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Predicting Advertising Volumes Using Structural Time Series Models: A Case Study

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Abstract

Media platforms typically operate in a two-sided market, where advertising space serves as a major source of revenues. However, advertising volumes are highly volatile over time and characterized by cyclical behavior. Firms' marketing expenditures in general are far from stable. Due to planning of future issues as well as financial planning, platforms have to forecast the demand for advertising space in their future issues. We use structural time series analysis to predict advertising volumes and compare the results with simple autoregressive models.

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1 Introduction

Media platforms such as newspapers, magazines, TV programs and online platforms often serve two or more customer groups, hence operate in at least two different but interrelated markets and face multiple possible sources of revenues (see Rochet and Tirole, 2003, 2006; Rysman, 2009). Media platforms are therefore typically referred to as two-sided platforms. One possible source of revenue are obviously content sales. However, consumers are usually charged for newspapers and magazines, but often not for free-to-air TV, radio programs and the biggest part of online services. The second and usually the larger part of media platforms' overall revenues is advertising. While newspapers earn about 50% of their revenues in the advertising market[1], most online media are completely financed by advertising. As a consequence, media outlets especially need precise forecasts of future demand for advertising space when planning future strategies.

A well-known stylized fact in marketing research is that advertising demand, however, is highly volatile, which is caused by the nature of advertising expenditures (see Dean, 1951 and Yang, 1964).[2] To some degree the cyclicality of advertising volumes is also caused by the business cycle, because firms' advertising activities naturally vary during booms and recessions (see, e.g., Ashley et al., 1980, Picard, 2009, and van Herde et al., 2013). A growing literature in marketing science shows that under certain circumstances pulsing campaigns can be superior to uniform advertising spending over time (see Mahajan and Muller, 1986). As a result, a firm spends a significant amount of advertising in a given period and waits until the effects of this spending on consumer demand wear out (see Rao, 1970 and Mesak, 1992).[3] Subsequently a new campaign starts. There is significant research effort in marketing science to develop pulsing or temporal advertising schemes (see, e.g., Vande Kamp and Kaiser, 2000). Due to this special kind of advertising campaign, demand for advertising space in the media and especially in magazines is highly volatile and difficult to forecast. Moreover, media consumption is also influenced by cyclical behavior due to seasonality as well as holidays. Both phenomena are major reasons for the cyclical behavior of advertising volumes in different media products.

As a result of the major importance of advertising as a source of revenues for magazines, forecasting the demand for advertising space is an important task for the management of any magazine or newspaper (see Ashton and Ashton, 1985). In order to forecast advertising volumes, we use data on advertising space of German news magazines. Similar to most (print) media, news magazines' ad volumes show a distinctive cyclical behavior as well as pronounced seasonality. Additionally, the huge increase in online advertising over the last decade led to a sustained reduction in advertising space which results in a negative trend over the last years. Thus, structural time series techniques seem to be an adequate method for ad space forecasting.

The paper is organized as follows. The next section briefly discusses the forecasting approach used in this paper. Section 3 discusses the data and presents the results from structural time series models as well as from simple autoregressive models. Section 4 finally concludes.

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[1] http://www.bpb.de/gesellschaft/medien/lokaljournalismus/151250/zeitungsfinanzierung.

[2] The cyclicality of advertising can also be identified as variations in the aggregate level of national advertising spending (see Blank, 1962).

[3] For demand conditions appropriate for pulsing campaigns see Hanssens et al. (2001).

2 Empirical Approach

2.1 Competing Approaches

Our benchmark model is a simple Autoregressive Process (AR), which we use because of its simplicity and generally good forecasting abilities. However, a graphical inspection of the time series in figure 1 shows that it is very likely that an AR-process is not the optimal choice to describe and predict the natural logarithm of advertising volumes. We propose an alternative which should, from a theoretical point of view, be better suited to describe and predict the cyclical behavior of advertising demand. We therefore use a structural time series approach proposed by Harvey (1991) which provides the major advantage, that different components can be incorporated to approximate the data generating process (see, e.g., Harvey et al., 1997). For our purposes, especially a stochastic constant and a stochastic trend seem to be appropriate. As a result, the structural time series approach should be superior in handling the volatility of the process compared to our benchmark AR model. Our local level model including a time varying level, a cycle, and a stochastic trend takes the form (see Hamilton, 1994a):

