Forecasting performance of market share attraction models: a comparison of different models assuming that competitors' actions are forecasts

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1 Introduction

Forecasting is an important marketing activity for evaluating the performance of marketing plans, especially in order to predict earnings, sales or market shares. In the last two decades an intensive debate has focussed on the advantages and benefits of using market share response models to forecast short-term and/or long-term market shares. The present paper bases on this research stream and extends previous studies by taking into account several new aspects.

To begin with, we reinvestigate the forecasting performance of market share attraction models at the brand level. Therefore market share attraction models with brand specific intercepts and brand specific marketing instruments are analyzed in various model specifications. With respect to several studies which document asymmetric competition between brands in one product category (e.g. Blattberg & Wisniewski 1989; Krishnamurthi & Raj 1988, 1991; Cooper 1988) we allow for asymmetric brand competition within the specification of the attraction model. In difference to Chen, Kanetkar and Weiss (1994) we do not use the fully crossed effects model but we estimate on the basis of the asymmetric market share model proposed by Carpenter, Cooper, Hanssens and Midgley (1988). The CCHM-model estimates only a subset of all possible cross-effects and is therefore less sensitive to misspecification as can be expected for the fully crossed effects model.

Secondly, we investigate the influences of standardizing variables (z-scores, zeta-scores, etc.) in market response models on the forecasting accuracy. The standardization of marketing variables has been motivated largely by the work of Cooper and Nakanishi (1983). They investigated several variable transformations in order to estimate the multiplicative choice model (an attraction model with multiplicative interactions of the marketing instruments). As Cooper and Nakanishi (1988) have subsequently shown, this kind of variable transformations accounts for time varying competitive conditions and therefore accounts for the varying strength of marketing activities. If cross-competitive market share attraction models are estimated these variable transformations provide a valuable means to overcoming the model intrinsic collinearity. Though collinearity may not be a serious problem in forecasting future market shares, collinearity can seriously affect the descriptive value of market response models. It is the authors' view that if market response models are used for forecasting, they should also provide valuable insights into the sources of competition.

Thirdly, we investigate the effects of different assumptions about the error structure (e.g. heteroskedasticity, autocorrelation) on the forecasting accuracy of the market share models. Previous research has revealed contradictory results whether ordinary least squares estimation (OLS) or generalized least squares estimation (GLS) is superior with respect to the forecasting performance of market share models.

Fourthly, we investigate the effects of forecasting competitors' actions on the predictive accuracy of the market share models under study. Special attention is given to the procedure of forecasting competitors' actions. Previous studies (e.g. Alsem, Leeflang & Reuyl 1989; Kumar 1994) have estimated future values for the price and promotion activities of the competitors on the basis of their corresponding time series. This procedure may not account for the high interdependencies between the promotional instruments. We introduce a new procedure to estimate competitors' actions that account for these interdependencies. According to almost all the previous studies we compare the forecasting performance of the attraction models with the forecasts of a naive model which is a simple first order autoregressive model that additionally assumes autocorrelated errors.

2 Previous research

Previous studies on the forecasting accuracy of market response models have yielded different results that were sometimes even contradictory. Naert and Weverbergh (1981) have investigated the forecasting performance with respect to (1) the method of estimating the model parameters, (2) the functional model specification, e.g. attraction models vs. linear models vs. multiplicative models and (3) unconstrained vs. constrained parameter estimation, i.e. simple effects models vs. differential-effects models. Their study bases on two markets. Market 1 consists of seven major gasoline brands. Estimations are carried out on 20 quarterly observations for each brand and 15 quarterly observations for prediction. The second market consists of three major electric razor brands with five yearly observations in four different regions for estimation and two yearly observations in each region for prediction. Explanatory variables in the first market are lagged market shares and distribution, and in the second market they are price and lagged market shares.

Naert and Weverbergh have achieved superior forecasting accuracy with a GLS-estimation independent of the model specification. They have also found attraction models with simple effects to outperform linear and multiplicative models as well as attraction models with brand-specific effects. On the basis of these results and the logical consistency requirement which is fulfilled by the attraction model (Naert & Bultez 1973) Naert and Weverbergh recommend the use of attraction models to forecast future market shares.

But subsequent studies (e.g. Brodie & de Kluyver 1984, 1987; Ghosh, Neslin & Shoemaker 1984; Leeflang & Reuyl 1984) have failed to confirm the results by Naert and Weverbergh (1981) and obtained even contradictory results. It is interesting to note that the data set of the later studies differ from the first with respect to product category, data aggregation and the number of marketing instruments included. Brodie and de Kluyver (1984) have analyzed three markets. The first (chocolate biscuits) consists of three major brands, market two (liquid detergents) of five and the third market (toothpaste) of seven brands. For each brand 28 bimonthly observations including market share, relative price, distribution intensity, and advertising share were available.

Brodie and de Kluyver use 22 bimonthly observations for estimation and 6 bimonthly observations for prediction. On the basis of their estimation results they conclude that linear and multiplicative market share models appear to have slightly better predictive properties than the attraction model. They also find that OLS- and GLS-estimations produce reliable parameter estimates for both linear and multiplicative models (the predictions of attraction models were superior with a GLS-estimation) and that unrestricted and restricted models fit the data equally well.

The study by Ghosh, Neslin and Shoemaker (1984) investigates the forecasting accuracy of linear, multiplicative and attraction models on the basis of 140 cereal brands that are aggregated to 29 brands in order to circumvent logarithms of zero advertising values. 30 monthly observations for each brand are used for the model estimation and the prediction accuracy is assessed on six monthly observations. Ghosh, Neslin and Shoemaker use price, distribution, advertising and lagged market shares as predictors. The estimation results reveal that naive market share models result in good predictions. These results are only consistently outperformed by an attraction model with a common brand intercept for all brands. In addition to that Ghosh, Neslin and Shoemaker conclude that OLS-estimation gives slightly more accurate forecasts and that no other functional form provides consistently better forecasts.

In contrast to these previous results, Leeflang and Reuyl (1984) have found slightly better forecasting accuracy for the linear and multiplicative models than for the attraction model. They also established slightly better results for models without parameter restrictions and no advantage on either the OLS- or the GLS-estimation procedure. Leeflang and Reuyl use 16 bimonthly observations of 4 cigarette brands for model calibration and 12 bimonthly observations for their predictions. The explanatory variables include advertising and lagged market shares.

Whereas the previous studies have determined the forecasting accuracy at the aggregate market level, Brodie and de Kluyver (1987) have re-addressed the problem by using the data set of their 1984-study but now they determine the forecasting accuracy at the brand level. In this later study, market response models did not outperform the naive model in terms of short-term forecasting accuracy. On the basis of these contradictory results, Bass (1987) has argued that market share models are typically misspecified so that the missing information is equally well accounted for in naive models than in incomplete market response models. Wittink (1987) on the other hand argues that aggregation of the data eliminates useful sources of variation and that the estimation of market response models on aggregated data puts unrealistic model constraints on the estimation.

