Forecasting the Primary Demand for a Beer Brand Using Time Series Analysis

Danijel Bratina, Armand Faganel

University of Primorska, Faculty of Management Koper, Cankarjeva 5, 6000 Koper, Slovenia,
danijel.bratina@fm-kp.si, armand.faganel@fm-kp.si

Market research often uses data (i.e. marketing mix variables) that is equally spaced over time. Time series theory is perfectly suited to study this phenomena's dependency on time. It is used for forecasting and causality analysis, but their greatest strength is in studying the impact of a discrete event in time, which makes it a powerful tool for marketers. This article introduces the basic concepts behind time series theory and illustrates its current application in marketing research. We use time series analysis to forecast the demand for beer on the Slovenian market using scanner data from two major retail stores. Before our analysis, only broader time spans have been used to perform time series analysis (weekly, monthly, quarterly or yearly data). In our study we analyse daily data, which is supposed to carry a lot of 'noise'. We show that - even with noise carrying data - a better model can be computed using time series forecasting, explaining much more variance compared to regular regression. Our analysis also confirms the effect of short term sales promotions on beer demand, which is in conformity with other studies in this field.

Key words: market research, time series forecasting, beer demand
JEL classification: C22, M31

1 Introduction

Despite being a powerful tool, Time series analysis (Dekimpe and Hannsens 1995) is rarely used in research by marketers. As the main reasons for this reluctance, they mention the availability of quality time series, the unavailability of time series analysis software, a lack of knowledge and a reluctance to use secondary data for modeling customers' behaviour. At the same time, they announce that wide use of time series is still to come with advances in information technology, software development and an increasing number of academic studies devoted to the subject.

This article presents uni- and multi-variate time series analysis applied to market research forecasting. We demonstrate how the primary demand for beer can be forecast better when using time series than with regular regression analysis. The rest of the article is organised as follows: first we present the basic time series analysis, starting with univariate ARMA models. Next, we provide some theory on multivariate analysis with special emphasis on the ARMAX models, which are considered as hybrid univariate models. We then analyse demand factors for a well established beer brand in Slovenia, illustrating the power of time series analysis in comparison with regression analysis. The conclusion summarises our findings.

2 Univariate time series analysis

It is assumed that the reader is familiar with basic time series analysis modeling (autoregressions and moving averages), this topic is thus discussed only briefly. Our analysis begins with univariate shock analysis theory and evolves into ARMAX (autoregression, moving average regression with exogenous variables), which is becoming popular among market researchers.

2.1 The Autoregression process

Let y_t be the sales value at a given time t. A simple method for analyzing the fluctuation in sales is by using the past levels of sales to determine future:

$$y_t = \mu + \varphi y_{t-1} + \varepsilon_t , \quad t = 1,....,T , \qquad (1)$$

where represents a constant, the regression parameter and noise, which it is often assumed to be white noise (where the mean value is 0, the variance is constant over time and has no serial correlation). The model shown in equation (1) is called the AR(1) process – autoregression process of the first order. It can be generalized into AR(n) by:

$$y_t = \mu + \varphi_1 y_{t-1} + ... + \varphi_n y_{t-n} + \varepsilon_t , \quad t = 1,....,T . \quad (1a)$$

In time series analysis, we often write equations with operator notation. Thus the equation (2a) can be written as:

$$\varphi_p(B)y_t = \mu + \varepsilon_t, \ t = 1, \ldots, T \quad , \text{where}$$

$$\varphi_p(B) = (1 - \varphi_1 B - \varphi_2 B^2 - \ldots - \varphi_p B^p) \quad \text{and } B \text{ is the}$$

lag operator: $B^k y_t = y_{t-k}$.   (2)

The order (n) of an AR process is determined by two functions: the autocorrelation function (ACF) and the partial autocorrelation function (PACF), defined as:

ACF: $\rho_k = \dfrac{\gamma_k}{\gamma_0}$, where $\gamma_k = E\big[(y_t - m)(y_{t-k} - m)\big]$ is

called the autocovariance y_t of the order k.

