainly broadcasted through various radio stations at different times of the day, and they concern the repair of part of a durable product. The data are complete in the sense that no other communication channels are employed.

Our paper continues with a section on methodology. Here we address model specification issues and the data collection process. Next, we discuss estimation results and the validation of the results. In the last section we discuss the main conclusions of our analysis and possible directions for future research.

MODELING ADVERTISING EFFECTIVENESS

This section first reviews the relevant literature and then discusses our specification and the data analyzed.

Earlier Literature

Clarke (1976) is one of the classic papers dealing with the carryover effect of advertising on sales. He concludes that the level of inter-temporal data aggregation is the focal issue that affects the estimates of the duration of advertising carryover effects. The relevant levels of data aggregation considered by Clarke are weeks, months, quarters or years. From his study it appears that the inter-purchase time intervals are the most suitable data interval and the duration of the advertising impact is found to be less than a year. Note that Tellis and Franses (2006) recently disputed this conclusion. Leone (1995) concludes that the advertising effects last 6 months.

Dekimpe and Hanssens (1995) were the first to examine the long-term effect of advertising by considering the potential unit root properties of advertising and sales data. They document that some of the advertising outings have a persistent effect.

Little (1979) provides a survey paper on aggregate advertising models. He reviews a large amount of material on the sales effects of advertising for established products. He argues that at least five aspects should be addressed when building dynamic models of advertising effectiveness. First, when the amount of advertising is changed, sales changes may move upward or downward with different rates. Second, there are sales even when there is no advertising and steady-state response can be concave or S-shaped. Third, sales are affected by competitive advertising. Changes in media, copy, and other factors can affect the cost effectiveness of advertising. Fourth, advertising effectiveness changes over the product life cycle and it differs across products. Finally, at least according to Little (1979), many advertising models are rearrangements of a few key ideas. He recommends that all the aspects that affect advertising effectiveness should be included in the model.

The study by Jedidi, Mela, and Gupta (1999) is mostly relevant when advertising is used as a tool for building brand awareness, leading to the inclusion of the brand in consumers' consideration sets and eventually leading to purchases. For example, these authors search for the short-run and long-run effects of advertising and promotions on consumer purchase behavior and on the long-run profitability of a brand. They find that in the long run advertising has a positive effect on brand equity.

More Recent Literature on Direct-Response Advertising

Recent years have seen the emergence of what is called direct-response advertising, characterized by an immediate call to action. Examples are web-based advertising, where impact measures can be based on behavioral responses such as click-through rates, site registration, requests for information and possibly actual purchases. In traditional advertising, direct response also became more important, for example by linking the advertising to 0800 numbers, which in turn leads to a direct registration of the advertising impact on the basis of higher numbers of incoming calls. The advertising effectiveness can then be measured by means of the amount of incoming calls (Verhoef, Hoekstra, and Van Aalst 2000).

Direct-response commercials can be applied for various purposes such as selling products or services, providing information to customers or building customer databases. According to Verhoef, Hoekstra, and Van Aalst (2000), there is a growing relevance of the role of radio on direct response. The effectiveness of direct-response commercials might be influenced by broadcasting over different radio or TV channels, by the varying length or appeal of commercials, and by varying broadcasting hours over the day and on days of the week. In sum, the success of the commercial shall depend on well-designed media plans incorporating these aspects. In this context, advertising effectiveness comprises an immediate or direct-response effect and a long-run or advertising-goodwill effect. The carryover effect of advertising can be assumed to decline gradually over time. Customers may not need the product or service immediately. For that reason, a commercial may not generate calls at the same time it is broadcasted, but it may contribute to awareness and choice behavior at the time of actual purchases.

There are many econometric time series models relating advertising and sales, see for example Aaker, Carman, and Jacobson (1982), Baghestani (1991) and Tellis, Chandy, and Thaivanich (2000). These studies usually concern single-equation models, although occasionally simultaneous-equation models have been tested, see for example Rao (1972). Rao (1972) compares five different models[1] for six companies. He reports that the specification of the dependent variable is a significant factor in model building. Second, the method of estimation has no significant effect on the degree of fit.

[1] These are an ordinary least squares regression with serially independent errors, an autoregressive ordinary least squares regression with serially dependent errors, a Koyck model with serially independent errors, a Koyck model with serially dependent errors, and a simultaneous-equation model using two-stage least squares regression.

The study that most looks like ours below is Tellis, Chandy, and Thaivanich (2000), where an advertising-response model is used to analyze data based on hourly observations concerning referrals to 0800 commercials. An autoregressive-distributed lag model (ADL) is specified and this linear model takes into account the effect of advertising exposure (GRPs), channels and time of day. While their model allows for an intra-day cycle and an intra-week cycle, longer seasonal cycles and calendar effects such as bank holidays are not taken into account. It is found that baseline calls (referrals) show a bell-shaped curve over the day, with a mid-morning peak. The number of calls shows a week cycle with the highest level on Mondays and a systematic decline throughout the rest of the week. The authors estimate an average carryover effect of about 8 hours and it changes according to the time of broadcasting. Additionally, the model allows for the effects of wear-in and wear-out of ads. Wear-in is the increase in advertising effectiveness during the first weeks after an advertising campaign is started, and wear-out is the decrease in advertising effectiveness by campaign age. It is concluded that wear-in leads to a fast increase in effectiveness, whereas wear-out which is more gradual in nature, sets in rapidly.

In Chandy et al. (2001) it is found that the effect of advertising on sales varies across markets, channels and according to the creative aspects or advertising appeals. This study addresses similar issues as the ones dealt with in the study of Tellis, Chandy, and Thaivanich. (2000). They categorize the appeals as argument-based (cognitive) or emotional. They find that argument-based advertising is more effective for new products. On the other hand, emotion-based advertising is more effective in mature markets.

Transfer-function analysis or Box-Jenkins modeling and Autoregressive Distributed Lags model are the traditional approaches applied in this context. Tellis, Chandy, and Thaivanich (2000) mention that for problems such as the one dealt in their paper, with a relatively high number of explanatory variables and a large sample size due to the high frequency of the data, transfer- function analysis is not quite adequate.

Disentangling Long-Run and Short-Run Effects

In our present study, and in contrast to the study in Tellis, Chandy, and Thaivanich (2000), we aim to estimate long-run and immediate effects of commercials, and we wish to correlate these with mediating factors as channel, commercial length and so on. A convenient modeling approach for the first level of our analysis is the ADL model mentioned earlier. The basic expression of the ADL model, with one lagged sales variable and one lagged advertising variable, hence an ADL(1,1) model, is

$$\ln(Sales_t) = \mu + \lambda \ln(Sales_{t-1}) + \varphi_1 \ln(Ad_t) + \varphi_2 \ln(Ad_{t-1}) + \varepsilon_t \tag{1}$$

where "ln" denotes the natural logarithm, and where Ad_t is total advertising at time *t*. As discussed in Pauwels, Srinivasan, and Franses (2007), ADL models may have two drawbacks. First, it is difficult to interpret the parameters. Second, for proper statistical inference all the variables have to be stationary, and in practice they might not be. In order to overcome these drawbacks, model (1) can best be written in error correction [ECM] format, see Fok et al. (2006) and Pauwels, Srinivasan, and Franses (2007), that is

$$\Delta \ln(Sales_t) = \mu + (\lambda - 1)[\ln(Sales_{t-1}) - \frac{\varphi_1 + \varphi_2}{1-\lambda} \ln(Ad_{t-1})] + \varphi_1 \Delta \ln(Ad_t) + \varepsilon_t \tag{2}$$

where Δ is the first-differencing operator. Parameter φ_1 measures the immediate effect of advertising and the long-run or total effect is measured by the ratio of parameters.

In the marketing literature there are various applications of the ECM model, see for example Erdem (1996), Erdem and Keane (1996) and Pauwels, Srinivasan, and Franses (2007). Paap and Franses (2000) apply a Bayesian estimation approach to a multiple-equation ECM for brand choice.

Fok et al. (2006) and Pauwels, Srinivasan, and Franses (2007) consider models like those in (2) for a range of brands or products. This gives a range of parameter estimates for the immediate and long-run parameters. In a second level of their models, they allow these estimated parameters to be dependent on various time-invariant regressors, like the type of product, average price, and so on. Fok et al. (2006) propose to use a hierarchical Bayes [HB] method, while Pauwels, Srinivasan, and Franses (2007) treat the second-level component as a separate regression. This last two-step method is also the method that we follow in our current paper, as we will see that the availability of first-level estimates strongly varies across the variables. In fact, in our model below we will deal with 168 of equations like (2), one for each hour in the week. And, for some hours we cannot estimate immediate or long-run (total) parameters and this makes a straightforward HB method less easy to implement.

DATA

In the present study we have data concerning a repair service with very low incidence or purchase frequency. Also, commercials are broadcasted at irregular spaced intervals. Together this means that the optimal data interval for analysis is hard to find, and we will later on aggregate the data up to a convenient level for analysis. The advertiser is the market leader and brand awareness is very high, and hence the long-run effect of advertising mainly serves to maintain this brand awareness. As individuals can immediately call the service and agree upon a visit at the repair location, we focus on direct effects, and hence a high measurement frequency is desirable.

For a number of years the advertiser has now been broadcasting direct-response radio commercials. Through these radio commercials listeners are directed to dial a 0800 number and to make an appointment with a service center. The call center operates on a 24 hour 7 day a week basis. The service can take the form of a direct intervention or of an appointment at a service center in case less urgent assistance is required.