On the basis of these results and the general availability of weekly store-level scanner data Kumar and Heath (1990) demand the use of these disaggregated data for determination of the forecasting accuracy of market response models. Kumar and Heath investigate the prediction accuracy of linear, multiplicative and attraction models for three brands in the diaper market (52 weeks for calibration, 8 weeks for prediction) and for five brands in the tissue market (44 weeks for calibration, 8 weeks for prediction). OLS-prediction results are opposed to those of a GLS-procedure. The forecasting horizon varies and applies to one, two, three and eight time-periods ahead. Kumar and Heath show that (1) market response models are superior to naive models, (2) GLS-estimations of an attraction model are superior in case the attraction model includes differential effects, (3) OLS-estimates of linear models are superior if all models omit important variables and (4) attraction models predict best of all the models.

Thus a fully specified attraction model, estimated by means of GLS, will in almost all cases yield better forecasts than the competing specifications. The results of Kumar and Heath also hold for short-term and long-term forecasting performance.

A major drawback has been that competitors' actions have simply been assumed to be known a priori. This rather unrealistic assumption has been cancelled by Kumar (1994) who (1) compares the forecasting performance of alternative market response models when competitors' actions are predicted with the results by using known values. In addition, Kumar investigates (2) the relative performance of the models when systematic errors are introduced to the competitors' actions in the prediction sample, (3) appropriate identification methods for forecasting competitors' marketing-mix, (4) the performance of market share models if the forecasts are evaluated at the brand level as opposed to the category level and (5) the model performance of alternative estimation methods.

On the basis of weekly store-level scanner data Kumar's results can be summarized as follows: Differentially specified attraction models (brand specific intercepts and brand specific marketing instruments) estimated by a GLS-procedure have the best forecasting performance even at the brand level and even if competitors' actions are merely forecasts. The superiority of the GLS-estimation procedure depends on the degree of autocorrelation.

However, Kumar's results also show that for large errors in the competitors' predictor variables naive models may outperform all the market response models. On the basis of these results the importance of superior forecasting methods for the competitors' actions becomes obvious if market response models have to outperform naive forecasting methods. A recent study by Brodie and Bonfrer (1994) has attempted to replicate the results of Kumar and Heath (1990). In difference to the latter, Brodie and Bonfrer evaluate the forecasting accuracy at the brand level and at the market level. The forecasting performance has furthermore been investigated in case the competitors' actions are forecasts. But Brodie and Bonfrer do not use the market share attraction model. They report superior forecasting performance for market response models compared to the naive model if competitors' actions are known. The results change significantly in favor of the naive model if competitors' actions are forecasts. The competitors' forecasts are estimated by using the approach of Alsem, Leeflang and Reuyl (1989). In this context Danaher (1994) shows that naive models are likely to outperform market response models if competitors' actions are forecasts. Following Danaher, market response models are only superior to naive models if they fit the data extremely well for all brands in the market. The results also depend on the number of observations and the number of brands. Large time series favor market response models in contrast to short time series where generally naive estimation techniques outperform market response models.

To summarize the previous results, market response models are useful for market share forecasting. Especially on the basis of weekly store-level scanner data as well as on an analysis at the brand-level and on a long time-horizon, market response models are likely to outperform naive models. The GLS-estimation technique should generally be preferred to the OLS-estimation although it is not guaranteed that the results of a GLS-estimation really outperform the results of an OLS-estimation. These conclusions, however, are confirmed only if the competitors' actions are known. In the more realistic case in which competitors' actions have to be estimated on the basis of previous market behavior the predictive accuracy of market response models may be outperformed by naive models. Unfortunately the current approaches to predict competitors' actions do not account for the high correlation between the marketing-instruments. The results may also be affected by possible misspecifications of the market response models. Especially in consumer goods markets of frequently purchased goods cross-competitive effects - i.e. asymmetric competition - may influence the competition between the brands. These asymmetric competitive effects have been documented in several studies, e.g. Allenby & Rossi 1991; Bemmaor & Mouchoux 1991; Blattberg & Wisniewski 1989; Carpenter, Cooper, Hanssens & Midgley 1988; Cooper 1988; Grover & Srinivasan 1992; Krishnamurthi & Raj 1988, 1991. The inclusion of cross-competitive effects into the analysis may offer additional value and the market response model may give superior market share forecasts and also extends descriptive value.

3 Research approach

As outlined in the introduction, we focus on four major research issues. Firstly, the forecasting performance of alternative market share attraction models is investigated. According to the previous results on the forecasting accuracy of market response models it seems reasonable to concentrate on attraction models. Studies based on disaggregate (weekly) store-level scanner data favor the class of attraction models if the problem of forecasting the competitors' actions is not taken into account (e.g. Chen, Kanetkar & Weiss 1994; Kumar 1994; Kumar & Heath 1990). Secondly, the forecasting performance of alternative attraction models using different variable transformations such as the zeta-transformation is investigated. Thirdly, the forecasting performance of alternative attraction models is analyzed with respect to different assumptions about the error structure. Fourthly, the forecasting performance of attraction models is analyzed in case the competitors' actions are forecasts. Therefore we introduce an approach which accounts for interdependencies between competitors' marketing instruments. To the best of our knowledge these problems have not been investigated for those market share attraction models which also allow for asymmetric brand competition.

3.1 Market share attraction models

In this section we provide differential-effects models and cross-effects models. A differential-effects model allows for brand-specific intercepts and brand-specific effects of the explanatory variables such as price and promotion. The general version of the differential-effects attraction model can be expressed as

$$\begin{aligned} s_{it} &= \frac{A_{it}}{\sum\limits_{j=1}^{m} A_{jt}} \\ A_{it} &= \exp(\alpha_i + \epsilon_{it}) \prod_{k=1}^{K} \left[f_{kt}(X_{kit})\right]^{\beta_{ki}} \qquad (1) \end{aligned}$$

where m is number of brands, K is the number of marketing-instruments, s_{it} is the market share of brand i in period t, A_{it} is the attraction of brand i in period t, $f_{kt}(X_{kit})$ is a dynamically-weighted measure of brand i's relative competitive position on the kth marketing-mix element, α_i is brand i's constant component of attraction, β_{ki} is the brand i's specific effect of the kth marketing-instrument and ϵ_{it} is the stochastic error of brand i in period t. For presentational purposes of the empirical results we will refer to this model by `DEM`.

If $f_{kt}(\cdot)$ is an identity transformation (`ID-TR`), model 1 is the well-known multiplicative competitive interaction model. Model 1 becomes a multinomial logit model if $f_{kt}(\cdot)$ is an exponential transformation (`EXP-TR`). If asymmetric cross-competitive effects are present, the asymmetric market share model of Carpenter, Cooper, Hanssens and Midgley (1988, henceforth CCHM) provides a useful approach to account for these asymmetries in competition. The CCHM-model bases on a two-step estimation procedure. In the first step a differential-effects model as in equation 1 is estimated. The residuals of this model are cross-correlated with the marketing instruments of all competitors. On the basis of significant correlations a subset of potential cross-effects is determined and introduced into the attraction model. After that model 2 is estimated and the parameters of the direct-effects and the potential cross-effects are calibrated. The CCHM-model can be expressed as

$$\begin{aligned} s_{it} &= \frac{A_{it}}{\sum_{j=1}^{m} A_{jt}} \\ A_{it} &= \exp(\alpha_i + \epsilon_{it}) \prod_{k=1}^{K} [f_{kt}(X_{kit})]^{\beta_{ki}} \prod_{(k^*j^*)\epsilon C_i} [f_{kt}(X_{k^*j^*t})]^{\beta_{k^*ij^*}} \end{aligned} \tag{2}$$

with the variable definitions as those of model 1 and where $\beta_{k^*ij^*}$ is the cross-effect of brand j^*'s k^*th marketing-instrument on brand i and C_i is the subset of potential cross-effects. The potential cross-effects may also be determined on the basis of a Lagrange multiplier test (see e.g. Harvey 1990) by regressing the brand specific residuals on the explanatory variables of the competitors. The first approach is indicated by `CCHM CORR`, the second by `CCHM LM`.