PACF: as the value of the regression coefficient of y_{t-i}, when is regressed on $y_1 \ldots y_{t-i}$ and a constant. The order n of the AR process can also be determined graphically, as by Box and Jenkins, or by using Akaikie's criterion, Schwarz-Bayes' criterion or the maximum-likelihood ratio test (Box and Jenkins, 1979).

2.2 Moving average processes

A moving average process can represent the functional dependency of the endogenous variable on past random shocks, which is formulated as:

$$y_t = \mu + \varepsilon_t - \theta \varepsilon_{t-1}, \quad t = 1, \ldots, T \ . \qquad (3)$$

Equation (4) is a moving average model of the first order – MA(1). The estimated value of the endogenous variable in time is dependent on random shocks that occurred in the past. We can draw several examples from marketing: a promotional budget is often set as a past period budget + additional non-planned expenses occurred in the past period, a sales forecast can be a function of the past forecasts adjusted with the unplanned shocks that occurred in the past, such as a new buyer (additional sales) or new competitor (lost sales) …

Like the AR processes, the MA processes can also be generalized to n-th order:

$$y_t = \mu + \theta_q(B)\varepsilon_t, \quad t = 1, \ldots, T \ , \qquad (3a)$$

where $\theta_q(B)$ means $1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q$ and B is the lag operator.

2.3 ARMA model

An ARMA process is the natural combination of autocorrelation and the moving average processes. It can be written as ARMA(p,q):

$$\varphi_p(B)y_t = \mu + \theta_q(B)\varepsilon_t, \ldots t = 1, \ldots, T \qquad (4)$$

The orders (p and q) can theoretically be determined using PACF and ACF. When using ARMA models to forecast a series, p and q must have a meaning in the re-search field (i.e. a functional dependency of sales upon past advertising expenditures makes sense, the opposite less so).

2.3.1 Univariate shock analysis

Dekimpe et al. (2005) introduced a model of the time persistency of shocks studying univariate time series (a shock occurs in the endogenous variable). The measure that assesses the impact of a shock in an ARMA(p,q) series over time is defined as the ratio of the AR and MA coefficients of its first difference:

$$A(1) = \theta_q(1)/\varphi_p(1) = \frac{1 - \theta_1 - \theta_2 - \ldots - \theta_q}{1 - \varphi_1 - \varphi_2 - \ldots - \varphi_p}, \qquad (5)$$

Equation (5) determines whether a time series is stationary or a trend following a shock. For a marketer, the difference means long term or short term effects.

2.4 ARMAX models

To avoid the complex multivariate time series analysis that comes with techniques like VARMA (Vector autoregressive moving average regressions), a hybrid model of univariate analysis has been introduced by some authors (Wichern 1977, Dekimpe and Hannssens 1995, Bronnenberg et. al 2001), namely the ARMAX (AutoRegressive Moving Average with eXogenous variable) Model. This model includes exogenous variables into the ARMA model, assuming that these variables cannot be dependent on endogenous variables (such as in the VAR models). For marketers these models open a variety of research possibilities (i.e. assessing the impact of any marketing activity on the marketing mix) (Franses 1991). Most marketing activities do not occur at the time of the activity but later. In comparison to multivariate models (VAR, VARX, VARMA) the ARMAX model remains a single equation model, which makes it easier to analyse but looses the generality of the VAR models. This is why Hanssens et al. (2001) call such model the dynamic univariate time series analysis. The model, also called the transfer function, can be written as:

$$y_t = \mu + \gamma_1 y_{t-1} + \gamma_2 y_{t-2} + \ldots + \gamma_p y_{t-p} + \beta_0 x_t +$$
$$+ \beta_1 x_{t-1} + \ldots + \beta_s x_{t-s} + \varepsilon_t - \theta \varepsilon_{t-1} - \ldots - \theta_q \varepsilon_{t-q} \qquad (6)$$

In equation (3), the variable x represents an exogenous variable while all other elements are ARMA elements. For more than one exogenous variable, the model can be written as:

$$y_t = \mu + \gamma_1 y_{t-1} + \gamma_2 y_{t-2} + \ldots + \gamma_p y_{t-p} +$$
$$+ \sum_{i=1}^{r} \vec{\beta}_i^T B^i \vec{x}_{t-i} + \varepsilon_t - \theta \varepsilon_{t-1} - \ldots - \theta_q \varepsilon_{t-q}, \qquad (6a)$$

117

where the part under the sum is a scalar product of the coefficient vector and the vector β of the exogenous variables (x).

