

Pharmaceutical Product Market Share Estimation: Full-Factorial Attraction Model

Patrick J. Howie and Ewa J. Kleczyk

The study objective is to test whether a newly proposed Full-Factorial Attraction Model allows for more precise estimation and predictability of market share when accounting for a new entrant. An Attraction Model is often used to predict market share, although its predictability power is limited to a constant market structure (Cooper et al. 1996). Assuming a constant market structure across time does not solve the issue as the new entrant behavior has a direct impact on the incumbents (Fok 2003). Howie and Kleczyk (2007) proposed a joined pre- and post- new brand introduction model based on a re-conceptualization of any market share as a series of two-brand groups (Howie & Kleczyk 2007). In this investigation, both model types are evaluated on their goodness-of-fit and regression estimate stability for joined and separate pre- and post- new brand introduction models. OLS and GLS panel estimation is utilized in econometric modeling. The study results reveal that the standard way of estimating market share does not account for the changing market structure. On the other hand, the Full-Factorial Attraction Model does account for the changing market structure. The impact of the explanatory variable stays unchanged across all model specifications and no structural break is observed. The predictive power of the model is also the highest for the Full-Factorial Attraction Model.

Keywords: market share estimation, Attraction Model, OLS/GLS estimation

Introduction

The “Attraction Model” is often used to predict product market share in the pharmaceutical industry. Market share is a function of the share of attractiveness of the product (Cooper & Nakanishi 1996). The attraction model is, however, limited in its ability to predict market share due to severe practical data limitations including changing market structures across product classes (Cooper & Nakanishi 1996).

A substantive number of articles such as those by Shankar (1999) and Gatignon et al., (1990) deal with the changing market structures by simply estimating pre- and post-entry/exit models; however, the pre- and post-entry models are interdependent and do not capture the dynamic market structure. Additionally, the approach might not guarantee an adequate sample for post-entry/exit model estimation and therefore provides unreliable share estimates (Fok 2003). Finally, the changing market structure could be tested within models that exclude new entrants from the analysis. This approach is, however, not appropriate because the new entrant behavior has a direct impact on the incumbents. So even with the assumption of constant competitive market structure, the parameter estimates are affected by the new market entrant (Fok 2003).

In this article, market share for three pharmaceutical brands is analyzed. Two of the three products are present over the entire time span of the data. In order to estimate the market share model, the Attraction Model specifications are utilized. Separate and joined models of pre- and post- new brand entry specifications are estimated utilizing the base-brand approach.

Additionally, a new and innovative model called a Full-Factorial Attraction Model is employed for the market share estimation. The new model re-conceptualizes any product market share as a series of two-entity groups which reduces the impact of the number of brands on the competitive structure. In order to test for market structure changes after a new brand introduction, market structure dummy variables are included in the model specifications. All model specifications are estimated utilizing the OLS and GLS estimation techniques.

Literature Review

Although there is vast literature on theoretical and empirical analysis of market share, the impact of a new brand introduction on an existing market structure still lacks a succinctly defined estimation process. An exit/entry of a brand from a market changes the market shares and as well as the impact of marketing instruments on the shares. In the literature, there are several studies examining the effect of the entry of a new brand on the competitive structure through utilizing either a non-cooperative game theoretic view or on empirical research using time-series or panel data (Fok 2003).

The first type of studies takes on a normative viewpoint focusing on how incumbent brands should respond to the entry of a new brand. For example, Basuroy and Nguyen (1998) derived theoretical conditions for which the entry of a new brand would establish price decreases for fixed and expanding markets. In the case of fixed markets, the incumbent brands are inclined to lower marketing expenditures, while in the expanding markets these expenditures are set at higher levels. The important component lacked by these types of research is, however, the empirical investigation (Fok 2003).

Bowman and Gatignon (1996) and Chintagunta (1999) utilized empirical research for market share analysis. Bowman and Gatignon (1996) study the effect of the order of entry on market shares and the effectiveness of marketing instruments. They show that the order of entry negatively influences the effectiveness of promotion as well as lowers price responsiveness to the entry of a brand. The main effects of the order of entry on own market share are found to be small, while in contrast there are strong effects of the order of entry on the effectiveness of marketing efforts. On the other hand, Robinson (1988) shows that the most common reaction pattern to entry of a new brand is no reaction or only a reaction with a single marketing instrument.