For estimation purposes the model 2 is conveniently linearized as follows (shown for $f_{kt}(\cdot)$ as identity transformation):

$$\ln(s_{it}) = \alpha_0 + \sum_{i \in C_i} \alpha_i' d_i + \sum_{t'=2}^{T} \gamma_t' c_{t'} + \sum_{k \in C_i} \beta_{ki} \ln X_{kit} + \sum_{k^*j^* \in C_i} \beta_{k^*ij^*} \ln X_{k^*j^*t} + \epsilon_{it} \tag{3}$$

Assuming the error terms to be uncorrelated with homoskedastic variance σ^2 OLS estimation of 3 is straightforward. EGLS estimation as described e.g. in Judge, Hill, Griffiths, Lütkepohl and Lee (1988) may be adopted if ϵ_{it} fails to be uncorrelated and identically distributed. One may assume ϵ_{it} to have brand specific variance (σ_i^2), or to exhibit first order autocorrelation

$$\epsilon_{it} = \rho\epsilon_{it-1} + u_{it} \tag{4}$$

with u_{it} representing a white noise error sequence. Both assumptions, heteroskedasticity and autocorrelation may also be combined. Complementary to standard specification tests the adequacy of competing assumptions concerning the distribution of ϵ_{it} may be evaluated within our forecasting exercise. Thus EGLS-estimation is performed within this study to cope with autocorrelation and heteroskedasticity. For presentational purposes of the empirical results we refer to ordinary least squares estimation by `OLS`, adjustments for heteroskedasticity by `EGLS 1`, autocorrelated errors by `EGLS 2` and adjustments for heteroskeasticity and autocorrelation by `EGLS 3`.

The calibration of market share models usually includes a variable transformation step, especially if cross-effects are estimated (e.g. Carpenter, Cooper, Hanssens & Midgley 1988; Chen, Kanetkar & Weiss 1994; Cooper 1988; Cooper, Klapper & Inuoe 1996). This variable transformation takes the competition in each time period into account and additionally reduces the model-intrinsic collinearity. For dummy variables such as promotions, we use the index of distinctiveness (Nakanishi, Cooper & Kassarjian 1974) which is identical to the square value of the corresponding z-score. In addition to that, we investigate the effects of z-scores and zeta-scores on the forecasting accuracy of market share models. Zeta-scores are defined as

$$\begin{aligned}\zeta_{kit} &= (1+z_{kit}^2)^{\frac{1}{2}}, \quad \text{if } z_{kit} \geq 0\\ \zeta_{kit} &= (1+z_{kit}^2)^{-\frac{1}{2}}, \quad \text{if } z_{kit} \leq 0.\end{aligned}$$

where $z_{kit} = (X_{kit} - \bar{X}_{kt})/\sigma_{kt}$ and where $\bar{X}_{kt}$ is the mean of X_{kit} over i and where σ_{kt} is the standard deviation of X_{kit} over i. In addition to that, the z-scores have been exponentially transformed so that they can be used within the linearized versions of the models 1 and 2. For the presentation of the empirical results we refer to raw data by `RAW`, to the exponentially transformed z-scores by `EXP(Z)` and to the zeta-scores by `ZETA`

3.2 Forecasting competitors' actions

For the forecasting of competitors' actions previous studies have used either a Box-Jenkins analysis of past competitive activities (e.g. Brodie & Bonfrer 1994) or an econometric model (e.g. Alsem, Leeflang and Reuyl 1989; Kumar 1994). As suggested by Alsem, Leeflang and Reuyl the forecasts of competitors' weekly prices can be generated by the model

$$P_{it} \quad = \quad a_i + \sum_{j=1}^{m} b_j P_{jt-1} + \nu_i t_t + \sum_{l=1}^{T} \gamma_l D_l + e_{it} \tag{5}$$

where P_{it} is the price of brand i at time t, a_i is brand i's intercept, b_j is the response parameter of brand j's lagged price, t_t is the time trend, ν_i is the effect of the time trend D_l is the lth dummy variable for capturing any seasonality, γ_l is the effect of the seasonal dummy variable and e_{it} is an error term. If the competitors' values for dummy variables such as display and feature have to be predicted, the following model may be used (shown for featuring):

$$P[F_{it} = 1] = \frac{1}{1 + \exp\left(-\delta_i - \sum_{j=1}^{m} \tau_{Fji} F_{jt-1}\right)} \tag{6}$$

where $P[F_{it} = 1]$ is the probability that brand i is featuring in week t, F_{jt-1} is the feature dummy for brand j, δ_i is the brand-specific intercept term. τ_{Fji} is the effect of brand j's featuring in time $t-1$ on brand i. If $P[F_{it} = 1]$ is greater than 0.5, then F_{it} assumes a value of one, otherwise zero. This procedure, however, does not account for the interdependencies of the marketing instruments. It is obvious that in many cases price reductions are also featured and/or combined with in-store displays.

In this paper the authors therefore introduce several new approaches to accommodate for these marketing-mix relations for predicting competitors' actions.

Since a time trend as well as seasonal effects can hardly be expected to be significant for price determination within our 2 year sample of weekly observations we start with a, say naive, restricted version of 5 by setting $\nu_i = \gamma_l = 0$:

$$P_{it} = a_i + \sum_{j=1}^{m} b_j P_{jt-1} + e_{it} \tag{7}$$

OLS-estimation of the model 7 yield highly autocorrelated error terms irrespectively of the brand under study. Therefore estimation and forecasting results for this model are not provided in the sequel of our study. To allow efficient estimation of b_j on the one hand and to improve the stochastic properties of one step ahead forecast errors on the other hand we assume e_{it} to follow an autoregressive process of order one as given in 4. Forecasting in case of autocorrelated error terms is also discussed in Judge, Hill, Griffiths, Lütkepohl and Lee (1988). The basic models employed for forecasting competitors' prices within our study are

$$P_{it} \quad = \quad a_i + b_i P_{it-1} + e_{it} \tag{8}$$

$$P_{it} \quad = \quad a_i + \sum_{j=1}^{m} b_j P_{jt-1} + e_{it} \tag{9}$$

both assuming $e_{it} = \rho e_{it-1} + u_{it}$. Note that model 8 states that the price for brand i is completely determined by its own history and follows an ARMA(1,1) process. For the ease of the presentation of empirical results we refer in the following to these models as `Pr1` for 8 and `Pr2` for 9.