The steps of the time series analysis with the transfer functions are the same as for the Box-Jenkins ARMA processes: identification, trial model, parameter identification, diagnosis of the regression model and its residuals through a function called CCF (cross correlation function), which is the equivalent of ACF and PACF in the ARMAX models.

The steps are as follows:

1. Define the ARMA model for the exogenous variable 1st and store its residuals.
2. Use the same ARMA model for the endogenous variables and store the residuals.
3. Compute the CCF between the residuals from points 1. and 2.

Marketers can use the ARMAX model to test how a change in an exogenous variable influence a time series over time. Special cases of such change are discrete events (i.e. regulation changes, competition entry, changes in prices …). Franses (1991) used this sort of study to assess changes in the demand for beer in The Netherlands due to a change in taxation that occurred in 1984. The method of using discrete events in ARMAX models is called Intervention analysis (Box and Tiao 1976).

3 Estimating the primary demand for beer using time series analysis

The demand for beer has been extensively researched in the past (Bourgeois and Barnes 1979, Franke and Wilcox 1987, Leeflang and Van Dujin 1982). All of up to date research use weekly, monthly or even yearly aggregated data from around 50-100 observations to assess the determinants of beer demand. Our study deals with the daily sales of a leading Slovenian beer brand in a major retail store. We assume that a typical sales promotion of 2-3 weeks can only be dynamically observed using daily sales as a 14-21 day period generates enough data for statistical significance. A weekly sales series would only include few data points for analysis, which is not enough. Monthly data and larger time spans is not appropriate for dynamically studying sales periods. Our data, shown in Picture 1, represents the daily sales of a beer brand dating from 1.1.2005 till 31.12.2006.

Slovenian retail stores are usually open 7 days a week. law enforcement only forbade shops from openings on Sundays between 1.1.2006 and 19.2.2006. Shops also remain closed during national holidays. The time series is broken on these days. To prevent losing the seasonality of the series, we filled in the closed dates with exponentially smoothed average sales of 5 days before the closing date. To avoid increasing the total sales, we decreased the sales prior to the closing day and added the sum of lowered sales to the closing date. Our rationale behind this procedure is that customers would know that a day is approaching with no possibility for purchasing and would stockpile the product. By leaving the series without these changes, the ACF and PACF functions would produce faulty autocorrelations. As there are 5 holidays and 8 Sundays during the above mentioned law enforcement, totalling 13 days out of 700 observations, we estimate that such a process (or any other procedure) could not affect the statistics.

3.1 Analysis of the graph

Picture 1 shows a spike in sales in the periods around New Year, which will be modelled using a dummy variable (NEW YEAR), the value of which is set to 1 between December 29 and December 31 and 0 otherwise. The time series also exerts a double seasonality. One is easily seen in Picture 2 and shows increased summer sales of beer in accordance with other existing models. This phenomenon will be modelled using the average daily temperature each day.
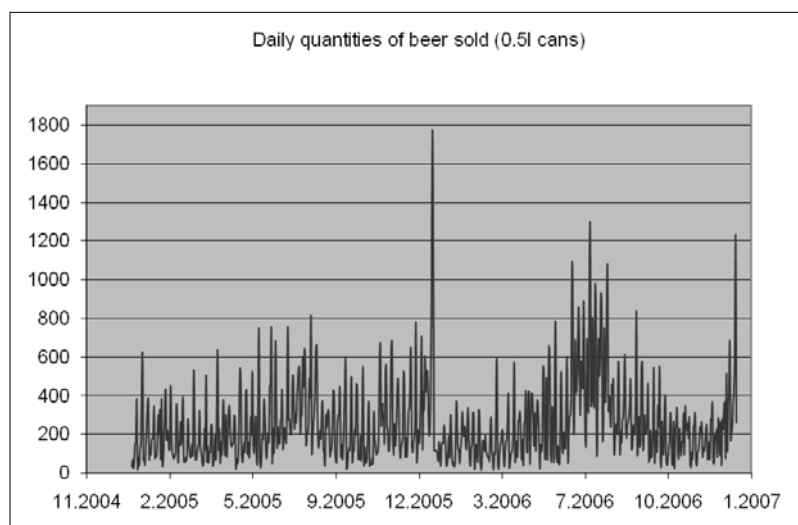