Calls arrive at the central office through two channels. There are incoming 0800 calls, and these are calls directly to the call center number advertised. And there are calls to regional service centers. The latter calls are redirected to the call center, but they are not registered as 0800 calls. While 0800 calls presumably are directly influenced by advertising, calls arriving through the service centers could be affected too. Incoming calls from both sources are categorized as relevant or non-relevant. Total relevant calls are calls involving an actual request for information, whether these result in an appointment at one of the service centers or not, including both calls originating from the toll free number or from the branch offices. Part of the total relevant calls is converted into appointments and eventually into actual repair jobs. For the advertiser, the total relevant calls constitute the preferred unit of analysis. However, because the registration of relevant calls has experienced changes within the observation period, they are not comparable over the full sample period. Non-relevant calls are calls apparently not related to the service provided. The next best are the relevant 0800 calls, which are the relevant calls originating from the 0800 line. They constitute the major part of the relevant calls. The 0800 calls series covers the period from May 13 2003 to December 1 2005. The relevant 0800 calls are only available for a shorter period. Because the 0800 calls series spans the full observation period, we will use it as the dependent variable in this analysis. The 0800 calls and the relevant 0800 calls are highly correlated, which is obvious from correlation between the two series of .96 for the overlapping samples. In Tellis, Chandy, and Thaivanich (2000) 'referrals' are used as the dependent variable and the referrals are defined as a successful telephone connection between customer and service provider. Given the discussion above, it is clear that basically our 0800 calls are the equivalent of the referrals in Tellis, Chandy, and Thaivanich (2000), and hence the results below can be seen as complementary. Good estimates of conversion rates (from incoming calls to relevant calls, to appointments and to actual jobs) are available to management and are applied to determine the return on investment for advertising.

--- Insert Figures 1 and 2 about here ---

Our real-time data are reported in 15 minutes intervals. In total 261167 0800 calls were recorded. Figure 1 shows the time evolution of the 0800 calls. For practical reasons, the data are aggregated to hourly data resulting in a dataset of 22416 observations (or hours). This level of aggregation leads to a limited occurrence of multiple spots within a time slot on a particular channel. Figure 2 demonstrates the distribution of 0800 calls by the hour in a week of 168 hours. From this graph, it can be concluded that the number of calls is highest on Mondays. The 0800 calls series can be considered as stationary and a Dickey-Fuller test confirms this conclusion. This means that advertising may have an immediate effect on incoming 0800 calls that persists over some time but there is no permanent effect. In Fok et al. (2006) it is shown that the parameter in parentheses in (2) can now be interpreted as the cumulative or total effect.

---Insert Table 1 about here---

Table 1 provides a summary of radio commercials in the full dataset. During the observation period, 5172 radio commercials were broadcasted on 6 radio stations at various times of the day (from 6 AM to 9 PM). The commercials have different lengths (5, 10, 15, 16, 20, 21, 25, 30, 35, 40 or 41 seconds). Because of their limited occurrences, 16 seconds commercials will be pooled with the 15 seconds commercials. Likewise 21 seconds commercials are added to the 20 seconds commercials. Finally, 30, 35, 40 and 41 seconds commercials are pooled in a single category, which is labeled as 30 seconds as this is the dominant length. Preliminary and unreported estimation results indicated that there is no significant impact for 5 and 10 seconds commercials, and, consequently, they are dropped from the model.

---Insert Table 2 about here---

For 4141 radio commercials we have additional information about campaign characteristics. Table 2 shows the distribution of the radio commercials in terms of the commercial length and the campaign theme. From this table, it may be concluded that there is a strong link between the length of the commercial and the campaign characteristics. Tellis et al. (2005) considered the creative characteristics of a campaign and investigated their effect in different market contexts. However, in our context we are operating in a single rather mature market, so this is not pursued here. Furthermore, we observe a high correlation between commercial length and campaign characteristics in our data. For that reason we prefer to rely on the length of the commercial, keeping in mind that the length effects and the campaign theme effects are largely confounded because of the strong relationship between the two characteristics.

---Insert Tables 3, 4 and 5 about here---

Tables 3 and 4 give the summary of scheduling by hour of day and by day of the week, showing a predominance of commercials at 7 AM, and 20% less commercials on Fridays as compared to other weekdays. There are very few commercials which are broadcasted during the weekend (73 for Saturdays, 28 for Sundays). Table 5 gives an overview of the channels by length and by hour.

---Insert Figure 3 about here---

Advertising pressure of a commercial is measured by means of Gross Rating Points (GRPs) (Tellis, 2004). The GRPs in our study relate to the age bracket 25-55, which is considered the relevant target market for the product. For 4 channels (out of 6 channels) Gross Rating Points (GRPs) were measured using a panel, by means of a portable people meter, which registers if the person is exposed to the commercial and to which channel. This results in GRPs at the level of the individual commercials. For the other channels GRPs are obtained from a diary panel, for which the data are processed in quarterly waves leading to constant GRPs during a particular wave for a given channel and time of broadcast. Figure 3 shows the distribution of commercials and related GRPs for the entire dataset. The number of TV commercials is small, and also due to the fact that they are highly concentrated in a single wave, there are limits to the reliability of these effectiveness estimates.

SPECIFICATION

The purpose of our study is to evaluate the impact of direct-response commercials on incoming calls at the call center, and to examine the mediating role of channels, time of broadcasting and duration of commercials. In order to model the relationship between the advertising variables and the 0800 calls, we propose a two-level model. First, we estimate 168 equations for each of the hours within a week to obtain the relevant advertising elasticities. In a second stage, these parameters are fed into a new regression model with the above factors as explanatory variables. All model parameters are estimated using a maximum likelihood approach, under the assumptions that the error terms of the different equations are uncorrelated and that there is no autocorrelation in the error terms.

The First Level

In the literature (Pauwels, Srinivasan, and Franses, 2007, Pauwels and Srinivasan, 2004 and Srinivasan et al., 2004) most models mainly contain first-order autoregressive terms and first-order distributed lags. In our case however first order distributed lag terms might be too restrictive. Quite often radio commercials are broadcasted in the last minutes of the hour, leaving little time to respond within that hour. Consequently, the next hour (and in the model: the first lag) may actually be interpreted as current impact, requiring a second hour (lag) for lagged impact. However, this is not necessarily true for all commercials, but we let the data tell us which structure is best by incorporating both lags in all 168 equations. Further, preliminary but unreported estimation results of distributed-lag models showed that the second lag of the radio advertising is highly significant. In order to take these timing issues into account, we thus opt for a second-order distributed lag model for radio advertising.

With respect to television, those commercials are mostly concentrated in evening or night hours. This results in very limited within-the-day effects of TV advertising. An unreported preliminary analysis indicated that the next-day effects are highly significant for television advertising. The next day effects for TV advertising are derived from the total of the GRPs of the previous day for all channels combined and these total GRPs are included for all hours of the next day.

The above considerations lead to the 168 time series models summarized below in (3), where incoming 0800 calls is the endogenous variable and radio and television advertising are the exogenous variables. For each hour we have a model where the data run for week 1 to week 133, that is,

$$
\begin{aligned}
&\ln(Calls_{h,w}) = \theta_h + \lambda_h \ln(Calls_{h-1,w}) + \varphi_{1,h} \ln(GRP^{Radio}_{h,w}) + \varphi_{2,h} \ln(GRP^{Radio}_{h-1,w}) \\
&+\varphi_{3,h} \ln(GRP^{Radio}_{h-2,w}) + \varphi_{4,h} \ln(GRP^{TV}_{h,w}) + \varphi_{5,h} \ln(GRP^{TV}_{h-1,w}) + \varphi_{6,h} \ln(GRP^{TV}_{d-1,w}) + \varepsilon_{h,w} \\
&h = 0,..,167 \\
&w = 1,..,133 \\
&Calls_{h,w} = ObservedCalls_{h,w} + 1 \\
&GRP^{Radio}_{h,w} = ObservedGRP^{Radio}_{h,w} + 1 \\
&GRP^{TV}_{h,w} = ObservedGRP^{TV}_{h,w} + 1
\end{aligned}
\qquad (3)
$$

where $GRP^{TV}_{d-1,w} = \sum_{h=0}^{23} GRP^{TV}_{h-24}$, $GRP^{Radio}_{h,w}$ is the total radio GRPs at hour h, $GRP^{TV}_{h,w}$ is the total television GRPs at hour h and $\varepsilon_{h,w}$ is a white noise error term. $GRP^{TV}_{d-1,w}$ represents the next-day effect of television advertising and it is derived from the total of the GRPs of the previous day for all channels combined. Next-day effects for television run throughout the next day from hours 0 to 23. Subscript h denotes the hour in a week, and w is the week number and runs from 1 to 133.

All variables are in logarithms. Both Calls and GRPs contain zero values therefore we add 1 before we take logs. In error correction format, the model is

$$
\begin{aligned}
&\Delta \ln(Calls_{h,w}) = \mu_h + \beta_{1,h}^{Radio} \Delta \ln(GRP_{h,w}^{Radio}) + \beta_{2,h}^{Radio} \Delta \ln(GRP_{h-1,w}^{Radio}) + \beta_{3,h}^{TV} \Delta \ln(GRP_{h,w}^{TV}) \\
&+\gamma_h \left[\ln(Calls_{h-1,w}) - \alpha_{1,h}^{Radio} \ln(GRP_{h-2,w}^{Radio}) - \alpha_{2,h}^{TV} \ln(GRP_{h-1,w}^{TV}) - \alpha_{3,h}^{TV} \ln(GRP_{d-1,w}^{TV}) \right] + \varepsilon_{h,w} \\
&h = 0,..,167 \\
&w = 1,..,133 \\
&\gamma_h = \lambda_h - 1 \\
&\alpha_{1,h}^{Radio} = \sum_{i=1}^{3} \varphi_{i,h} / (1-\lambda_h) \\
&\alpha_{2,h}^{TV} + \alpha_{3,h}^{TV} = \sum_{i=4}^{6} \varphi_{i,h} / (1-\lambda_h)
\end{aligned}
\tag{4}
$$

The parameters β_h measure the short-run effects of advertising on 0800 calls, the α_h parameters measure the long-run (or total) effects of GRPs and γ_h measures the short-run deviation from the long-run (here: cumulative) effects of GRPs and it is equal to ($\lambda_h - 1$). The long-term effects of radio advertising ($\alpha_{1,h}^{Radio}$) and television advertising ($\alpha_{2,h}^{TV} + \alpha_{3,h}^{TV}$) are equal to $\sum_{i=1}^{3} \varphi_{i,h} / (1-\lambda_h)$ for radio advertising and $\sum_{i=4}^{6} \varphi_{i,h} / (1-\lambda_h)$ for television advertising.