$$\begin{aligned} y_t &= c_t + \varepsilon_t,\ \varepsilon_t \sim i.i.d.\, N\left(0,\sigma_\varepsilon^2\right) \\ y_{t+1} &= c_t + \xi_t,\ \xi_t \sim i.i.d.\, N\left(0,\sigma_\xi^2\right). \end{aligned} \tag{1}$$

c_t is the unobserved level at time t, ε_t is the observation disturbance at time t, and ξ_t is the level disturbance at time t. We allow the level of our model to vary in time and include a cycle as well as a stochastic trend into our model. Due to these components, the structural time series model should clearly outperform the benchmark AR-model.

We choose the lag order of our model according to standard information criteria as the Akaike- and Schwarz-Bayes-criteria. This approach is well established in time series analysis for the purpose of model selection (see Judge et al., 1985: 870-875). The task of information criteria is to solve the trade-off between model complexity and minimization of squared residuals (see Hendry and Doornik, 2014: 212-215). As one usually wants the simplest model minimizing the squared residuals, the Akaike- and Schwarz-Bayes-criteria include penalty terms, which penalize the models for including too many lags.

2.2 Weaknesses and limitations

In comparison to the ARIMA approach, structural time series models show number of advantages such as a high flexibility and a less restricted parameter space. Structural models can also deal with data gaps and can handle any frequency, which might cause problems using ARIMA models (Harvey & Todd, 1983; Proietti, 1991). Structural time series models also assume that their components are stochastic.

However, there are also some weaknesses and limitations of structural time series models. Because of the use of the Kalman filter, the (computational) complexity is much higher in comparison to other models. As many applications are nowadays characterized by the availability of big data, structural time series models may not be feasible in those cases. Moreover, even though structural models allow for time varying parameters, they are rather inflexible in structure. As the implied structure is subject to certain constraints, hence it may be unsuitable for some series, which are undergoing relevant changes in their nature.

Moreover, structural models are possibly not the most appropriate methods for predicting magazines' advertising volumes. There has been considerable change over the last years in advertising markets. The advertising crisis as well as the rise of different types of online and targeted advertising led to a considerable decrease in print advertising. However, using magazine advertising data allows us to illustrate the technique presented. Despite the structural changes of recent years, the methods used appears to produce reasonable results.

3 Empirical Evidence

3.1 The Data

We obtained weekly data on advertising volumes for the German news magazines *Focus*, *Der Spiegel* and *Stern* from pz-online.de, an online database provided by the German Association of Newspaper and Magazine Publishers (see Figure 1 for advertising volumes). PZ-Online (see PZ-Online, 2009) provides data containing the amount of advertising pages in German periodicals from 1994 up to recent issues.[4] Our dataset consists of at most 589 observations per magazine from January 1994 until September 2009. *Focus*, *Der Spiegel* and *Stern* are the most important weekly issued German news magazines with a total circulation of more than 2.4 Mio on average per issue in 2009 (see IVW, 2009). On inspection of weekly advertising volumes from 1994 to 2009 in Figure 1, the demand for advertising space is found to be highly volatile. Furthermore, a graphical inspection shows some evidence for pulsing campaigns, because after periods characterized by high advertising spending, demand for advertising volumes falls to lower levels until demand for advertising space jumps up again. Overall, the presented time series could be assumed to possess some trend components, some cyclic components and other variation remaining to explain.

It is also evident that there is an upward trend of advertising volume from the beginning of the time series in 1994 until around 2000. From 2000 onwards, it can be observed a harsh downward trend pulling through until the end of the time series in 2008. In addition, highs and lows recurring every year at roughly the same time can be noticed. Seemingly, there exist two surges a year, i.e. in each year there are two peaks with significantly higher advertising volumes. Given the time series shown in Figure 1, periods with many advertising pages are on the one hand the beginning of the year and on the other hand the end of the year with periods of rather low advertising volume in the middle and in the very beginning of each year. As a result, our structural models suggested in section 3.1 should clearly outperform the simple AR-models.