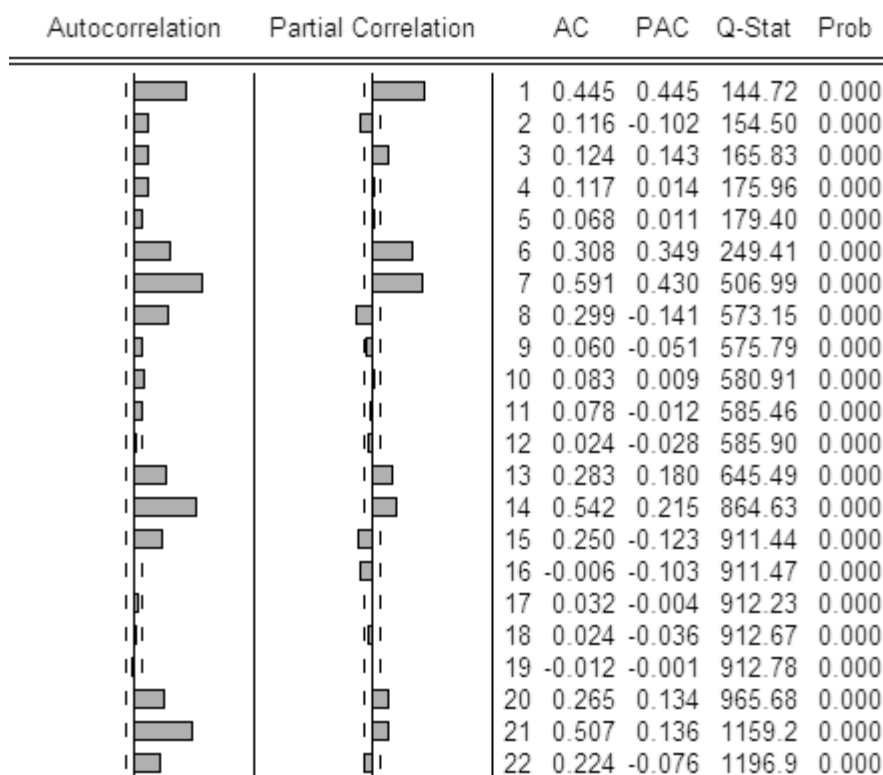Figure 1: – Daily quantities of beer sold

			AC	PAC	Q-Stat	Prob
Autocorrelation	Partial Correlation	1	0.445	0.445	144.72	0.000
		2	0.116	-0.102	154.50	0.000
		3	0.124	0.143	165.83	0.000
		4	0.117	0.014	175.96	0.000
		5	0.068	0.011	179.40	0.000
		6	0.308	0.349	249.41	0.000
		7	0.591	0.430	506.99	0.000
		8	0.299	-0.141	573.15	0.000
		9	0.060	-0.051	575.79	0.000
		10	0.083	0.009	580.91	0.000
		11	0.078	-0.012	585.46	0.000
		12	0.024	-0.028	585.90	0.000
		13	0.283	0.180	645.49	0.000
		14	0.542	0.215	864.63	0.000
		15	0.250	-0.123	911.44	0.000
		16	-0.006	-0.103	911.47	0.000
		17	0.032	-0.004	912.23	0.000
		18	0.024	-0.036	912.67	0.000
		19	-0.012	-0.001	912.78	0.000
		20	0.265	0.134	965.68	0.000
		21	0.507	0.136	1159.2	0.000
		22	0.224	-0.076	1196.9	0.000

Figure 2: – ACF and PACF functions for the original model

The second seasonal fluctuation we expect from the series is the weekly seasonality i.e. the Sunday sales are similar… Due to daily noise, this is hardly seen with visual inspection. However, by computing the ACF and PACF functions, they can easily be found (Picture 2).