Due to a sometimes limited availability of the data, we face a few estimation problems. For example, for some hours we do not have advertising data. If this is the case the current impact cannot be estimated for the hour concerned. This implies that it is not possible to estimate the short-run and long-run (total) effects of advertising for these particular hours. In such cases our model will deliver only partial long-term effects. For example, if the first lag of radio advertising is equal to zero for one hour, the long-term (total) effect of radio advertising will be $(\varphi_{1,h} + \varphi_{3,h})/(1-\lambda_h)$. And, if the second lag of radio advertising is equal to zero for one hour, the total effect of radio advertising will be $(\varphi_{1,h} + \varphi_{2,h})/(1-\lambda_h)$.

The Second Level

In the second step the coefficients in (3) obtained are modeled as functions of the commercial characteristics and of time. A weighted least squares model is estimated for each of the parameters obtained where the weights are the inverse of the standard errors of the parameters obtained from the first-level model. Franses and Paap (2005) propose the use of goniometrical time-varying coefficients in order to obtain a parsimonious modeling of seasonality. The parameters from the first stage show an intra-day pattern which suggests a goniometric cycle with a length of one day. The explanatory variables in the second-level models are proportions of the GRPs in each channel, the fraction of the GRPs for each length of a commercial, dummies for the days in the week, and a sinusoidal time wave with a frequency of one day. The second level of the model is thus given by

$$\begin{aligned}\varphi_{1,h} &= \varphi'_{0,h} + \sum_{Ch=1}^{5} \varphi'_{1,h} Ch_h^{Radio} + \sum_{length=1}^{3} \varphi'_{2,h} Length_h^{Radio} \\ &+ \varphi'_{3,h} \mathrm{Sin}_h[2\pi h/24] + \varphi'_{4,h} \mathrm{Cos}_h[2\pi h/24] + \sum_{d=2}^{7} \varphi'_{5,h} D_d + \varepsilon_{1,h}\end{aligned} \tag{5}$$

$$\begin{aligned}\varphi_{2,h} &= \varphi''_{0,h} + \sum_{Ch=1}^{5} \varphi''_{1,h} Ch_h^{Radio} + \sum_{length=1}^{3} \varphi''_{2,h} Length_h^{Radio} \\ &+ \varphi''_{3,h} \mathrm{Sin}_h[2\pi h/24] + \varphi''_{4,h} \mathrm{Cos}_h[2\pi h/24] + \sum_{d=2}^{7} \varphi''_{5,h} D_d + \varepsilon_{2,h}\end{aligned} \tag{6}$$

$$\varphi_{3,h} = \varphi'''_{0,h} + \sum_{Ch=1}^{5} \varphi'''_{1,h} Ch_h^{Radio} + \sum_{length=1}^{3} \varphi'''_{2,h} Length_h^{Radio} \\ + \varphi'''_{3,h} \mathrm{Sin}_\mathrm{h}[2\pi h/24] + \varphi'''_{4,h} \mathrm{Cos}_\mathrm{h}[2\pi h/24] + \sum_{\mathrm{d}=2}^{7} \varphi'''_{5,h} D_d + \varepsilon_{3,h} \tag{7}$$

$$\varphi_{4,h} = \varphi_{0,h}^{TV} + \sum_{Ch=1}^{2} \varphi_{1,h}^{TV} Ch_h^{TV} + \sum_{length=1}^{1} \varphi_{2,h}^{TV} Length_{h-1}^{TV} \\ + \varphi_{3,h}^{TV} \mathrm{Sin}_\mathrm{h}[2\pi h/24] + \varphi_{4,h}^{TV} \mathrm{Cos}_\mathrm{h}[2\pi h/24] + \sum_{\mathrm{d}=2}^{7} \varphi_{5,h}^{TV} D_d + \varepsilon_{4,h} \tag{8}$$

$$\varphi_{5,h} = \varphi_{0,h}^{TV'} + \sum_{Ch=1}^{2} \varphi_{1,h}^{TV'} Ch_h^{TV} + \sum_{length=1}^{1} \varphi_{2,h}^{TV'} Length_{h-1}^{TV} \\ + \varphi_{3,h}^{TV'} \mathrm{Sin}_\mathrm{h}[2\pi h/24] + \varphi_{4,h}^{TV'} \mathrm{Cos}_\mathrm{h}[2\pi h/24] + \sum_{\mathrm{d}=2}^{7} \varphi_{5,h}^{TV'} D_d + \varepsilon_{5,h} \tag{9}$$

$$\varphi_{6,h} = \varphi_{0,h}^{TV''} + \sum_{Ch=1}^{2} \varphi_{1,h}^{TV''} Ch_h^{TV} + \sum_{length=1}^{1} \varphi_{2,h}^{TV''} Length_{h-1}^{TV} \\ + \varphi_{3,h}^{TV''} \mathrm{Sin}_\mathrm{h}[2\pi h/24] + \varphi_{4,h}^{TV''} \mathrm{Cos}_\mathrm{h}[2\pi h/24] + \sum_{\mathrm{d}=2}^{7} \varphi_{5,h}^{TV''} D_d + \varepsilon_{6,h} \tag{10}$$

$$\lambda_h = \lambda_0 + \lambda_1 \mathrm{Sin}_\mathrm{h}[2\pi h/24] + \lambda_2 \mathrm{Cos}_\mathrm{h}[2\pi h/24] + \sum_{\mathrm{d}=2}^{7} \lambda_3 D_d + \varepsilon_{7,h} \tag{11}$$

$$\theta_h = \theta_1 + \theta_2 \mathrm{Sin}_\mathrm{h}[2\pi h/24] + \theta_3 \mathrm{Cos}_\mathrm{h}[2\pi h/24] + \sum_{\mathrm{d}=2}^{7} \theta_4 D_d + \varepsilon_{8,h} \tag{12}$$

Missing coefficients in the first level result in fewer observations in the second level for some coefficients, but do not otherwise have an impact on the procedure. In fact, the results of the second level models allow to asses the effectiveness for missing hours.

ESTIMATION RESULTS

Table 6 summarizes the significance of the estimation results for the first level of the model in the format of (3).

---Insert Table 6 about here---

In sum there are 877 parameters that can be estimated. Out of these, 320 parameters are significant (at the 5% significance level). This means that approximately 37% of the parameters is significant. In the second level, the moderating effects are tested by an F-test. Even at a significance level of 10%, we find little or no effects of the mediating variables. The only finding is that daytime scheduling does have an impact, at least to some extent. This conclusion is different from those obtained in studies like Chandy et al. (2001).

---Insert Table 7 about here---

Table 7 shows the significance of the goniometric waves for each of the parameters. For the first and second lag of radio GRPs ($\varphi_{2,h}$ and $\varphi_{3,h}$) and for the next-day effect of television GRPs ($\varphi_{6,h}$), none of the goniometric functions is significant.

---Insert Figures 4, 5 and 6 about here---

Using the estimation results for the second-level models, we can extrapolate parameter values for the hours where we do have missing data. Figures 4 to 6 show the extrapolated and observed parameter distribution of the current ($\varphi^{i}_{1,h}$), first lag ($\varphi^{i}_{2,h}$) and second lag ($\varphi^{i}_{3,h}$) of the radio GRPs. Extrapolated estimates are smoother than observed estimates. These graphs show that outliers become more consistent with the pattern.

Managers are mostly interested in the long-run (or total) impact of the advertising (Dekimpe and Hanssens, 1995). We also estimate the long-run impact of the advertising, and for that we use extrapolated parameters. In the logarithmic autoregressive distributed lag model, the long-term effects of television and radio advertising are calculated as .877 and .340, respectively. Across the 168 equations in (3), the average long-term elasticity for television advertising [when averaging $\sum_{i=4}^{6} \varphi_{i,h} /(1-\lambda_h)$] is .952 and the average long-term elasticity for radio advertising [when averaging $\sum_{i=1}^{3} \varphi_{i,h} /(1-\lambda_h)$] is .189. As expected, long-run (total) effects of advertising on radio and television are positive.

---Insert Figure 7 about here---

Figure 7 shows that there is a linear relationship between the total impact per commercial and radio GRPs. This result is also confirmed by the second level of the model. As we found a constant effect of advertising irrespective of channel, duration or hour effect, we can conclude that the effect of advertising is simply related with GRPs.

---Insert Figures 8 and 9 about here---

Figures 8 and 9 indicate the relationships between baseline calls, incremental calls and logarithms of GRPs for radio and television advertising, respectively. The baseline calls series is calculated as the average calls by time of week in non-active weeks, that is, weeks with no advertising during the entire week. Incremental calls are calculated using the extrapolated long-run elasticities. In these graphs we notice a few outliers in terms of incremental calls. These figures show that, if we do not take outliers into account, after a certain point of logarithm of GRPs and baseline calls, higher GRPs generate more incremental calls. These results are consistent with our previous results which confirmed that advertising effectiveness depends on reach. Higher reach means higher advertising effectiveness irrespective of channels or durations of the commercials. Figure 8 reveals that impact is correlated with the baseline calls. This means that advertising generates more calls for hours when there is high baseline calls.

Figure 10 presents the relationship between hour of broadcast, incremental calls and logarithms of GRPs for television advertising. This graph shows that for the most of the hours there are no GRPs and this means there is no advertising during the entire time span.