There are several methods of dealing with new brand introduction into the market. One way of implementing market share analysis is to ignore the new entrant. This method, however, omits the indirect effects of the new brand's marketing instruments on the performance of the incumbent brands. So even if the competitive structure among the incumbent brands remains constant, parameters will change due to the effect of the marketing instruments of the new brand. Omission of the new brand in the model leads to more uncertainty in the parameter estimates. To test the changes in a market from new brand introduction, a model should describe both pre- and post - new brand introduction periods as well as include all brands (Fok 2003).

A substantive empirical analysis of the effects of a brand introduction calls for a model that jointly captures the pre- and post - new brand introduction periods. Separate models for the pre- and post-entry period are not very informative. If the goal of the analysis is to find any changes in the competitive structure or marketing instruments associated with new brand introduction, the separate models should be used. In this model specification, all model parameters are allowed to change including the brand intercepts, parameters concerning all marketing instruments, and the covariance matrix. This finding, however, does not inform which aspects of the competitive structure have really changed. Indeed only in a combined model it is possible to perform statistical tests on the constancy of the parameters or the changes in the competitive structure (Fok 2003).

In order to deal with this problem, Fok (2003) proposed a method to empirically analyze the effects of a brand introduction on the competitive structure and constancy of the marketing instrument parameters. By jointly estimating the pre- and post- new brand introduction models, he finds some parts of the competitive structure to remain unchanged due to the new brand introduction. Contrary to the game theory hypothesis, he also finds no support for price decreases after the introduction of a new brand. This finding could be explained by the lack of optimal response of brand managers to the new brand entry (Fok 2003).

Howie and Kleczyk (2007) also proposed a joined pre- and post- new brand introduction model called a Full-Factorial Attraction Model. Different from previously analyzed market share models, the Full-Factorial Attraction Model is based on a re-conceptualization of any market share as a series of two-entity groups. Due to the transformation, every group has the same market structure equal to 50%, which reduces the impact of number of brands on the competitive structure and parameters of marketing instruments. As a result, no distinction between market structures pre- and post- new brand introduction is necessary. The changing group dynamic through participants' entry/exit into/from the market does not affect the model since the structure is always comprised of only two entities (Howie & Kleczyk 2007).

The Full-Factorial Attraction Model's re-conceptualization of any market share as a series of two-entity groups also allows for analyzing empirical data across markets with differing competitive structures (i.e. pooling across different industries). The issue of pooling data of different markets has not been discussed in the current market share investigations (Howie & Kleczyk 2007).

Data

The data set utilized in this study includes three hypertension products for April 2002 to February 2006. Two products existed continuously during this time span and the third product entered the hypertension market in February 2003. The dependent variable is market share while the explanatory variable is represented by a share of voice variable. Market share is defined as a group of products' prescribing volume expressed as a percentage of a defined total market. The share of voice variable is defined as a group of products' advertising weight expressed as a percentage of a defined total market.

Empirical Model

Attraction Model

Market share theorem states that the market share of brand i at time t (M_{it}) is equal to its attraction relative to the sum of all attractions (Cooper & Nakanishi 1996):

$$M_{it} = A_{it} / \sum_{j=1}^I A_{jt}^{\beta_{kjt}} \quad \text{for } i = 1 \dots I.$$

A_{it} is the attraction of brand i at time t , given by:

$$A_{it} = \exp(\mu_i + \varepsilon_{it}) \prod_{j=1}^I \prod_{k=1}^K f(x_{kjt})^{\beta_{kjt}} \quad \text{for } i = 1 \dots I \text{ and } t = 1 \dots T$$

where x_{kjt} is the k -th explanatory variable for brand j at time t , $f(x_{kjt})$ denotes a transformation function of the k -th explanatory variable (x_{kjt}) for brand j at time t and where β_{kjt} is the corresponding coefficient for brand i . The explanatory variables usually employed in the Attraction Model include promotional spending and price levels for each brand. The parameter μ_i is a brand-specific constant and the error term $(\varepsilon_{1t} \dots \varepsilon_{It})'$ is normally distributed with zero mean and Σ as a non-diagonal covariance matrix (Cooper & Nakanishi 1996).