3.2 Results

Unobserved component models as well as autoregressive models are used to predict German news magazines' advertising volumes. To select optimal unobserved component models for the three time series, Akaike and Bayesian information criteria are applied. Table 1 compares the different models and reports information criteria as well as root mean square errors. Interestingly, information criteria suggest the use of different models for the three magazines. While for *Der Spiegel* a local level model including a deterministic trend seems to be adequate, *Stern* is associated with a local level model with trend and *Focus* with a simple local level model.

[4] Meanwhile the database has been restricted to observations not earlier than 2003.

Table 1: Selection of Unobserved Component Models

	Local Level & Trend	**Local Level**	**Deter-ministic Constant**	**Deter-ministic Trend**	**Ran-dom Walk**	**Ran-dom Walk & Drift**	**Local Level & Deter-ministic Trend**
Spie-gel							
AIC	-61.13	-145.09	-145.099	-167.17	-127.71	-137.46	-184.78
BIC	-43.61	-123.20	-123.207	-145.27	-110.20	-119.95	-158.51
RMSE	0.2013	0.1819	0.1908	0.1857	0.1944	0.1910	0.1819
Focus							
AIC	-251.70	-263.82	-258.06	-256.50	-151.21	-141.73	-251.70
BIC	-225.46	-237.58	-236.20	-234.63	-138.09	-128.61	-225.46
RMSE	0.1684	0.1680	0.1691	0.1678	0.1838	0.1835	0.1684
Stern							
AIC	-285.33	-264.52	-264.52	-278.40	-223.10	-218.24	-258.84
BIC	-259.07	-242.63	-242.63	-256.51	-214.35	-205.11	-241.33
RMSE	0.1651	0.1651	0.1701	0.1665	0.1762	0.1721	0.1697

Table 2 summarizes the results from predictions of news magazines' advertising volumes. The respective unobserved component model shows the smallest root mean square error in comparison to an autoregressive process and a Markov switching model with two states for each news magazine.[5] Additionally, we apply the Diebold-Mariano-Test to check which model provides the best forecast in our sample (see Elliott and Timmermann, 2016: 398-400). This kind of test does not test, which model is optimal in a given sample, but whether a certain model provides better forecasts than a benchmark model chosen in the relevant analysis. The major advantage over simple information criteria and RMSE is that we do not only rely on certain values of these measures, but the Diebold-Mariano-Test enables us to apply formal test procedures to find superior forecasting models. Diebold-Mariano statistics (see Diebold and Mariano, 1995) for comparing predictive accuracy prefer the unobserved component model over the other two techniques, independently of the measure used (MSE, MAE and MAPE). However, the unobserved components models do not lead to significant improvements over the standard AR(2)- or AR(3)-models, which perform remarkably well given the structure of our data.

[5] Philipps-Perron-tests indicate that our data is stationary.

Table 2: Predictive accuracy of advertising volumes

	Focus UCM	**Focus AR(2)**
AIC	-263.828	-219.654
BIC	-237.589	-206.534
RMSE	0.1680	0.1997
Diebold-Mariano MSE, S(1)	-5.38 (0.00)	
Diebold-Mariano MAE, S(1)	-4.48 (0.00)	
Diebold-Mariano MAPE, S(1)	-4.501 (0.00)	
	Spiegel UCM	**Spiegel AR(3)**
AIC	-184.788	-158.941
BIC	-158.518	-141.427
RMSE	0.1819	0.2101
Diebold-Mariano MSE, S(1)	-4.731 (0.00)	
Diebold-Mariano MAE, S(1)	-3.733 (0.01)	
Diebold-Mariano MAPE, S(1)	-4.009 (0.01)	
	Stern UCM	**Stern AR(3)**
AIC	-264.520	-158.941
BIC	-242.636	-141.427
RMSE	0.1650	0.2030
Diebold-Mariano MSE, S(1)	-4.582 (0.00)	
Diebold-Mariano MAE, S(1)	-3.569 (0.01)	
Diebold-Mariano MAPE, S(1)	-3.627 (0.02)	

We chose not to use directional forecasts or asymmetric loss functions, because from a theoretical point of view it is unclear whether over- or underprediction of advertising volumes might create different losses. In each case the result would not be profit maximizing, but one cannot state a priori if there would be differences in losses. Instead we rely on the Diebold-Mariano-test which applies the squared error loss, which is a symmetric loss function. Quadratic loss provides the major advantage that its properties are well known and it is commonly used in the applied forecasting literature (see Hamilton, 1994: 72-73).