---Insert Figures 10, 11 and 12 about here---

Figures 11 and 12 represent the extrapolated long-term elasticities for radio and television, respectively. These graphs show that there is a weekly pattern for elasticities. In other words, elasticities vary with the hour within the week. This finding is important in terms of media planning.

In order to calculate the net impact in terms of calls, baseline calls are an important factor.

---Insert Figures 13, 14 and 15 about here---

Figure 13 shows the average baseline calls by hour in the week. Figure 14 shows the average GRPs for one of the channels, that is, Radio 6. Figure 15 represents the calculated total impact using long-term elasticities for radio. As advertising generates a varying number of calls according to hour of broadcast, effective media planning is really important for the cost effectiveness.

CONCLUSIONS

In this paper, we proposed and analyzed a two-level model to explain the long-run (total) and short-run effects of advertising on incoming 0800 calls. First level-estimation results indicated the presence of immediate and carryover effects of radio and television advertising. In the second level we considered potential mediating effects of channels and commercial lengths on short-run and total effects of advertising.

The most important finding in this paper is that the advertising effectiveness depends on the GRPs of the commercials. In contrast to other studies, the effectiveness of ads is itself only related with GRPs. Another contribution of this study is that, beyond threshold values of GRPs and baseline calls, advertising generates more calls.

The management implications of our study are related to the main finding that media planning should focus on a budget allocation that maximizes reach given the budget constraint. Of course this does not take into account practical constraints. Concentrating the commercials too much around ‘low cost per GRP’ slots may result in too much audience replication, a factor not accounted for in our model. In terms of effective media planning however, we find that the GRPs scheduled are the key drivers of the effect of advertising. This study also confirms that advertising generates more calls for hours when there is high baseline calls. To the extent that high impact or reach is linked to peaks in the day cycle, advertising may accentuate these peaks.

Limitations and Further Research

One of the limitations of this study is that it concerns a specific market and product. The model and results might be validated for other products, markets and contexts. The second drawback is the limited diversification of advertising themes. Evaluation of commercial themes with higher diversity, might lead to more outspoken differences in effectiveness that the ones we find. Another limitation might be that for some hours there are no commercials. This may limit the reliability of the goniometrical wave for the time varying coefficients at the second level of the model. Another limitation of the present study might be that it does not take into account the effectiveness of advertising on attitude and memory. From our communication with management we know that yearly waves of consumer research find consistently high levels of brand awareness, but we have no further attitudinal data or attitudes towards the advertisements. Finally, while did not integrate a profitability analysis of the media scheduling, the company does follow up on return on investment implications. In this study we only analyze the effectiveness of advertising and we do not have any data related to the cost of advertising which could be help to introduce the cost of effectiveness and profitability of the media scheduling.

We see various avenues for further research. One of them is stability and sensitivity of advertising effectiveness under time aggregation. The differences in the estimates of advertising impact might be investigated when using different aggregate levels. Channel, length of commercial and hour of broadcast are the key features of the commercial. Data aggregated across the channel, length of commercial or hour of broadcast lead to different data that require different models, see Tellis and Franses (2006) among others. Together with the aggregation, summarizing the data across variables might be an important issue in terms of decreasing the cost of data collection, storage and analysis. The second future research topic is likely to be the estimation of dynamic effects of different advertising themes in a campaign and wear-out and forgetting the effects of an ad. The saturation issue in the sense of intensity of campaign might also be investigated. At the point of saturation, increasing the number of commercials may not enhance advertising effectiveness. In this case, in order to improve its effectiveness, the company should change any aspect of advertising. Determination of the saturation threshold of advertising shows whether the managers need to invest more in order to make the advertising more effective.

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Tables

TABLE 1

DISTRIBUTION OF RADIO COMMERCIALS OVER RADIO AND COMMERCIAL LENGTH

	Commercial Length											
Station	**5"**	**10"**	**15"**	**16"**	**20"**	**21"**	**25"**	**30"**	**35"**	**40"**	**41"**	**Total**
Channel 1	0	58	26	10	341	7	23	178	0	6	5	654
Channel 2-Region 1	6	46	28	0	256	5	26	230	6	0	0	603
Channel 2-Region 2	6	46	28	0	256	5	26	230	6	0	0	603
Channel 2-Region 3	6	46	28	0	256	5	26	230	6	0	0	603
Channel 2-Region 4	6	46	28	0	256	5	26	230	6	0	0	603
Channel 2-Region 5	6	46	28	0	256	5	26	230	6	0	0	603
Channel 3	0	0	0	15	105	9	0	0	0	8	7	144
Channel 4	0	0	9	0	180	0	0	0	0	12	0	201
Channel 5	0	0	36	0	174	0	0	0	0	20	0	230
Channel 6	0	62	35	14	472	10	36	280	10	5	4	928
Total	30	350	246	39	2552	51	189	1608	40	51	16	5172

TABLE 2
DISTRIBUTION OF RADIO COMMERCIALS OVER COMMERCIAL LENGTH AND CAMPAIGNS

	Campaigns					
Commercial Length	**Testimonials**	**A to Z**	**Direct Marketing**	**Price Promotion**	**Your Place or Ours**	**Total**
10''	0	0	355	0	0	355
15''	0	0	0	96	24	120
20''	0	1453	0	0	374	1827
25''	0	187	0	0	0	187
30''	1612	0	0	0	0	1612
35''	40	0	0	0	0	40
Total	1652	1640	355	96	398	4141

TABLE 3

DISTRIBUTION OF RADIO COMMERCIALS OVER RADIO STATION AND HOUR OF BROADCAST

	Hour of Broadcast															
Station	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**Total**
Channel 1	59	72	50	59	28	32	93	8	12	19	34	124	53	11	0	654
Channel 2-Region 1	81	177	39	16	25	21	59	12	8	23	65	57	5	15	0	603
Channel 2-Region 2	81	177	39	16	25	21	59	12	8	23	65	57	5	15	0	603
Channel 2-Region 3	81	177	39	16	25	21	59	12	8	23	65	57	5	15	0	603
Channel 2-Region 4	81	177	39	16	25	21	59	12	8	23	65	57	5	15	0	603
Channel 2-Region 5	81	177	39	16	25	21	59	12	8	23	65	57	5	15	0	603
Channel 3	0	1	37	12	30	19	5	0	0	0	2	1	34	3	0	144
Channel 4	2	46	27	28	33	21	20	0	0	0	3	14	7	0	0	201
Channel 5	0	19	36	41	0	8	48	5	7	9	5	24	28	0	0	230
Channel 6	39	127	129	83	150	56	108	11	5	8	82	60	16	45	9	928
Total	505	1150	474	303	366	241	569	84	64	151	451	508	163	134	9	5172

TABLE 4

DISTRIBUTION OF RADIO COMMERCIALS OVER RADIO STATION AND DAY OF BROADCAST

	Day of Broadcast							
Station	**Monday**	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Saturday**	**Sunday**	**Total**
Channel 1	141	142	128	133	101	5	4	654
Channel 2-Region 1	129	122	113	127	97	11	4	603
Channel 2-Region 2	129	122	113	127	97	11	4	603
Channel 2-Region 3	129	122	113	127	97	11	4	603
Channel 2-Region 4	129	122	113	127	97	11	4	603
Channel 2-Region 5	129	122	113	127	97	11	4	603
Channel 3	32	31	30	25	24	2	0	144
Channel 4	44	40	42	41	34	0	0	201
Channel 5	48	46	47	49	39	1	0	230
Channel 6	195	198	176	179	166	10	4	928
Total	1105	1067	988	1062	849	73	28	5172

TABLE 5

STATION, LENGTH AND HOUR DISTRIBUTION

Station	Length	Hour 6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	Total
Channel 1	15	4	9	9	10	4	9	15	1	2	3	8	16	4	0	0	**94**
	20	20	28	26	37	19	16	73	5	7	11	12	41	42	11	0	**348**
	25	1	1	0	4	4	4	1	1	3	3	0	1	0	0	0	**23**
	30	34	34	15	8	1	3	4	1	0	2	14	66	7	0	0	**189**
Channel 2	5	0	25	5	0	0	0	0	0	0	0	0	0	0	0	0	**30**
	15	65	170	30	10	10	10	30	0	0	5	20	15	5	0	0	**370**
	20	195	380	55	20	20	25	235	20	10	45	120	130	15	35	0	**1305**
	25	25	55	5	0	0	0	5	0	0	0	20	20	0	0	0	**130**
	30	120	255	100	50	95	70	25	40	30	65	165	120	5	40	0	**1180**
Channel 3	15	0	0	5	1	3	1	0	0	0	0	0	0	5	0	0	**15**
	20	0	1	29	9	23	15	5	0	0	0	2	1	26	3	0	**114**
	30	0	0	3	2	4	3	0	0	0	0	0	0	3	0	0	**15**
Channel 4	15	0	5	0	1	1	2	0	0	0	0	0	0	0	0	0	**9**
	20	2	37	26	26	30	18	17	0	0	0	3	14	7	0	0	**180**
	30	0	4	1	1	2	1	3	0	0	0	0	0	0	0	0	**12**
Channel 5	15	0	2	6	5	0	0	10	0	1	1	1	4	6	0	0	**36**
	20	0	14	28	31	0	8	34	5	4	7	4	19	20	0	0	**174**
	30	0	3	2	5	0	0	4	0	2	1	0	1	2	0	0	**20**
Channel 6	15	10	16	15	11	23	6	10	0	0	0	8	3	4	5	0	**111**
	20	19	68	66	39	77	30	79	3	2	2	33	15	0	40	9	**482**
	25	3	9	7	0	8	2	0	1	0	0	1	5	0	0	0	**36**
	30	7	34	41	33	42	18	19	7	3	6	40	37	12	0	0	**299**
	Total	**505**	**1150**	**474**	**303**	**366**	**241**	**569**	**84**	**64**	**151**	**451**	**508**	**163**	**134**	**9**	**5172**

TABLE 6

THE DISTRIBUTION OF THE PARAMETERS AND SIGNIFICANCE (EQUATION (4))

	Equation (4)	
Parameters	**Significant**	**Number of Observations**
θ_h	161	168
λ_h	115	168
$\varphi_{1,h}$	14	82
$\varphi_{2,h}$	5	82
$\varphi_{3,h}$	2	82
$\varphi_{4,h}$	4	64
$\varphi_{5,h}$	5	63
$\varphi_{6,h}$	14	168
Total	**320**	**877**

TABLE 7

SIGNIFICANCE OF THE SINUSOIDAL AND COSINE WAVE (EQUATION (6-13))*

	Equation (6-13)	
Parameters	$\mathrm{Sin}_h[2\pi h/24]$	$\mathrm{Cos}_h[2\pi h/24]$
θ_h	**- .307 (.053)**	**- .627 (.056)**
λ_h	**- .126 (.017)**	**- .226 (.016)**
$\varphi_{1,h}$	- .004 (.016)	**.060 (.027)**
$\varphi_{2,h}$	- .012 (.025)	.005 (.026)
$\varphi_{3,h}$	.020 (.030)	.035 (.026)
$\varphi_{4,h}$	**.359 (.182)**	**.317 (.121)**
$\varphi_{5,h}$	**.508 (.228)**	- .218 (.136)
$\varphi_{6,h}$	- .023 (.015)	.005 (.014)

*Coefficients with standard errors in parentheses; estimates significant at the 10% level in bold.