The model introduced above is called the Attraction Model with unobserved A_{it} . There are two types of Attraction Model specifications: Multiplicative Competitive Interaction (MCI) and Multinomial Logit (MNL) (Fok 2003):

$$\text{MCI: } A_{it} = \exp(\mu_i + \varepsilon_{it}) \prod_{j=1}^I \prod_{k=1}^K x_{kjt}^{\beta_{kjt}} \quad \text{for } i = 1 \dots I \text{ and } t = 1 \dots T$$

$$\text{MNL: } A_{it} = \exp(\mu_i + \varepsilon_{it} + \prod_{j=1}^I \prod_{k=1}^K (\beta_{kjt} x_{kjt})) \quad \text{for } i = 1 \dots I \text{ and } t = 1 \dots T.$$

In the case of the MCI model specification, the explanatory variables are restricted to only positive values in the market share estimation process. The Attraction Model presented above can be transformed utilizing the brand-based transformation resulting in the following Attraction Model definition:

$$\ln M_{it} - \ln M_{It} = (\mu_i - \mu_I) + \sum_{j=1}^I \sum_{k=1}^K (\beta_{kji} - \beta_{kjl}) \ln x_{kjt} + \sum_{j=1}^I \sum_{p=1}^P ((\alpha_{pji} - \alpha_{pjl}) \ln M_{j,t-p} + \sum_{k=1}^K (\beta_{pkji} - \beta_{pkjl}) \ln x_{k,t-p}) + \eta_{it}, \quad \text{for } i = 1 \dots I-1$$

where M_{it} is the market share for brand i at time t and the error variable is defined as $\eta_{it} = \varepsilon_{it} - \varepsilon_{It}$ with $(\eta_{1t} \dots \eta_{It})'$ being normally distributed (mean equal to zero and covariance matrix equal to $\Sigma^{tilde} = L \Sigma L'$) (Fok 2003).

An alternative method of model reduction is a log-centering approach (Cooper & Nakanishi 1996). This method subtracts a logarithmic function of geometric mean market share from all brands in I logarithmically transformed equations. Fok (2003) showed, however, that the brand-based transformation and the geometric average brand yield the same parameters. Additionally, the brand-based approach is a straightforward statistical model and accounts for most of the heteroskedasticity problem from the fluctuating number of brands in the market (Fok 2003).

There are three restrictions put on the Attraction Model in order to improve its identification by reducing the number of parameters specified: restricted competition, restricted effects, and restricted dynamics. The first Attraction Model restriction assumes brand i to depend only on its own explanatory variables by implying that $\beta_{kji} = 0$ for $j \neq i$. The restricted effects assumption states that β parameters are the same for each brand, $\beta_{ki} = \beta_k$ which implies that marketing efforts for brand i only have an effect on the market share of brand i and that these effects are also the same across brands. The final restriction is on the dynamic structure of the model implying that the attraction of brand i at time t only depends on its own lagged market shares M_{it} ($\alpha_{pji} = 0$ for $j \neq i$). When the Attraction Model is constrained using the three restrictions listed above, the following model specification is employed:

$$\ln M_{it} - \ln M_{I,t} = (\mu_i - \mu_I) + \sum_{j=1}^I \sum_{k=1}^K (\beta_{kji} - \beta_{kI}) \ln x_{kjt} + \eta_{it}, \text{ for } i = 1 \dots I-1.$$