The PACF graph of autocorrelations shows the expected statistical significance for period 7. Spikes at 6 and 8 should also be taken into consideration. Visually, we could assess the unviariate ARMA process to be:

$$(1 - L^7)(1 - \varphi L)y_t = \mu + (1 - L^7)(1 + \theta L)\varepsilon_t \qquad (7)$$

Equation 7 would mean that the daily sales can be estimated by taking the sales a week ago and its shocks 8 and 6 days ago. Equation 7 needs to be tested to determine whether its residuals' PACF and ACF show any significance. Picture 3 shows the PACF and ACF functions for residuals showing no statistically important spikes. Equation 7 can formally be written as an ARMA(1,1) process of the differenced time series of order 7.

3.2 Factors affecting primary demand

Primary demand for beer has been researched extensively by Bourgeois and Barnes (1979), Franke and Wilcox (1987), Leeflang and Van Dujin (1982) and Frasens (1991). Authors use the following as exogenous variables: beer prices, outside temperature, advertising expenditures and the consumer purchasing index. According to Bourgeois and Barnes (1976), advertising has little effect on sa-

Lag	ACF	PACF
1	0.116	0.116
2	-0.086	-0.101
3	-0.047	-0.025
4	-0.022	-0.023
5	-0.084	-0.088
6	-0.053	-0.039
7	0.022	0.017
8	-0.004	-0.025
9	0.014	0.015
10	0.043	0.031
11	0.059	0.046
12	-0.055	-0.061
13	0.032	0.061
14	0.044	0.030
15	-0.009	-0.006

Figure 3: – Modified ACF and PACF model

les. Advertising alcoholic beverages is strictly regulated in most EU countries, diminishing its effect on sales. Furthermore, the Slovenian beer market is dominated by two major brands, accounting for more than 90 % of total market (one of the two brands is analysed here). The preferences of consumers for each brand are geographically spread and there is strong loyalty to each of the two brands (meaning that consumers of one brand would rarely try the other). Such strong preferences for either brand make advertising very inefficient for gaining new

customers. Poor advertising effects have also been confirmed by the marketing managers of both market leaders companies.

All researchers agree that outside temperature is a good estimator for the quantities sold. Most beer is sold during the summer season. This seasonality could be formulated using the difference operator of order 365 ($\triangle_{365}$), but this would halve our data if we use a two years time series. Thus we model the outside temperature using data from government weather statistics. The highest daily temperature in Ljubljana has been used as exogenous variable.

As mentioned, all the other researchers use a wider time span between two points (at least a week) smoothing out any effects of the holidays. Our research, using daily sales, needs to account for any deterministic spikes that could occur. One such spike is certainly New Year's Eve, which we modelled using a dummy variable.

Sales promotions are a proven tool for short term boosts in sales. They usually have a short term impact that lasts for the period of promotion, but can have a long term impact if applied to a nonstationary time series (i.e. a growing market). The sales promotion will be modelled as a pulse function:

$$SALESP = \begin{cases} 0; t < k \\ 1; k \leq t \leq k+l \\ 0; t > k+l \end{cases} \tag{8}$$