As mentioned above competitors' actions may be regarded as interdependent. To account for price dependence on the contemporal choice of other marketing instruments model 9 was extended as follows:

$$P_{it} = a_i + \sum_{j=1}^{m} b_j P_{jt-1} + \sum_{j=1}^{m} f_j F_{jt} + \sum_{j=1}^{m} d_j D_{jt} + \sum_{j=1}^{m} s_j S_{jt} + e_{it} \tag{10}$$

Again we assume e_{it} to be autocorrelated of order 1. In 10 the binary variables F_{jt} and D_{jt} indicate whether brand j is featuring or displayed in week t. S_{jt} is also binary and indicates special price offers for brand j in week t. Whereas estimation of 10 is straightforward the computation of ex-ante price forecasts affords knowledge of competitors actions in future time. Instead of assuming the realizations of F_{jt}, D_{jt} and S_{jt} to be known even for the forecasting period we adopt alternative modeling and specification procedures to provide ex-ante forecasts for the binary variables in 10. We adopt the common logit model which was already provided for featuring in 6. As a natural extention of this model one may regard the inclusion of other lagged marketing instruments as follows:

$$P[F_{it} = 1] = \frac{1}{1 + \exp\left(-\delta_i - \sum_{j=1}^{m} \tau_{Fji} F_{jt-1} - \sum_{j=1}^{m} \kappa_{Dji} D_{jt-1} - \sum_{j=1}^{m} \theta_{Sji} S_{jt-1}\right)} \tag{11}$$

For the logit models 6 and 11 alternative specification strategies were under study which take problems evolving from possible overparametrization into account. "Univariate" models as in 6 were estimated unrestricted on the one hand (indicated as `Lo1`) and alternatively zero restrictions were imposed on those estimated coeffcients which turned out to be insignificant at the 10% significance level (`Lo2`). Own effects, e.g. for feature advertising $\tau_{Fii} F_{it-1}$ were always included in the empirical model. An augmentation of `Lo1` and `Lo2` with other lagged binary variables was made stepwise. E.g. in 11 single variables D_{jt-1}, $j = 1, \ldots, m$ and S_{jt-1}, $j = 1, \ldots, m$ have been introduced sequentially. If the estimated coefficient of a variable under study was significant at the 10% level the empirical model was augmented with this variable. Logit models with an enhanced set of explaining variables are indicated as `Lo3` (augmented version of `Lo1`) and `Lo4` (augmented version of `Lo2`) in the following.

Distinguishing unrestricted and restricted specifications of 6 on the one hand and making a similar classification of the augmented model in 11 we obtain four competing devices

(`Lo1` to `Lo4`) to obtain ex-ante forecasts for each of the binary variables in 10.

An alternative procedure which is designed to cope for interdependence of marketing instruments bases on the idea to transform the marketing actions within brands to so-called events that characterize the simultaneous use of marketing activities. This modeling device leads to a multinomial logit specification (e.g. Kmenta 1986) as follows: For each brand one may consider the adopted combination of marketing instruments F_{it}, D_{it} and S_{it} directly by defining additional binary variables such as FD_{it} which indicates that brand i was featured and displayed in week t simultaneously. Adopting this definition of binary variables let e.g. $\bar{F}_{it}$ denote that advertising was the only relevant competitive action for brand i in period t. Along these lines one may find seven possible combinations of marketing instruments. It turned out that $\bar{F}_{it}$, SF_{it} and DF_{it} were rarely observed so that these binary variables were summarized in one variable F^*_{it}. For the multinomial logit model marketing actions $Y_{it}(k)$ were defined as follows

k	1	2	3	4	5
$Y_{it}(k)$	$\bar{S}_{it}$	$\bar{D}_{it}$	F^*_{it}	DS_{it}	FDS_{it}

$k = 0$ indicates that no marketing instrument was chosen for a specific brand in question. With $\mathbf{x}_t$ denoting a set of explaining variables the probabilities of choosing an activity $Y_{it}(l)$ are given as

$$\text{prob}(k = l) = \frac{\exp(\beta_l' \mathbf{x}_t)}{1 + \sum_{k=1}^{5} \exp(\beta_k' \mathbf{x}_t)} \tag{12}$$

$$\text{prob}(k = 0) = \frac{1}{1 + \sum_{k=1}^{5} \exp(\beta_k' \mathbf{x}_t)} \tag{13}$$

For each possible value of $k = 1, \ldots, 5$ a separate parameter vector β_k is to estimate. One may imagine that the multinomial logit model easily suffers from a high number of parameters such that the selection of possible explaining variables to be included in $\mathbf{x}_t$ becomes a crucial issue. Within our study we choose apart from an intercept term six binary variables, i.e.

$$\mathbf{x}_t = 1, F_{it-1}, D_{it-1}, S_{it-1}, \tilde{F}_{it-1}, \tilde{D}_{it-1}, \tilde{S}_{it-1}$$

$F_{it-1}, D_{it-1}, S_{it-1}$ are as defined above and $\tilde{F}_{it-1}$ denotes whether any brand other than i was featured in week $t-1$. $\tilde{D}_{it-1}$ and $\tilde{S}_{it-1}$ are defined accordingly. In our empirical study we will refer to this forecasting method by `ML`.

Ex-ante forecasts obtained from the multinomial logit model were used to forecast competitors' prices using the following models alternatively:

$$P_{it} = a_i + \sum_{j=1}^{m} b_j P_{jt-1} + d_i \bar{D}_{it} + s_i \bar{S}_{it} + f_i^* F^*_{it} + ds_i DS_{it} + fds_i FDS_{it} + e_{it} \tag{14}$$

and

$$
\begin{aligned}
P_{it} &= a_i + \sum_{j=1}^{m} b_j P_{jt-1} + \sum_{j=1}^{m} d_j \bar{D}_{jt} + \sum_{j=1}^{m} s_j \bar{S}_{jt} \\
&+ \sum_{j=1}^{m} f_j^* F_{jt}^* + \sum_{j=1}^{m} ds_j DS_{jt} + \sum_{j=1}^{m} fds_j FDS_{jt} + e_{it} \qquad (15)
\end{aligned}
$$

Note that the two models 14 and 15 differ with respect to the relevant information set which is necessary to estimate and forecast P_{it}. Apart from lagged prices the model 14 uses only brand specific combinations of marketing instruments whereas in the second model (15) P_{it} is conditioned on the adopted marketing mix of all competitors. Empirical results obtained from the multinomial logit model are indicated as `ML_Pr1` for model 14 and `ML_Pr2` for model 15 in the following.

4 The empirical study

The empirical study is carried out in order to evaluate all the major objects of the study: (1) evaluating the forecasting accuracy of different attraction model specifications, (2) investigating the effects of different variable transformations on the quality of the forecasts, (3) investigating the effects of different assumptions with regard to the error structure on the forecasting accuracy and (4) investigating the effects of different methods to predict competitors' actions on the forecasting accuracy of the attraction models.

4.1 Data and research setup

Store-level scanner data from a German instrumental test market are used to answer the research questions outlined above. The product category applies to the personal hygiene market and the data have been collected from over 104 weeks. The market is dominated by 9 major brands that account for approximately 90 percent of the total market volume. The explanatory variables are price, display and feature activities. Table 1 gives a summary description of the market shares and marketing activities of the 9 brands. Prices in Table 1 have been transformed so that the minimal price is equal to "1" in order to impose secrecy. TPR indicates the number of temporary price reductions over the period of 104 weeks. Identical information is provided for display and feature actions.