Full-Factorial Attraction Model

Another way of estimating market share is to employ a Full-Factorial Attraction Model (for detailed description see Howie & Kleczyk 2007). The approach is based on a re-conceptualization of any market share variable for each brand as a series of two-product markets. For a market K (k represents number of markets in the study) with I number of brands, the transformed two-product market is described as follows:

$$m_{ijt} = M_{it}/(M_{it} + M_{jt}), \text{ where } i = 1 \dots I-1 \text{ and } j = 1 \dots I-1 \text{ and } i \neq j; t = 1 \dots T$$

$$m_{jit} = M_{jt}/(M_{it} + M_{jt}), \text{ where } i = 1 \dots I-1 \text{ and } j = 1 \dots I-1 \text{ and } i \neq j; t = 1 \dots T$$

$$m_{ijt} + m_{jit} = 1, \text{ where } i = 1 \dots I-1 \text{ and } j = 1 \dots I-1 \text{ and } i \neq j; t = 1 \dots T$$

for $I!/2!$ (every combination of two brand markets), where i, j are brands in market K . As a result, at any point in time, t , the market structure is equal to 50% (Howie & Kleczyk, 2007). The explanatory variables are transformed to conform to the new data definition. A difference between the two products' explanatory variables is computed and denoted as X_{ijt} :

$$X_{ijt} = x_{it} - x_{jt}, \text{ where } i = 1 \dots I, j = 1 \dots I \text{ and } i \neq j; t = 1 \dots T.$$

In order to control for the market size, dummy variables can be included in the model specification. Based on the above variable specification, the Full-Factorial Attraction Model is defined as follows:

$$m_{ijt} = \alpha_i + \beta X_{ijt} + \varepsilon_{it}, \text{ where } i = 1 \dots I-1 \text{ and } j = 1 \dots I-1 \text{ and } i \neq j; t = 1 \dots T.$$

Attraction Model Specification

In order to analyze the hypertension brand market share data, the Attraction Model and Full-Factorial Attraction Model are employed. The variables used in the market share estimation include market share and share of voice. Market share is the dependant variable and is defined as the group of products' prescribing volume expressed as a percentage of a defined total market. The share of voice variable represents the explanatory variable and is defined as the group of products' advertising weight expressed as a percentage of a defined total market. The restricted competition, effects, and dynamics are assumed for this investigation. To transform market share data for the Attraction Model estimation, the brand-based approach is utilized. As explained earlier, the brand-based approach results in a more straightforward reduced model form and controls for the heteroskedasticity problem when the base brand is present for the entire time span of the data. The parameter estimates are the same as when the log-centering approach is utilized.

In order to analyze the Attraction Model, the pre- and post- new brand introduction model specifications are employed. The following brand-based specification of the Attraction Model is to be estimated:

Pre-new brand introduction:

$$\ln M_{it} - \ln M_{1t} = (\mu_i - \mu_1) + \sum_{j=2}^I \sum_{k=1}^K (\beta_{kji} - \beta_{kjl}) \ln x_{kjt} + \eta_{it}, \text{ for } i = 2 \dots I-1, t = 1, \dots T-1.$$

Post-new brand introduction:

$$\ln M_{it} - \ln M_{1t} = (\mu_i - \mu_1) + \sum_{j=1}^I \sum_{k=1}^K (\beta_{kji} - \beta_{kjl}) \ln x_{kjt} + \eta_{it}, \text{ for } i = 1 \dots I-1, t = 1, \dots T.$$

As suggested by Fok (2003), a joined pre- and post-new brand entry model should be utilized to investigate the changes in market structure and marketing variable coefficients. The proposed joined model is defined as follows:

$$\ln M_{it} - \ln M_{1t} = (\mu_i - \mu_1) + \sum_{j=1}^I \sum_{k=1}^K (\beta_{kji} - \beta_{kjl}) \ln x_{kjt} + \eta_{it}, \text{ for } i = 1 \dots I-1 t = 1, \dots T.$$

To test for the competitive structure changes in the joined Attraction Model, a dummy variable representing the changing market structure is input into the model. A dummy variable (\mathbf{D}) takes a value of 1 for a three-brand market size and 0 otherwise. If the dummy variable is found statistically significant, than the estimated model specification does not account for varying market structure across cross-sections and time-series. The joined pre- and post- new brand introduction model is defined as follows:

$$\ln M_{it} - \ln M_{1t} = (\mu_i - \mu_1) + \sum_{j=1}^I \sum_{k=1}^K (\beta_{kji} - \beta_{kjl}) \ln x_{kjt} + \delta_i \mathbf{D} + \eta_{it}, \text{ for } i = 1 \dots I-1 t = 1, \dots T$$