According to Hanssens et. al., there is a long term effect from SALESP if the operator's order ($\triangle$) required to differentiate the series to obtain stationarity is greater than 0. The series under observation was on sales promotion from 26.10.05 till 23.12.2005, roughly a month. To test any post-promotion effects, we'll include the terms SALESP(-1) and SALESP(-2) in the regression to see

whether a statistically significant coefficient would confirm any long-term effects. As our time series also behaves stochastically (ARMA), we need to include that behaviour in the regression equation. Putting all the factors into the equations, we get:

$$y_t = \mu + \varphi_1 y_{t-1} + \varphi_7 y_{t-7} + \varphi_8 y_{t-8} +$$
$$+ \varepsilon_t + \theta \varepsilon_{t-1} + \theta \varepsilon_{t-7} + \theta \varepsilon_{t-8} +$$
$$+ \delta NEWYEAR + \omega SALESP_t + \omega_1 SALESP_{t-1} +$$
$$+ \omega_2 SALESP_{t-2} + \lambda TEMPERATURE \tag{9}$$

Using the least-squares methods, the coefficients are calculated and presented in Picture 4.

All the coefficients are statistically significant except for SALESP and SALESP(-1). After eliminating these two variables, SALESP(-2) also becomes statistically non-significant, which confirms that no long-term effects are to be expected from sales promotions. Only a two day effect could be seen as too short for any meaningful significance and could catch the post-promotion dip effect (diminishing of sales immediately after the price promotion period due to stockpiling). We have tried to regress the sales by several lagged SALESP, but none has significant statistics. By eliminating the SALESP(-1) and SALESP (-2) terms, we get the equation:

$$y_t = 164 + 0.96 \cdot y_{t-1} + 0.98 \cdot y_{t-7} - 0.96 \cdot y_{t-8} +$$
$$+ \varepsilon_t - 0.84 \cdot \varepsilon_{t-1} - 0.85 \cdot \varepsilon_{t-7} + 0.68 \cdot \varepsilon_{t-8}$$
$$+ 609 \cdot NEWYEAR + 132 \cdot SALESP +$$
$$+ 4.93 \cdot TEMPERATURE \tag{10}$$

Regressor	Coefficient	Std. Error	t-test	prob.
NEWYEAR	624.24	40.45	15.43	0.0000
SALESP	46.51	81.73	0.57	0.5695
SALESP(-1)	-31.89	107.19	-0.30	0.7662
SALESP(-2)	161.35	82.19	1.96	0.0500
TEMPERATURE	5.22	1.08	4.82	0.0000
C	154.35	23.04	6.70	0.0000
AR(1)	0.97	0.01	80.85	0.0000
AR(7)	0.99	0.01	153.68	0.0000
AR(8)	-0.96	0.01	-76.19	0.0000
MA(1)	-0.85	0.03	-32.66	0.0000
MA(7)	-0.83	0.02	-34.77	0.0000
MA(8)	0.70	0.03	20.79	0.0000

R2	0.679744
Adjusted R2	0.674761

Figure 4: – Initial model regression analysis

Regressor	Coefficient	Std. Error	t-test	prob.
NEWYEAR	609.32	40.16	15.17	0.0000
SALESP	132.33	43.86	3.02	0.0026
TEMPERATURE	4.93	1.07	4.59	0.0000
C	163.98	21.99	7.46	0.0000
AR(1)	0.97	0.01	76.62	0.0000
AR(7)	0.99	0.01	151.03	0.0000
AR(8)	-0.96	0.01	-71.14	0.0000
MA(1)	-0.85	0.03	-30.66	0.0000
MA(7)	-0.83	0.02	-34.56	0.0000
MA(8)	0.69	0.03	19.92	0.0000
R2	0.678121			
Adjusted R2	0.674046			

Figure 5: – Final model of the ARMAX regressors

The statistics are shown in Picture 5. The demand for the analysed beer is thus dependent on the outside temperature, New Year and the promotional price. R square accounts for 67%. It is interesting to note that sales promotion accounts for a very small proportion of the variance (only 0.8%) and could thus easily be ignored.

It needs to be stressed that the above model is only usable for the time series analysed and could not be generalized to all beer. Also, this brand has only been on promotion once off-season making it impossible to conclude that sales promotion on beer has negligible long term effects.