The forecasting performance is measured by the mean squared error (MSE) of 26 one-period-ahead forecasts for each model. For this reason we have reduced the calibration sample successively from 103 weeks to 78 weeks and each time the market shares of the following week (one-week-ahead) have been predicted. This procedure ensures that the market share predictions do not depend on only one calibration but on 26 calibration sets and that the amount of random effects on the forecasting performance is reduced to a minimum.

Which alternative market share attraction models have been investigated with respect to their forecasting performance? Table 2 lists the 72 possible model specifications relying on the labels previously documented. According to Table 2 we have considered the identical and the exponential transformations (`ID-TR`, `EXP-TR`) of the differential-effects model (`DEM`) and the cross-effects models (`CCHM CORR`, `CCHM LM`). `OLS`, `EGLS 1`, `EGLS 2` and `EGLS 3` specify the assumptions about the error term. `OLS` assumes independent identically distributed errors with a mean of zero and a constant variance. `EGLS 1` specifies the adjustment for possible heteroskedasticity, `EGLS 2` assumes autocorrelated errors and finally `EGLS 3` represents the error adjustment for heteroskedasticity and autocorrelation. With respect to possible variable transformations we distinguish between raw data (`RAW`), exponentially transformed z-scores (`EXP(Z)`) and zeta-scores (`ZETA`).

The forecasting performance of the 72 different market share attraction models has been evaluated for 9 different validation data sets. `DATA 0` refers to the case in which competitors' actions are a priori known. `DATA 1` to `DATA 8` are data sets about competitors' actions that have been predicted by using the models described above and listed in Table 3.

4.2 Forecasting results when predicting competitors' actions

Before discussing the forecasting performance of the alternative market share models we will report the forecasting results by predicting competitors' actions. Thus we first describe the forecasting accuracy with respect to the marketing instruments and not to the market share forecasts. Forecasting results for the competing modeling devices are given in Tables 4 and 5. The performance of univariate and multinomial logit models in forecasting marketing actions differs with regard to the brand under study (Table 4). Irrespective of the marketing instrument the probability of forecasting a competitor's action correctly appears to be smaller for highly competitive brands (e.g. brand 3, 7 and 9) than for less competitive ones. Relative to price and display actions feature actions are less frequently observed. Since the ex-ante probability of feature advertising is generally low the forecasting performance of logit modeling is better with regard to this marketing instrument than to display actions or price offers.

Only minor differences can be observed regarding the information set used for forecasting. For a given marketing instrument the summary statistics provided for `Lo1` to

`Lo4` are similar. Evaluating the forecasting performance of the multinomial logit model it appears that this modeling device shows the weakest forecasting performance. However, the forecasting issue is more complex within this framework, because ex-ante probabilities for more than one event are to estimate. Often the multinomial logit model fails to predict the exact combination of marketing instruments. However, even predicting a false combination of marketing instruments might yield convenient conditional variables for forecasting prices by means of model 10.

In Table 5 MSE-measures for ex-ante price-forecasts obtained from 8, 9 or 10 are given. In addition, we provide LM-tests statistics against first order autocorrelation of one-step-ahead forecasts errors (Spanos 1986). In order to facilitate the overall comparison of competing modeling devices we also provide the sum of normalized MSE-measures over all brands under study. The normalization was done with respect to the performance of the pure autoregressive model (`Pr1`) for which the sum of normalized MSE-measures is m ($m = 9$ brands). All other modeling devices show a higher sum of normalized MSE-measures relative to the reference model. Second best MSE-measures are obtained for `Pr2` and `ML_Pr1` which both yield a sum of normalized MSE about 11. However, the inclusion of binary explaining variables helps to improve the stochastic properties of the obtained forecast errors. The pure autoregressive model (`Pr1`) yields for 5 brands autocorrelated forecast errors which are significant at the 5 % level. For the specification `ML_Pr1` only 3 error sequences show significant autocorrelation at the 5% level. Note that all models under investigation were assumed to have autocorrelated error terms. One may easily imagine that without such an assumption the obtained forecasting errors would suffer severely from autocorrelation.

4.3 Empirical results

In this section we are going to focus our attention on the forecasting performance at the brand level first before considering the forecasting performance at the market level. Regarding presentational restrictions we are not able to report the mean squared errors (average of 26 one-period-ahead forecasts) of the 9 brands across 72 alternative models and across 9 different validation data sets. We have therefore performed a dummy variable regression of the mean squared errors on dummy variables indicating the validation data sets, the brands and the alternative model specifications. Due to linear dependencies of the indicator matrix we had to construct a base model. The parameters of the dummy variables then provide the information of how the substitution of a certain model specification or of a certain brand improves or impairs the forecasting performance. Our base model refers to brand 1, an identity transformation within the differential-effects model, using raw data and ordinary least squares for parameter estimation. Data set `DATA 0` provides the basis for validation, assuming that competitors' actions are a priori known. Thus the dummy variable parameters of the validation data sets indicate how strong the forecasts of competitors' actions improve or impair the forecasting accuracy. The dummy variable regression results are given in Table 6. The regression is highly significant with an F-value of 950.257 which has to be compared with a critical value obtained from a F(24,5807)-distribution. The parameter estimates of `DATA 1` to `DATA 8` show that the forecasting performance impairs if competitors' actions are forecasts. However, the best forecasting performance if competitors' actions are forecasts is obtained (on average) from the validation data set `DATA 2`. Thus, price predictions including own past prices and past prices of the competitors without including other marketing instruments should be combined with binary logit models to predict the promotional activities such as display and feature. More complex forecasting methods which have been used to construct the validation data sets `DATA 3` to `DATA 6` are not necessary if market share attraction models are used for forecasting purposes. If the forecasts of competitors' actions are based on events (`DATA 7`, `DATA 8`) rather than on the marketing instruments themselves, the forecasting performance is even further impaired. We can therefore conclude that simple methods predicting future marketing activities of the brands out of past own and past competitive marketing activities within an instrument will outperform more advanced prediction methods.

Let us now investigate to which degree alternative model specifications affect the forecasting performance. The brand parameters need not be discussed as they only control brand specific effects. In fact, if the 8 brand dummies had been excluded from the estimation, the remaining parameter estimates would have been identical. The parameter of the dummy variable `EXP(TR)` indicates that the forecasting performance will be impaired if the exponential transformation and not the identical transformation is used within the differential- or cross-effects models. Table 6 also shows that variable transformations can improve the forecasting accuracy and that exponentially transformed z-scores should be preferred to zeta-scores. The inclusion of cross-effects, however, does not improve the forecasting performance, irrespective of whether the potential cross-effects are determined or not. But alternative assumptions about the error structure different from those of `OLS` do affect the forecasting accuracy. An adjustment for heteroskedastic errors impairs the forecasting accuracy whereas adjusting for autocorrelated errors improves the forecasting performance. The best accuracy with respect to the error structure can be derived if one simultaneously adjusts for heteroskedasticity and autocorrelation.

To summarize, we can say that the best forecasting accuracy at the brand level can be expected if a differential-effects model is used with an identity transformation and exponentially transformed z-score variables (which is identical to a multinomial logit model with z-score variables) adjusting for autocorrelation and heteroskedasticity. We have also proved that these results will hold at the brand level.