where \mathbf{D} denotes the market structure dummy variable and δ_i is the corresponding dummy variable coefficient for brand i . Additionally, to test for the constancy of the parameter estimates of the share of voice variable, the explanatory variable is interacted with a market structure dummy variable. This model specification is equivalent to the separate pre- and post-new brand introduction models. For the purpose of this study, the joined model is estimated and reported on. The resulting model is specified as follows:

$$\ln M_{it} - \ln M_{jt} = (\mu_i - \mu_j) + \sum_{k=1}^I \sum_{l=1}^K (\beta_{kji} - \beta_{kjl}) \ln x_{kjt} + \gamma_i \mathbf{D} \ln x_{kjt} + \delta_i \mathbf{D} + \eta_{it},$$

for $i = 1 \dots I-1, t = 1, \dots T$

where $\mathbf{D} \ln x_{kjt}$ represents the interaction variable between the share of voice variable (x_{kjt}) and the market structure dummy variable (\mathbf{D}) while γ_i is the corresponding interaction variable coefficient for brand i .

Full-Factorial Attraction Model Specification

As specified by Howie and Kleczyk (2007), the Full-Factorial Attraction Model is a re-conceptualization of market share as a series of two-brands in the market. The transformed market share dependent variable is defined as the ratio of market share for brand i at time t and the sum of market share for brand i and j at time t : $m_{ijt} = M_{it}/(M_{it} + M_{jt})$. The Full-Factorial Attraction Model is specified as follows:

$$m_{ijt} = \alpha_i + \beta X_{ijt} + \varepsilon_{it}, \text{ where } i = 1 \dots I-1 \text{ and } j = 1 \dots I-1 \text{ and } i \neq j; t = 1 \dots T$$

where X_{ijt} is the difference between the two products' explanatory variables ($x_{it} - x_{jt}$).

To test for the impact of the competitive structure change, a dummy variable representing the changing market structure is input into the model. A dummy variable takes a value of 1 for three-brand market size and 0 otherwise. If the dummy variable is found statistically significant, then the estimated model specification does not account for varying market structure across cross-sections and time-series. The model is specified as follows:

$$m_{ijt} = \alpha_i + \beta X_{ijt} + \delta_i \mathbf{D} + \varepsilon_{it}, \text{ for } i = 1 \dots I-1 \text{ and } j = 1 \dots I-1 \text{ and } i \neq j; t = 1 \dots T$$

where \mathbf{D} denotes the market structure dummy variable and δ_i is the corresponding dummy variable coefficient for brand i . Additionally, to test for the constancy of the parameter estimates of the share of voice variable, the explanatory variable is interacted with the market structure dummy variable. The resulting model is specified as follows:

$$m_{ijt} = \alpha_i + \beta X_{ijt} + \gamma_i \mathbf{D} X_{ijt} + \delta_i \mathbf{D} + \varepsilon_{it}, \text{ for } i = 1 \dots I-1 \text{ and } j = 1 \dots I-1 \text{ and } i \neq j; t = 1 \dots T$$

where $\mathbf{D} X_{ijt}$ represents the interaction variable between the share of voice variable (X_{ijt}) and the market structure dummy variable (\mathbf{D}) while γ_i is the corresponding interaction variable coefficient for brand i .

Estimation Procedures

As discussed by Cooper and Nakanishi (1996), the standard method of estimating pharmaceutical products' market share is to utilize the ordinary least square (OLS) regression estimation. As the OLS estimation results in consistent yet inefficient estimates, the generalized least squares (GLS) estimation is utilized. All of the introduced model specifications are estimated utilizing the OLS and GLS estimation methods.