Figures

FIGURE 1

0800 CALLS OVER TIME

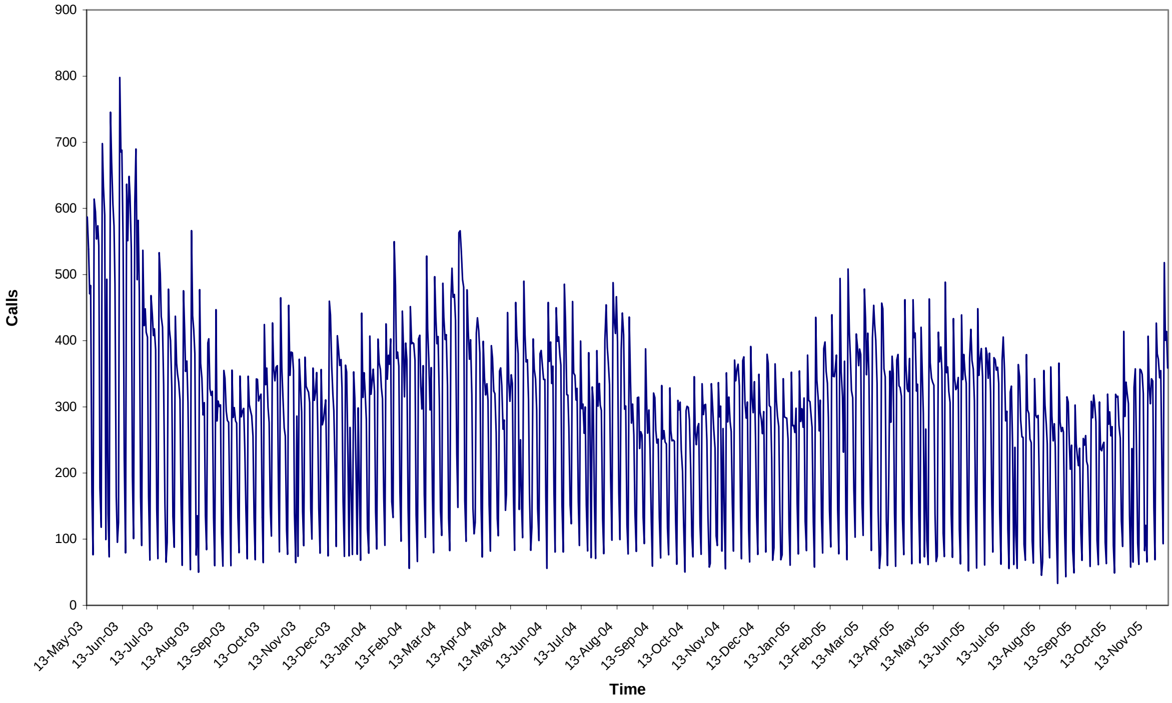

FIGURE 2

0800 CALLS BY WEEKLY CYCLE (WEEK 15)

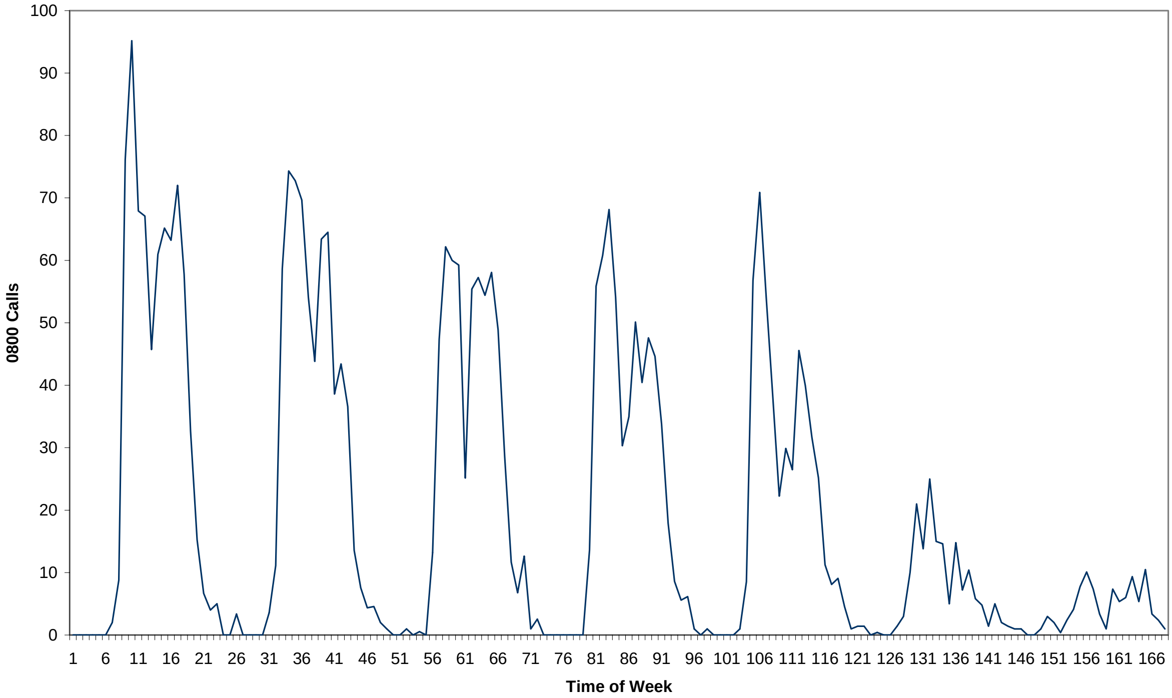

FIGURE 3

RADIO GRPS OVER TIME

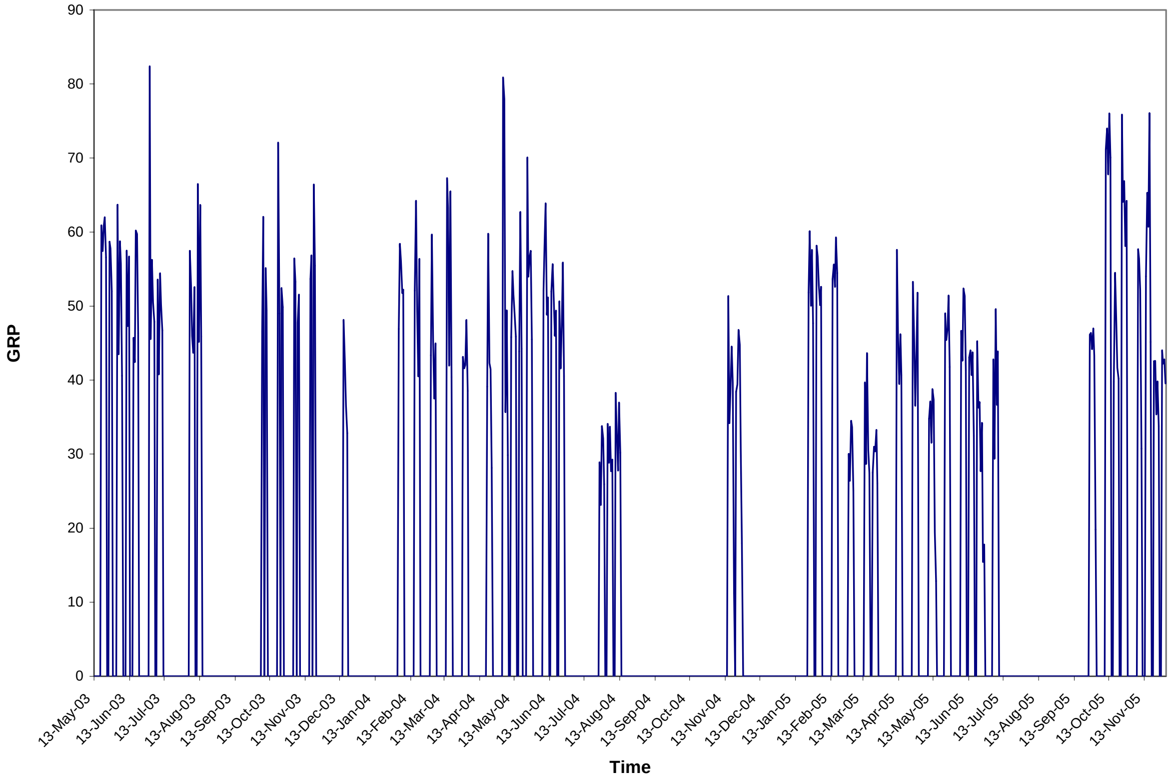

FIGURE 4

RELATIONSHIP BETWEEN THE FORECASTED CALLS AND LOG (RADIO GRP)