In addition to these results we will also compare the forecasting performance of the 72 alternative market share attraction models to that of a naive model. The naive model we have used predicts brand specific future market shares from a first order autoregressive model assuming autocorrelated errors. Thus, our naive model is not as naive as it has been in previous studies. Again 26 one-week-ahead forecasts for each brand have been averaged to get mean squared errors for each brand from the naive model. We will focus our attention only on the case assuming that competitors' actions are a priori known (`DATA 0`, results given in Table 7) and when competitors' actions are predicted with the models `Pr2` and `Lo1` (`DATA 2`, results given in Table 8). As the forecasting accuracy is measured at the brand level, each of the 72 alternative models using either validation data set `DATA 0` or `DATA 2` can outperform the naive model 9 times. The values in Tables 7 and 8 indicate how often the naive model has been outperformed by the corresponding market share model. Most of the 72 alternative models provide superior forecasts than the naive mode if competitors' actions are a priori known (Table 7). If the identity transformation is used and the parameter estimation is adjusted to autocorrelated errors (`EGLS 2` or `EGLS 3`) the naive model is outperformed irrespective of which variable transformations are used and which assumptions are made regarding the presence of cross-effects. We can therefore conclude that if market share attraction models are properly specified and competitors' actions are a priori known, estimates will provide the basis for superior forecasts compared to the forecasts of the naive model.

However, if we have to predict competitors' actions using the models `Pr2` and `Lo1` no market share model can outpredict the market share forecasts of the naive model on all 9 brands. But we have to ascertain that again an identity transformation of the market share attraction models and adjustments for autocorrelation can outperform the naive predictions on more than half of the brands. This indicates that even if competitors' actions have to be predicted, attraction models (if properly specified) are likely to outperform the naive model at the brand level.

Let us now briefly examine the forecasting accuracy at the market level. The mean squared errors of each model have been aggregated across brands and compared to the aggregated mean squared error of the naive model. We only need to consider the case in which competitors' actions have been predicted because the naive model has already been outperformed at the brand level by almost all attraction models on all 9 brands if competitors' actions are a priori known. The values in Table 9 report the difference between the aggregated mean squared error of the attraction model and that of the naive model. Hence, a negative value indicates that the naive model is outperformed by the corresponding attraction model. According to Table 9, market share attraction models - even if competitors' actions are forecasts - can outperform the market share predictions of naive models at the market level. If an attraction model is used with an identity transformation and if error corrections are made for autocorrelation and the variables are either z-scores or zeta-scores, irrespective of which assumptions are made about potential cross-effects, the market share predictions outperform those of the naive model.

5 Conclusions

The present study investigates the forecasting performance of market share attraction models. We have evaluated the effects of alternative model specifications combined with different variable transformations and different assumptions regarding the error structure on the forecasting performance at the brand level and also at the market level. According to previous research within this research area the forecasting performance has also been compared to the market share predictions of a naive model. Our naive model predicts future shares with an autoregressive model assuming autocorrelated errors. The study has put extensive emphasize on the prediction of competitors' actions. Using attraction models for predicting future shares in real world applications compels the user to assume or to predict the actions of the competitors. Therefore alternative methods for predicting competitors' actions have been proposed and evaluated. These prediction methods include simple autoregressive price predictions using only own past prices or also competitors' past prices and price predictions on the basis of all competitive marketing actions across all competitors. The binary promotion instruments such as feature or display actions have been predicted by using binary logit models. Explanatory variables within these logit models have been own effects, competitor effects of the same and of other instruments. In order to account for the high dependencies between the promotional instruments (e.g. display and feature actions are often combined with temporary price reductions) we have also transformed the promotional activities to so-called events. An event describes the combined presence of promotional instruments and their prediction bases on a multinomial logit model.

The forecasting performance of 72 alternative market share models has been investigated for the case in which competitors' actions are a priori known and for 8 different validation data sets that contain alternative predictions of the future competitive actions. The performance measure is the mean squared error of 26 one-week-ahead forecasts for each brand. We have therefore sucessively reduced the calibration sample from 103 weeks down to 78 weeks and estimated the one-week-ahead prediction error each time.

To summarize the key results of the study, the best model with respect to the forecasting accuracy is a differential-effects model (not including cross-competitive effects) using an identity transformation and exponentially transformed z-score variables (which results in a multinomial logit model) and adjusting for autocorrelation and heteroskedasticity. These results hold at the brand level and at the market level.

The best method to predict competitors' actions with repect to the forecasting performance uses simple autoregressive price predictions and binary logit models for the display and feature actions. The price predictions base on past own and competitors' prices but not on other marketing instruments. The binary logit models include only competitive actions within the corresponding instrument. The inclusion of other marketing instruments does not improve the forecasting accuracy. Predictions on the basis of events also do not improve the forecasting accuracy even if the competitors' actions are highly correlated. The adjustment for these dependencies among the marketing instruments is inferior to possibly wrong predictions of a whole marketing event. These results imply that simple models for predicting competitors' actions are superior to models that try to account for often high dependencies among the instruments.

If the forecasting results of the alternative market share attraction models are opposed to the forecasting results of the naive model, we have to ascertain that the market share attraction models considered here consistently outperform the naive model at the brand and at the market level if competitive actions are a priori known. However, if competitors' actions are forecasts, the forecasting performance of the naive model comes out better. But in any case, an attraction model with an identity transformation and error adjustments for autocorrelation can outperform the naive model on more than half the brands and generally also at the market level. We must also emphasize that our naive model assumes autocorrelated errors, thus it is not as naive as it has been in previous studies.

The results presented in this study therefore give further insights into the forecasting performance of market share attraction models. The empirical results support the usage of attraction models for forecasting purposes even if competitors' actions have to be predicted. Future work within this research area may try to replicate these findings with different data sets.

6 Literature

Allenby, G.M., Rossi, P.E., 1991. Quality perceptions and asymmetric switching between brands. Marketing Science 10, 185-204.

Alsem, K.J., Leeflang, P.S.H., Reuyl, J.C., 1989. The forecasting accuracy of market share models using predicted values of competitive marketing behavior. International Journal of Research in Marketing 6, 183-198.

Bass, F.M., 1987. Misspecification and the inherent randomness of the model are at the heart of the Brodie and de Kluyver enigma. International Journal of Forecasting 3, 441-444.

Bemmaor, A.C., Mouchoux, D., 1991. Measuring the short-term effect of in-store promotion and retail advertising on brand sales: A factorial experiment. Journal of Marketing Research 28, 202-214.

Blattberg, R.C., Wisniewski, K.J., 1989. Price-induced patterns of competition. Marketing Science 8, 291-309.

Brodie, R.J., Bonfrer, A., 1994. Conditions when market share models are useful for forecasting: Further empirical results. International Journal of Forecasting 10, 277-285.

Brodie, R.J., De Kluyver, C.A., 1984. Attraction versus linear and multiplicative market share models: An empirical evaluation. Journal of Marketing Research 21, 194-201.

Brodie, R.J., De Kluyver, C.A., 1987. A comparison of the short term forecasting accuracy of econometric and naive extrapolation models of market share. International Journal of Forecasting 3, 423-437.

Carpenter, G.S., Cooper, L.G., Hanssens, D.M., Midgley, D.F., 1988. Modeling asymmetric competition. Marketing Science 7, 393-412.