The improvement in predictive ability can be related to the inclusion of a time varying level, a cycle, and a stochastic trend, which is better able to predict the cycles of advertising volumes than AR-models (exemplarily see Figure 2 for estimated components of *Der Spiegel*). However, simple AR-models lack the flexibility of structural time series models, which can be easily modified to include time varying levels, stochastic trends as well as cycles and hence suit our advertising volumes series best (see Durbin and Koopman, 2012).

4 Conclusions

Advertising is an important source of revenue for many kinds of media outlets, especially newspapers and magazines. As a result, precise predictions of advertising demand are of crucial importance for media companies. Advertising demand, however, is highly volatile, which is caused by the nature of advertising expenditures (see, e.g., Feichtinger and Novak, 1994). Similar to most (print) media, news magazines' advertising volumes show a distinctive cyclical behavior as well as pronounced seasonality. These components make forecasting more difficult. Thus, structural time series techniques seem to be an adequate method for advertising space forecasts. Our analysis reveals that structural time series models provide better predictive accuracy compared with standard AR-models, because of their flexibility, which makes it easy to include trends, cycles and other stochastic components. However, the AR-models perform surprisingly well and improvements using structural time series techniques are only moderate. The main result of our study is that structural time series models outperform simpler approaches in predicting advertising volumes given their flexibility to include different characteristics of the underlying series. As a starting point standard AR-models are still viable tools predicting advertising volumes as well as other series despite their strong cyclicality.

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Appendix

Figure 1: Advertising pages

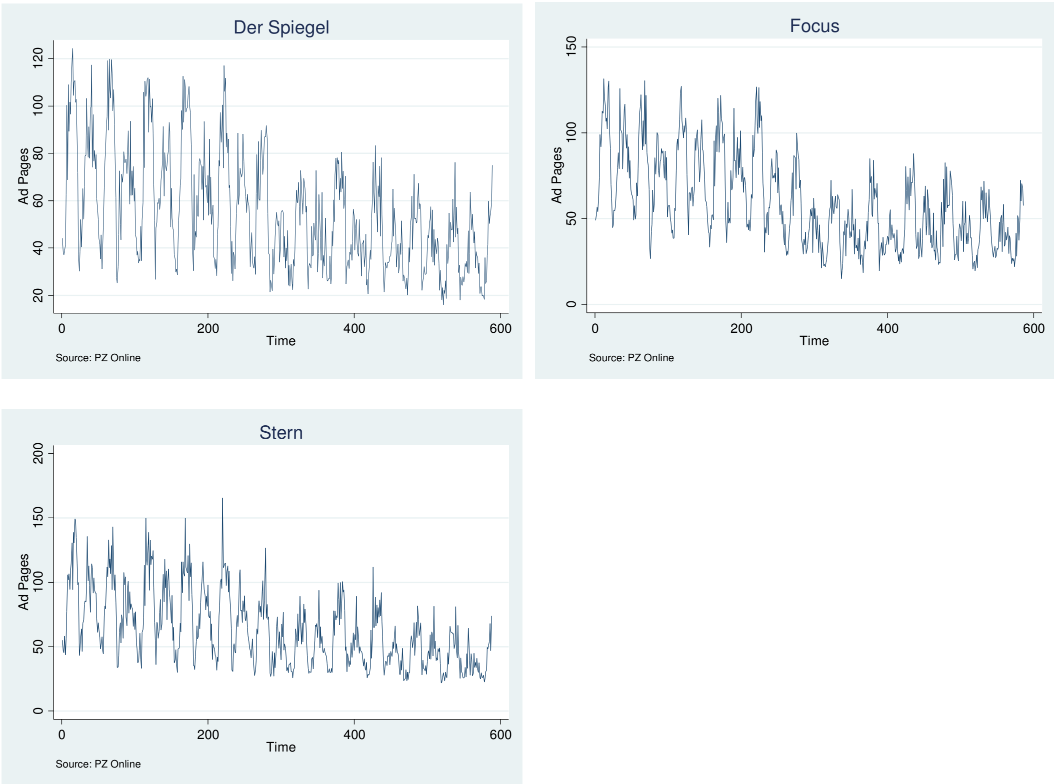

Figure 2: Components of the UCM and predicted values