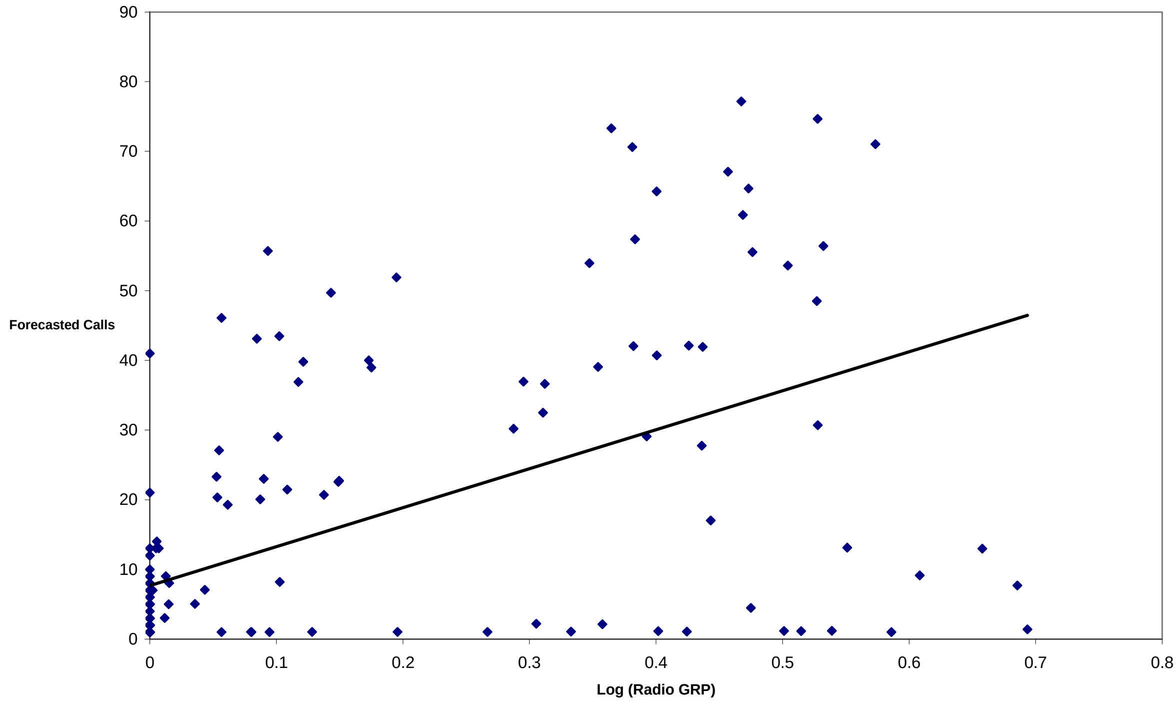

FIGURE 5

DISTRIBUTION OF $\varphi^{i}_{1,h}$

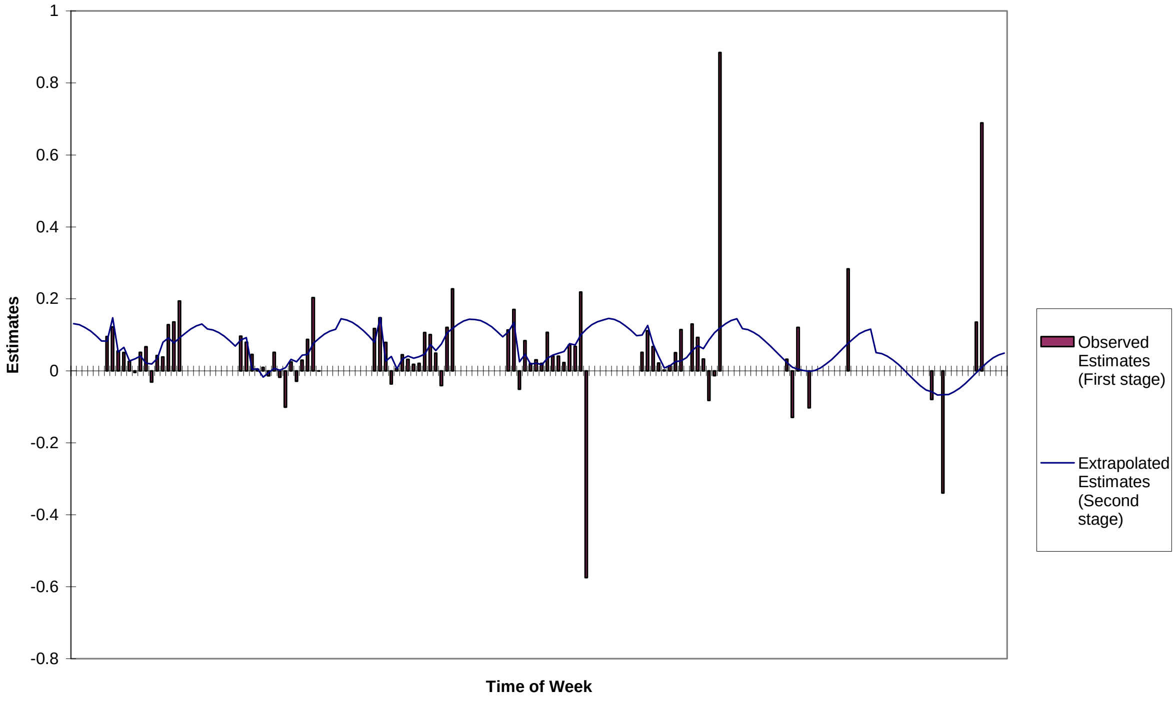

FIGURE 6

DISTRIBUTION OF $\varphi^{i}_{2,h}$

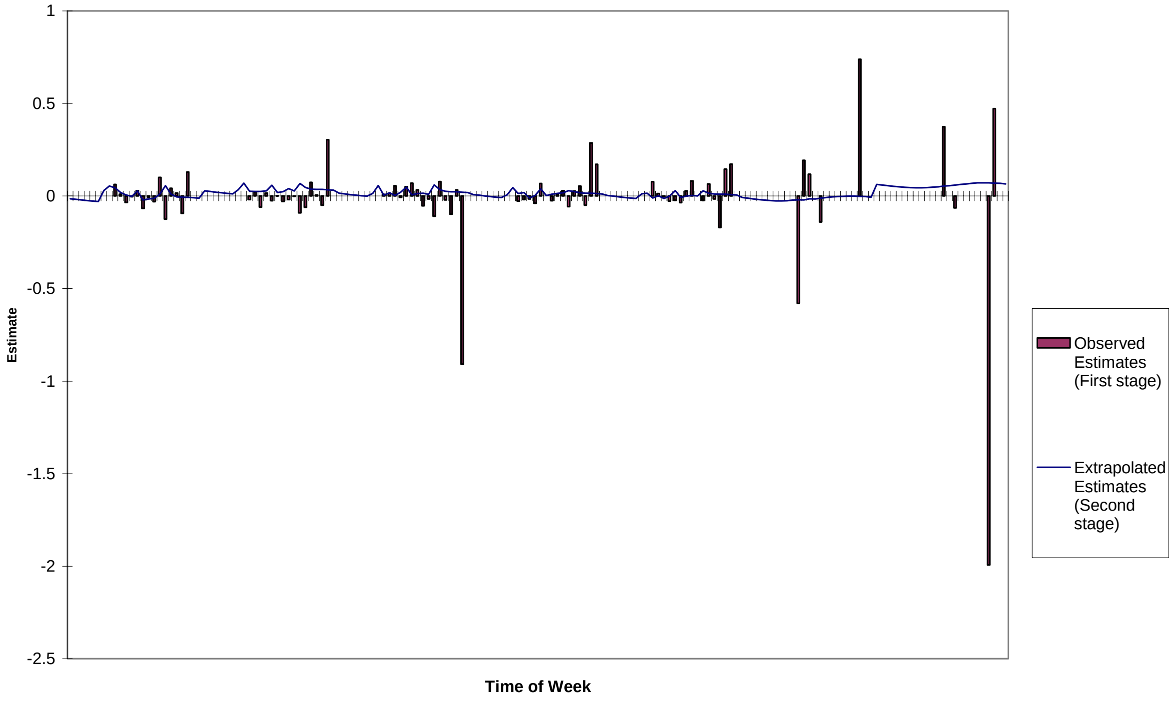

FIGURE 7

DISTRIBUTION OF $\varphi'^{i}_{3,h}$

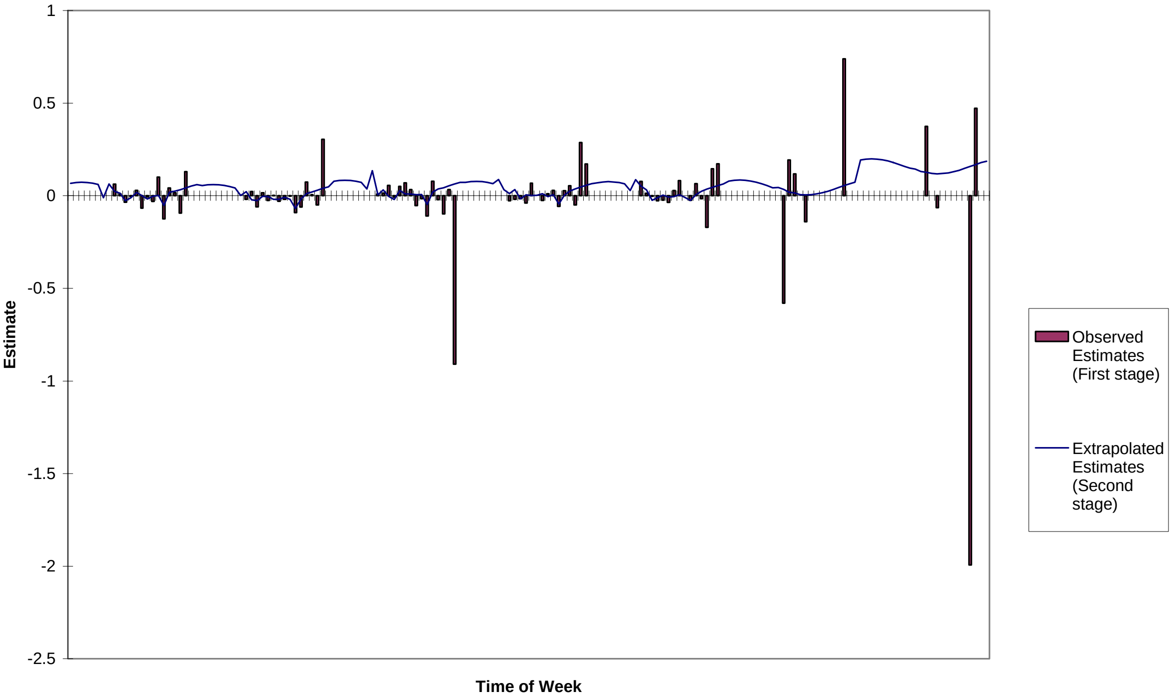

FIGURE 8

RELATIONSHIP BETWEEN THE BASELINE CALLS, INCREMENTAL CALLS AND LOG (RADIO GRP)