Chen, Y., Kanetkar, V., Weiss, D.L., 1994. Forecasting market shares with disaggregate or pooled data: A comparison of attraction models. International Journal of Forecasting 10, 263-276.

Cooper, L.G., 1988. Competitive maps: The structure underlying asymmetric cross elasticities. Management Science 34, 707-723.

Cooper, L.G., Klapper, D., Inoue, A., 1996. Competitive-component analysis: A new approach to calibrating asymmetric market-share models. Journal of Marketing Research 33, 224-238.

Cooper. L.G., Nakanaishi, M., 1983. Standardizing variables in multiplicative choice models. The Journal of Consumer Research 10, 96-108.

Cooper, L.G., Nakanishi, M., 1988. Market-Share Analysis. Boston: Kluywer.

Danaher, P.J., 1994. Comparing naive with econometric market share models when competitors' actions are forecast. International Journal of Forecasting 10, 287-294.

Ghosh, A., Neslin, S., Shoemaker, R., 1984. A comparison of market share models and estimation procedures. Journal of Marketing Research 21, 202-210.

Grover, R., Srinivasan, V., 1992. Evaluating the multiple effects of retail promotions on brand loyal and brand switching segments. Journal of Marketing Research 29, 76-89.

Harvey, A., 1990. The Econometric Analysis of Time Series. New York: Philip Allan.

Judge, G.G., Hill, R.C., Griffiths, W.E., Lütkepohl, H., Lee, T. C., 1988, Introduction to the Theory and Practice of Econometrics, New York: Wiley.

Kmenta, J., 1986, Elements of Econometrics. New York: Macmillan.

Krishnamurthi, L., Raj, S.P., 1988. A model of brand choice and purchase quantity price sensitivities. Marketing Science 7, 1-20.

Krishnamurthi, L., Raj, S.P., 1991. An empirical analysis of the relationship between brand loyalty and consumer price elasticity. Marketing Science 10, 172-183.

Kumar, V., 1994. Forecasting performance of market share models: An assessment, additional insights, and guidelines. International Journal of Forecasting 10, 295-312.

Kumar, V., Heath, T.B., 1990. A comparative study of market share models using disaggregate data. International Journal of Forecasting 6, 163-174.

Leeflang, P. S. H., Reuyl, J.C., 1984. On the predictive power of market share attraction models. Journal of Marketing Research 21, 211-215.

Naert, P. A., Bultez, A., 1973. Logically consistent market share models. Journal of Marketing Research 10, 334-340.

Naert, P. A., Weverbergh, M., 1981. On the prediction power of market share attraction models. Journal of Marketing Research 28, 146-153.

Nakanishi, M., Cooper, L.G., Kassarjian, H.H., 1974. Voting for a political candidate under conditions of minimal information. Journal of Consumer Research 1, 36-43.

Pierce, D.A., Haugh, L.D., 1977. Causality in temporal systems: Characterizations and a survey. Journal of Econometrics 5, 265-293.

Spanos, A., 1986, Statistical Foundations of Econometric Modelling, Cambridge: Cambridge University Press.

Wittink, R.D., 1987. Causal market share models in marketing. International Journal of Forecasting 3, 445-448.

Table 1: Description of the data

	Average Market Shares	Average Price	# TPR	# Display	# Feature
Brand 1	5.10	1.29	10	19	1
Brand 2	10.01	1.14	7	12	2
Brand 3	4.87	1.07	14	25	5
Brand 4	10.21	1.10	23	22	13
Brand 5	12.10	1.60	7	25	4
Brand 6	3.36	1.17	6	1	1
Brand 7	24.98	1.17	28	60	13
Brand 8	13.26	1.00	15	41	14
Brand 9	16.20	1.22	14	49	7

TPR = temporary price reductions

Table 2: Alternative market share attraction models for estimation

variants	label			
2	ID-TR	EXP-TR		
3	DEM	CCHM CORR	CCHM LM	
4	OLS	EGLS 1	EGLS 2	EGLS 3
3	RAW	EXP(Z)	ZETA	

Table 3: Models used to predict competitors' actions

DATA SET	Models used for predicting Price	Display & Feature
DATA 1	Pr1	Lo1
DATA 2	Pr2	Lo1
DATA 3	Pr3	Lo1
DATA 4	Pr3	Lo2
DATA 5	Pr3	Lo3
DATA 6	Pr3	Lo4
DATA 7	ML_Pr1	ML
DATA 8	ML_Pr2	ML

Table 4: One-step-ahead ex–ante forecasting performance of alternative strategies infering on competitors actions. Entries indicate the fraction of correct forecasts relative to the number of performed forecasting exercises (26). $\sum$ denotes the sum of the reported probabilities over 9 brands under study.

	Brands									
	1	2	3	4	5	6	7	8	9	$\sum$
	Display									
Lo1	0.92	0.92	0.73	0.62	0.85	1.00	0.77	0.96	0.77	7.54
Lo2	0.92	0.85	0.73	0.69	0.92	1.00	0.77	0.96	0.77	7.61
Lo3	0.92	0.92	0.69	0.62	0.92	1.00	0.77	0.96	0.73	7.53
Lo4	0.92	0.85	0.73	0.69	0.92	1.00	0.77	0.96	0.73	7.57
	Feature									
Lo1	1.00	1.00	0.92	0.92	1.00	1.00	0.85	1.00	0.92	8.61
Lo2	1.00	1.00	0.92	0.92	1.00	1.00	0.85	1.00	0.92	8.61
Lo3	1.00	1.00	0.92	0.89	0.96	1.00	0.85	0.92	0.92	8.46
Lo4	1.00	1.00	0.92	0.92	1.00	1.00	0.85	1.00	0.92	8.61
	Temporary price reductions									
Lo1	1.00	0.96	0.81	0.85	1.00	0.85	0.69	0.96	0.85	7.97
Lo2	1.00	1.00	0.77	0.77	1.00	0.89	0.65	1.00	0.89	7.97
Lo3	1.00	0.96	0.81	0.77	0.96	0.85	0.69	0.81	0.85	7.70
Lo4	1.00	1.00	0.77	0.77	1.00	0.92	0.65	1.00	0.89	8.00
	Multinomial Logit									
Ml	0.92	0.85	0.69	0.62	0.92	0.84	0.58	0.85	0.58	6.85

Table 5: One-step-ahead ex–ante forecasting performance of alternative strategies to estimate future prices. Upper entries indicate the mean squared forecast error (MSE·1000) over 26 forecasting exercises lower entries are the LM–statistic on first order autocorrelation of one-step-ahead forecast errors. $\sum$ denotes the sum of normalized MSE where the normalization is done with respect to the performance of the basic model (`Pr1`).