The ordinary least square estimate is specified as follows (Fok 2003):

$$\beta^{hat}_{OLS} = (x'x)^{-1}x'y$$

$$\Sigma^{hat} = 1/T \sum_{t=1}^T \eta^{hat}_t \eta^{hat}_t'$$

where y is the dependent variable (Attraction Model: $\ln M_{it} - \ln M_{I,t}$ and Full-Factorial Attraction Model: m_{ijt}), x is a k -dimensional vector of explanatory variables (share of voice), and the estimated error term is defined as $\eta^{hat}_{it} = y_{it} - x_{it}'\beta^{hat}_{OLS,i} - z_{it}'\alpha^{hat}_{OLS}$ (where $\eta_{it} = \varepsilon_{it} - \varepsilon_{I,t}$ and z_{it} represents the n -dimensional vector of the explanatory variable with regression coefficient vector α which is the same across the equations $i = 1 \dots I-1$) (Fok 2003).

The underlying assumptions of the OLS model are: 1) the explanatory variables (x_{it}) in each time period are uncorrelated with the error term in each time period: $E(x_{it}' \varepsilon_{it}) = 0$, $i = 1, \dots, I-1$, $t = 1, \dots, T$; and 2) the explanatory variables are uncorrelated with the unobserved effect in each time period: $E(x_{it}' \alpha_i) = 0$, $i = 1, \dots, I-1$, $t = 1, \dots, T$. The OLS regression estimation leads to consistent but inefficient estimates where the inefficiency is due to the covariance structure of the error term (Briggs 2002).

In order to correct for the inefficiency of the estimates, the GLS regression estimation is employed to estimate the Attraction Model parameters. The covariance matrix is usually unknown during the estimation process and therefore Zellner's seemingly unrelated equation system (SUR) method is utilized. Under the assumption of normality, the set of SUR is estimated leading to the maximum likelihood (ML) estimator of the model parameters. For the regression model with restricted competition, restricted effects, and dynamics, the iterative SUR estimator is utilized (Fok 2003):

$$\beta^{hat}_{SUR} = (x' (\Sigma^{hat-1} \otimes I_T)x)^{-1} x' (\Sigma^{hat-1} \otimes I_T)y.$$

The notation symbol \otimes represents the Kronecker product which defines an operation on two matrices of an arbitrary size that result in a block matrix (Fok, 2003). The estimate of the covariance matrix Σ^{hat} is replaced by the new estimate of Σ^{bar} , where η^{hat}_t consists of stacked $\eta^{hat}_{it} = y_{it} - x_{it}'\beta^{hat}_{SUR,i} - z_{it}'\alpha^{hat}_{SUR}$ to obtain new SUR estimate of β . This routine is repeated until the β^{hat} and Σ^{bar} converge (Fok 2003).

Results

As discussed above, ten different market share model specifications were estimated utilizing the OLS and GLS-SUR estimation methodology. The estimated model specifications included separate and joined pre- and post- new brand introduction Attraction Models as well as Full-Factorial Attraction Models. For each of the model types, the market structure changes and constancy of the marketing variables were tested. The models were assumed to have restricted competitiveness, effects, and dynamics. In order to compare the models on their explanatory power and the regression goodness-of-fit measure, R-square, was computed. The R-square statistics varied in value from 0.223 to 0.996 which implies that anywhere from 22% to 99% of the variation in the market share variable was explained by the variation in the share of voice variable.

Following Cooper and Nakanishi (1996) and Fok (2003), the separate and joined pre- and post-new brand introduction models were estimated utilizing OLS and GLS-SUR estimation. Each of the specifications utilized the brand-based transformation method to simplify the Attraction Model form. All three hypertension products were included in the estimation. For the joined Attraction Model, the coefficient estimate on the share of voice variable was 1.548. The regression results are presented in Table 1 in the Appendix. Since the OLS estimate is consistent yet inefficient, the joined Attraction Model was estimated utilizing the GLS-SUR estimation. As shown in Table 4, the GLS-SUR coefficient estimate on the marketing variable was 0.229, which is much smaller than the OLS share of voice estimate.

In order to test for the changing market structure due to the new brand introduction, the Attraction Model specification included the market structure dummy variable. The dummy variable takes a value of 1 when there are three brands present in the market and 0 otherwise. As before, the OLS and GLS-SUR estimations were employed. In both cases the market structure dummy variable was statistically significant which implies that indeed the market structure changes when a new brand enters the market. As shown in Table 2, the coefficient estimate of the OLS share of voice variable was 0.229, which is lower than the OLS model without the dummy variable. It is, however, the exact value as the GLS-SUR model specification. The standardized coefficient on share of voice variable was only 0.071 while the standardized coefficient on the market structure dummy variable was 0.966. The dummy variable had a greater impact on market share as compared to the share of voice. The GLS-SUR model specification with a dummy variable was not estimated due to insufficient sample size and a nearly singular covariance matrix.