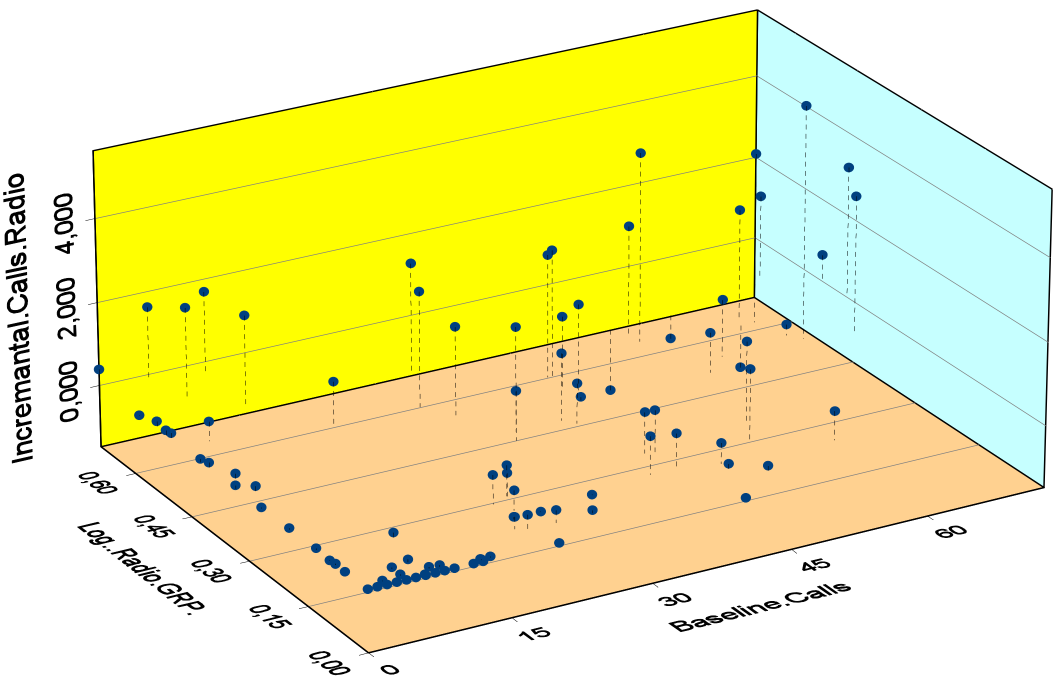

FIGURE 9

RELATIONSHIP BETWEEN THE BASELINE CALLS, INCREMENTAL CALLS AND LOG (TV GRP)

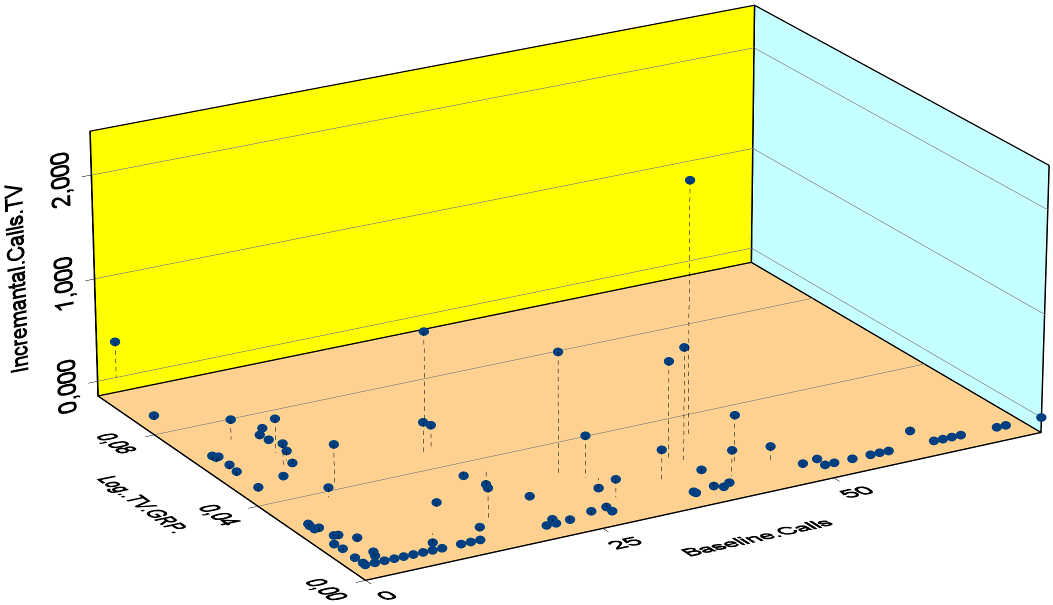

FIGURE 10

RELATIONSHIP BETWEEN THE HOUR OF BROADCAST, INCREMENTAL CALLS AND LOG (TV GRP)

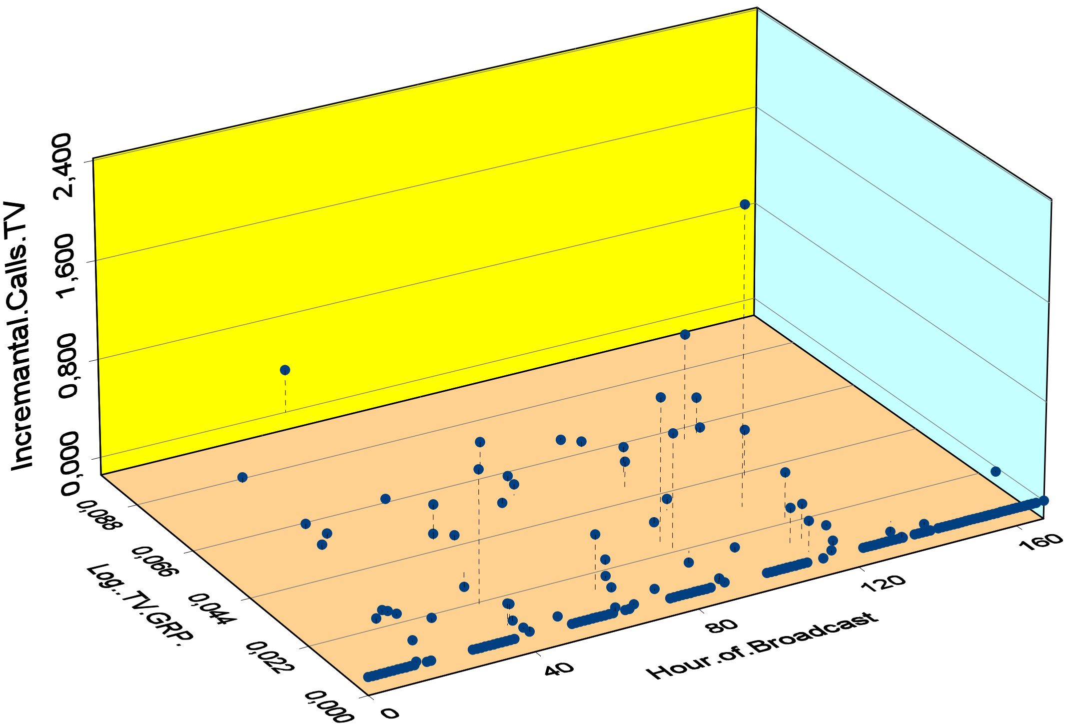

FIGURE 11

LONG TERM ELASTICITY FOR RADIO (INFERRED FROM SECOND STAGE)