	Brands									
	1	2	3	4	5	6	7	8	9	$\sum$
`Pr1`	0.03	0.13	2.95	2.43	2.28	0.65	4.83	0.91	3.32	9.00
	23.60^c	5.35^b	3.58^a	0.23	23.80^c	5.89^b	0.00	18.80^c	1.57	
`Pr2`	0.09	0.11	3.39	3.62	0.46	0.55	5.54	1.24	3.61	11.13
	6.34^b	6.02^b	2.42	4.96^b	5.37^b	2.49	0.04	12.60^c	0.43	
`Lo1`	0.19	0.31	3.04	2.64	0.98	1.21	5.39	0.45	4.21	16.00
	4.67^b	0.00	2.12	1.18	7.71^c	0.55	1.19	3.44^b	0.04	
`Lo2`	0.17	0.22	3.60	3.72	0.66	1.07	6.35	0.45	3.65	14.95
	4.60^b	4.41^b	1.33	0.05	5.96^b	4.10^b	1.58	3.91^b	0.05	
`Lo3`	0.29	0.39	3.13	2.83	6.28	0.95	5.24	1.03	4.29	22.62
	6.65^c	5.56^b	2.21	1.49	0.04	0.33	1.40	5.04^b	0.50	
`Lo4`	0.16	0.24	3.47	3.45	0.55	1.37	5.69	0.48	3.73	14.95
	5.33^b	4.97^b	1.18	0.49	6.19^b	5.30^b	1.26	4.55^b	0.03	
`ML_Pr1`	0.08	0.10	3.67	4.05	0.14	1.01	5.28	0.75	4.36	11.19
	5.71^b	3.89^b	2.69	3.07^b	2.86^a	0.95	1.92	7.06^c	2.07	
`ML_Pr2`	0.12	0.20	3.46	3.55	0.76	1.21	5.07	0.69	4.52	13.54
	1.72	7.59^c	1.38	2.14	0.62	0.79	0.61	4.77^b	0.88	

Table 6: The results of the dummy variable regression

Valid cases:	5832
Missing cases:	0
Total SS:	1.120
R-squared:	.797
Residual SS:	.227
F(24,5807):	950.257
Probability of F:	.000

Variable	Estimate	Standard Error	t-value	Prob >|t|
CONSTANT	-.007422	.000410	-18.120472	.000
DATA 1	.007326	.000348	21.078069	.000
DATA 2	.007264	.000348	20.899263	.000
DATA 3	.007548	.000348	21.718230	.000
DATA 4	.008702	.000348	25.036185	.000
DATA 5	.007568	.000348	21.773480	.000
DATA 6	.007683	.000348	22.106707	.000
DATA 7	.008977	.000348	25.828055	.000
DATA 8	.009064	.000348	26.080063	.000
BRAND 2	.003538	.000348	10.180739	.000
BRAND 3	.003776	.000348	10.863211	.000
BRAND 4	.006967	.000348	20.046051	.000
BRAND 5	.001701	.000348	4.894504	.000
BRAND 6	.000140	.000348	.401511	.688
BRAND 7	.035735	.000348	102.815327	.000
BRAND 8	.006935	.000348	19.952985	.000
BRAND 9	.026233	.000348	75.477267	.000
EXP-TR	.002454	.000164	14.978831	.000
EXP(Z)	-.001746	.000201	-8.703007	.000
ZETA	-.001405	.000201	-7.002534	.000
CCHM CORR	.001489	.000201	7.418673	.000
CCHM LM	.001310	.000201	6.528410	.000
EGLS 1	.001230	.000232	5.306344	.000
EGLS 2	-.000549	.000232	-2.369410	.018
EGLS 3	-.000773	.000232	-3.333941	.001

Table 7: Forecasting performance of market share attraction models compared to the naive model for DATA 0. The values indicate how often the naive model has been outpredicted (maximum = 9).

OLS	ID-TR			EXP-TR		
	DEM	CCHM CORR	CCHM LM	DEM	CCHM CORR	CCHM LM
RAW	9	8	8	9	5	4
EXP(Z)	9	9	9	8	9	9
ZETA	8	9	8	9	7	7

EGLS 1	ID-TR			EXP-TR		
	DEM	CCHM CORR	CCHM LM	DEM	CCHM CORR	CCHM LM
RAW	9	9	9	9	5	5
EXP(Z)	8	9	9	8	9	8
ZETA	8	8	8	8	6	7

EGLS 2	ID-TR			EXP-TR		
	DEM	CCHM CORR	CCHM LM	DEM	CCHM CORR	CCHM LM
RAW	9	9	9	9	6	7
EXP(Z)	9	9	9	8	8	8
ZETA	9	9	9	7	9	9

EGLS 3	ID-TR			EXP-TR		
	DEM	CCHM CORR	CCHM LM	DEM	CCHM CORR	CCHM LM
RAW	9	9	9	9	8	9
EXP(Z)	9	9	9	8	8	9
ZETA	9	9	9	9	8	9

Table 8: Forecasting performance of market share attraction models compared to the naive model for DATA 2. The values indicate how often the naive model has been outpredicted (maximum = 9).

OLS	ID-TR			EXP-TR		
	DEM	CCHM CORR	CCHM LM	DEM	CCHM CORR	CCHM LM
RAW	4	4	5	4	1	0
EXP(Z)	4	6	5	4	4	5
ZETA	4	5	5	4	3	3

EGLS 1	ID-TR			EXP-TR		
	DEM	CCHM CORR	CCHM LM	DEM	CCHM CORR	CCHM LM
RAW	4	5	5	5	0	0
EXP(Z)	4	4	5	3	5	4
ZETA	4	5	4	4	2	2

EGLS 2	ID-TR			EXP-TR		
	DEM	CCHM CORR	CCHM LM	DEM	CCHM CORR	CCHM LM
RAW	5	4	5	5	1	4
EXP(Z)	5	6	6	4	4	4
ZETA	5	5	5	5	5	4

EGLS 3	ID-TR			EXP-TR		
	DEM	CCHM CORR	CCHM LM	DEM	CCHM CORR	CCHM LM
RAW	5	5	5	5	4	5
EXP(Z)	5	6	6	4	4	4
ZETA	5	5	5	4	4	4

Table 9: Forecasting performance of market share attraction models compared to the naive model at the market level for DATA 2, values multiplied by 1000, a negative value indicates that the naive model has been outperformed by the corresponding market share model

OLS	ID-TR			EXP-TR		
	DEM	CCHM CORR	CCHM LM	DEM	CCHM CORR	CCHM LM
RAW	-0.82	0.08	1.75	6.08	69.12	40.22
EXP(Z)	-1.10	0.31	0.39	14.09	10.32	12.78
ZETA	-1.56	-1.45	-0.92	2.38	24.43	17.45

EGLS 1	ID-TR			EXP-TR		
	DEM	CCHM CORR	CCHM LM	DEM	CCHM CORR	CCHM LM
RAW	-0.67	1.96	0.45	6.17	99.28	92.25
EXP(Z)	-0.76	-1.11	-0.23	15.11	9.45	11.51
ZETA	-1.43	-1.77	-0.02	4.75	58.26	61.21

EGLS 2	ID-TR			EXP-TR		
	DEM	CCHM CORR	CCHM LM	DEM	CCHM CORR	CCHM LM
RAW	-1.32	3.12	-1.54	3.86	29.23	35.88
EXP(Z)	-1.69	-2.24	-2.20	9.09	12.50	15.30
ZETA	-2.53	-4.87	-4.81	0.37	4.50	17.55

EGLS 3	ID-TR			EXP-TR		
	DEM	CCHM CORR	CCHM LM	DEM	CCHM CORR	CCHM LM
RAW	-1.20	0.72	-2.42	4.28	19.02	22.94
EXP(Z)	-1.74	-3.07	-2.89	10.01	9.65	6.45
ZETA	-2.46	-5.12	-3.56	1.51	2.03	7.16