What is more interesting is to compare our time series analysis with classical regression analysis, thus omitting stochastic trends. We use the least square method with the NEWYEAR, SALESP, TEMPERATURE regressors and a constant to compute the equation:

$$y_t = 117 + 729 \cdot NEWYEAR + 144 \cdot SALESP +$$
$$+ 7.17 \cdot TEMPERATURE \qquad (11)$$

The statistics are shown in Figure 6. All coefficients are statically relevant, but the explained variance is only 25%. The effect of each single regressor is higher than when using time series analysis, but the relations are quite similar.

4 Conclusion

The article builds a model for forecasting the demand for beer with time series analysis. In the introductory chapter the time series analysis theory is presented with special devotion to univariate time series analysis. Time series are useful for analysing economical variables ordered in series that are equally spaced over time. The Box-Jenkins ARMA model is presented as the basic model for time series analysis, which is upgraded to ARMAX model. Time series techniques are applied to model demand for beer on Slovenian market. It has been shown that this method considerably increases the power of forecasting compared to ordinary regression analysis.

Analysis shows that the primary demand for beer, on a bi-polar market such as Slovenian, is mainly dependent on the seasonality (modelled with outside temperature), price and New Year dummy regressors. Time series analysis determines the true value of the coefficients for these

Regressor	Coefficient	Std. Error	t-test	prob.
NEWYEAR	728.98	57.49	12.68	0.0000
SALESP	144.59	25.41	5.69	0.0000
TEMPERATURE	7.72	0.74	10.49	0.0000
C	117.80	13.51	8.72	0.0000
R2	0.252409			
Adjusted R2	0.249315			

Figure 6: – Regression analysis without the time series

variables by introducing autoregressing and moving average factors. It is shown that, by introducing moving average and autoregression factors, the exogenous demand factors' coefficients (temperature, New Year and price) are adjusted (lowered). Autoregression analysis shows a typical weekly seasonality as well as the dependence of the series on the previous day's sales, which is to be expected.

The attempt to show any long term effects of sales promotions fails, confirming the evidence from other empirical studies on such effects. Traditionally, the effects of a sales promotion are measured on a panel of households using behavioural theory to assess any effects of marketing actions on the consumers' brand choice (Keane 1997, Seetharaman et al. 1999). The majority of models show no long term effects from sales promotions. Newer models (using weekly, monthly, quarterly or yearly data) and our study (using daily data) uses within-store POS data in a time series framework, showing same results. Daily data is particularly useful for studying the dynamics of the sales function when an affecting factor changes rapidly.

Literature

Autobox, Case studies – Regression versus Box-Jenkis (Times series analysis) Case studies, Available from http://www.autobox.com/pdfs/regvsbox.pdf] (Accessed, 31. January .2007)

Bourgeois, J.C., & J.G. Barnes. (1979). Does Advertising Increase Alcohol Consumption? *Journal of Advertising Research* **4**(August): 19-29.

Box, G. E. P., & G. M. Jenkins. (1976). *Time Series Analysis: Forecasting & Control*. San Francisco: Holden-Day.

Box, G. E. P., & C. Tiao. (1976). Intervention Analysis with Applications to Economic & Environmental Problems. *Journal of American Statistical Association* **70**: 70-79.

Bronnenberg, B. J., & L. Wathieu. (1996). Asymmetric Promotion Effects & Br& Positioning. *Marketing Science* **15**(4): 291-309.

Dekimpe, M. G., & D. M. Hannsens. (1995). The Persistence of Marketing Effects on Sales. *Marketing Science* **14**(1):1-21.

Dekimpe M., D. M. Hanssens, V. R. Nijs, & J. M. B. Steenkamp. (2005). Measuring short- & long-run promotional effectiveness on scanner data using persistence modelling. *Applied Stochastic Models in Business Industry* **21**: 409-416.

Franke, G. R., & G.B. Wilcox. (1987). Alcoholic Beverage Advertising & Its Impact on Model Selection. *Applied Mathematics & Computation* **34** (November): 22-30.