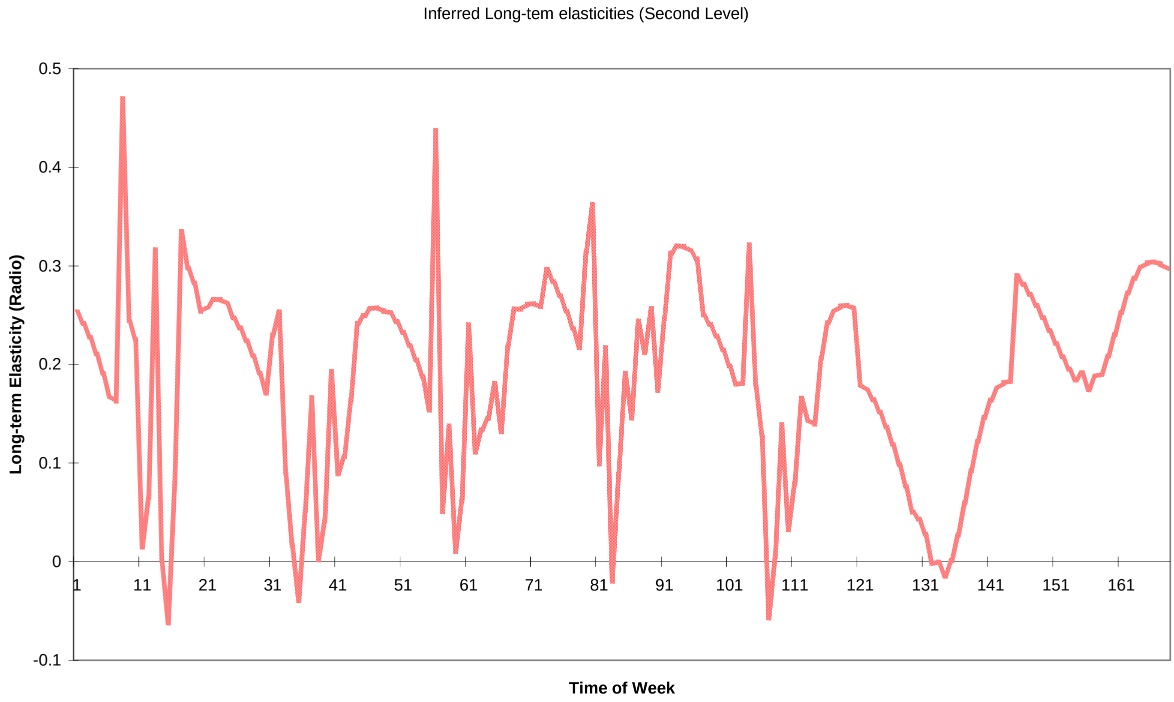

FIGURE 12

LONG TERM ELASTICITY FOR TV (INFERRED FROM SECOND STAGE)

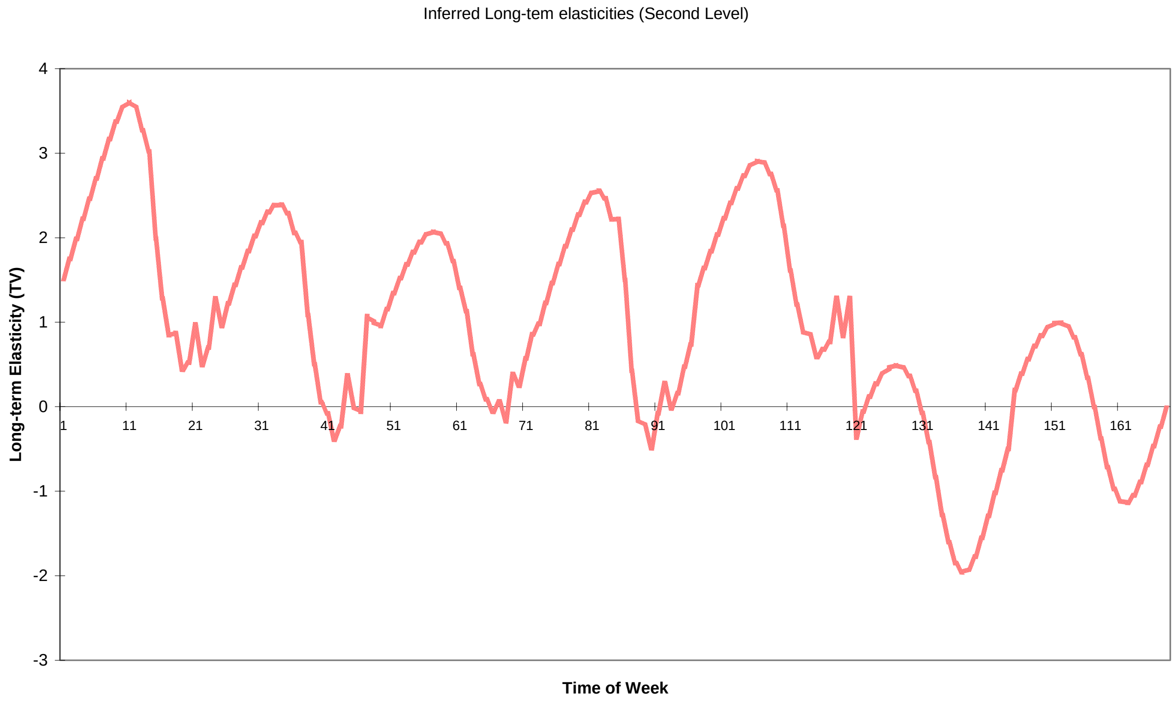

FIGURE 13

BASELINE CALLS

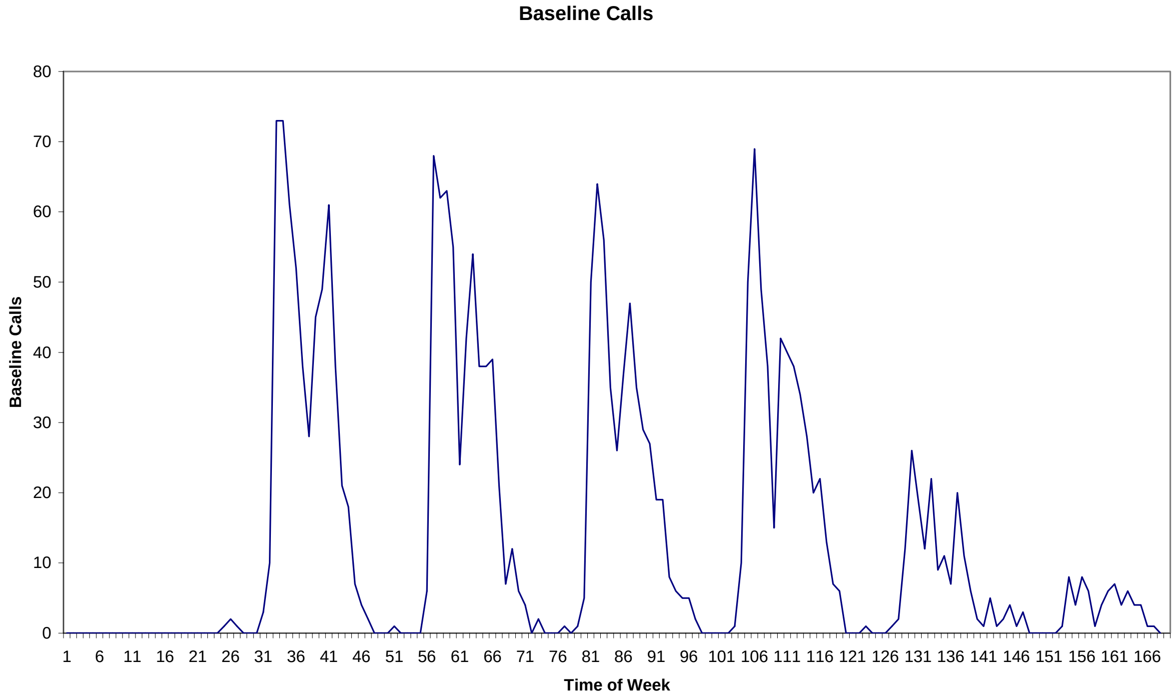

FIGURE 14

GRPS FOR RADIO 6

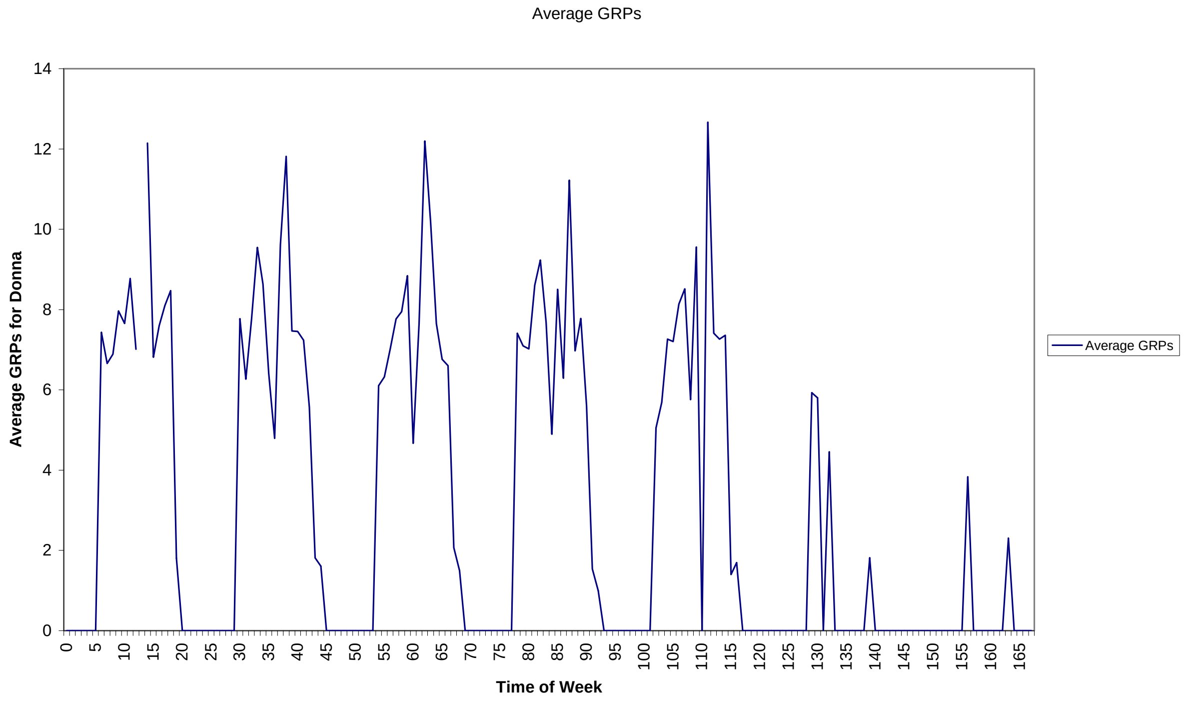

FIGURE 15

TOTAL IMPACT