Franses, P. H. (1991). Primary Dem& for Beer in The Netherl&s: An Application of ARMAX Model Specification. *Journal of Market research* **28**: 240-245.

Hanssens, D. M., L. J. Parsons, & R.L. Schultz. (2001). *Market Response Models – Econometric & Time Series Analysis*, Boston: ISQM Kluwer Academic Publishers.

Keane, M. P. (1997). Modeling Heterogeneity & State Dependence in Consumer Choice Behaviour. *Journal of Business & Economic Statistics* **15**(3): 310-327.

Leeflang, P. S. H., & J. J. Van Dujin (1982). The Use of Regional Data in Marketing Models: The Dem& for Beer in The Netherl&s. *European Research* **10** (January): 29-40.

Maddala, G. S. (1992). *Introduction to Econometrics*. New York: MacMillian Publishing Company.

Seetharaman, P. B., A. Ainslie, & P. K. Chintagunta. (1999). Investigating Household State Dependence Effects across Categories. *Journal of Market research* **36**(4): 488-500.

Wichern, D., & R. H. Jones. (1977). Assessing the Impact of Market Disturbances using Intervention Analysis. *Management Science* **24**(3): 329-337.

Danijel Bratina is a lecturer at the Koper Faculty of Management (FM), University of Primorska, where he lectures on Marketing, Market research and Services Marketing. His field of study is quantitative market research and brand equity evaluation. He is currently preparing his doctoral thesis on the effectiveness of marketing promotion on grocery sales at the Faculty of Economics in Ljubljana. His bibliography consists of several contributions to scientific conferences and one scientific paper. He is editor of the scientific journal Management. He also has managerial experience in international business, where he has been working for Slovenian companies outsourcing projects to the far East.

Armand Faganel is a senior lecturer and doctoral student at the University of Primorska, Faculty of Management Koper (FM). He has acquired 3 years of experience in business as sales manager, marketing manager, director of production unit. His areas of research include marketing, the higher education sphere, intercultural competencies, communication studies and the quality perception of services. His bibliography consists of four scientific papers, one review article, two short scientific articles, two professional articles, 20 scientific conference contributions, three independent scientific component parts in a monograph, etc. He is acting as Head of the Marketing Institute and Head of the Quality and Evaluations Centre at FM. At present, he is lecturing on Marketing, B2B Marketing, Marketing Communications, Consumer behaviour and Industrial products marketing.

Model povpraševanja po blagovni znamki piva z uporabo analize časovnih vrst

Trženjski raziskovalci pogosto operirajo s podatki, ki so ekvidistančno porazdeljeni v času. Teorija časovnih vrst je primerno orodje za analizo tovrstnih podatkov. Tipično se uporablja za napovedovanje, ugotavljanje vzročnosti pojavov, v trženju pa je največkrat uporabljena pri analizah učinkov diskretnih dogodkov skozi čas. Članek prikaže osnovne koncepte regresijske analize časovnih vrst in predstavi njihovo aplikacijo v trženjskem raziskovanju. S pomočjo analize časovnih vrst postavimo model napovedovanja povpraševanja po znani Slovenski blagovni znamki piva z uporabo POS podatkov z dveh večjih slovenskih hipermarketov. Naša analiza je prva, ki kot podatke zajame dnevno prodajo blagovne znamke (dosedanje so uporabljale širše časovne intervale – tedenska, mesečna ali celo letna prodaja). Slabost dnevne prodaje naj bi predstavljal visok nivo šuma v podatkih. Čeprav vsebujejo podatki veliko nepojasnjene variance, v prispevku pokažemo, da z uporabo časovnih vrst pojasnimo precej več variance kot z uporabo klasične multiple regresije. Analiza časovnih vrst nam tudi pokaže, da so učinki cenovnih akcij, kot enega izmed dejavnikov prodaje, kratkoročni, ter tako potrdi druge raziskave iz področja analiz učinkovitosti cenovnih akcij.

Ključne besede: trženjsko raziskovanje, analiza časovnih vrst, povpraševanje po pivu