In the final Attraction Model specification, not only the changing market structure was tested but also the constancy of the marketing variable. For the purpose of the analysis, the pre- and post- new brand entry models were joined into one regression. The market dummy variable was interacted with the share of voice factor. Based on the regression results presented in Table 3, the pre-new brand introduction model had a parameter estimate on the marketing variable of 0.237. The post-new brand introduction model had a share of voice coefficient of -0.454. As shown, the marketing variable estimate is sensitive to the number of brands in the market and changes once a new brand is introduced. Additionally, the standardized coefficients on share of voice were smaller than the standardized coefficient on the dummy variable. This implies that the market structure variable has a greater impact on market share

than the marketing variables do. Again only the OLS estimation was performed for this model specification, as the sample size was insufficient and the covariance matrix was singular for the GLS - SUR estimation.

The Full-Factorial Attraction Model was also estimated for this study. The model specification followed Howie and Kleczyk's (2007) model discussion. The model specifications allowed for testing of the changing market structure and parameter constancy issues. The estimation methods utilized the OLS and GLS with SUR model estimations. Due to the re-conceptualization of a brand market as a series of 2-brand markets, the sample size increased to $1!/2!$, which is a major benefit of this model specification. The first Full-Factorial Attraction Model specification estimated the market share model with only the share of voice as the explanatory variable while utilizing the OLS and GLS-SUR estimation. As presented in Table 5, the OLS share of voice variable has a coefficient of 2.822. As the OLS estimate is not efficient when OLS estimation is employed, the GLS-SUR estimation was utilized. The GLS-SUR share of voice estimate was also 2.822, which is the same as the OLS estimate (Table 8).

In order to test whether the market structure changes when a new brand enters the market, a market structure dummy variable was included (Table 6 and Table 9). The dummy variable in both OLS and GLS-SUR estimation is statistically insignificant and nearly zero in value. The coefficient on the share of voice variable is 2.822, which is the exact value as the coefficient obtained from the Full-Factorial Attraction Model without the dummy variable. Additionally, the standardized coefficient on the share of voice variable was 0.872 and had a greater impact than the market structure dummy variable which had a value of 0.002. Lack of change on the share of voice estimate as well as an insignificant market structure dummy variable implies that market structure does not change when the Full-Factorial Attraction Model is employed in market share analysis.

To test for the constancy of the parameters in the Full-Factorial Attraction Model, the market structure dummy variable was interacted with the share of voice. As shown in Table 7 and Table 10, the market structure changes when a new brand is introduced to the model. The separate two- and three-brand share of voice impacts on the market share are 1.71 for two-brand market and 3.54 for three product market for both the OLS and GLS-SUR estimations. The standardized coefficients were also different for the two- and three-brand markets (0.540 vs. 0.428 respectively). The standardized coefficient on the market structure dummy variable was only 0.002 which implies that the market share is mostly explained by the marketing variables.

Conclusions

This study investigated the market share analysis for a hypertension market with three brands. Two of the brands were part of the market over the entire time span of the data while a third brand entered the market later. Two types of models were employed in market share estimation: Attraction Model and Full-Factorial Attraction Model. The Attraction Model was transformed using the brand-based transformation approach. The Full-Factorial Attraction Model re-conceptualizes markets into a series of two-brand markets which eliminates the

effect of new market entrants as the market structure stays constant across time. The entry of a brand into the market impacts the market structure as well as parameter estimates of the marketing variables. In order to test the changes, a dummy variable representing the changing market structure was included in the model specifications. The constancy of marketing variable's response is picked up by interrelating the dummy variable with the explanatory variables. If the variables are statistically significant, then the model does not fully account for the changing market structure and marketing variable response. To estimate the market share model, the OLS as well as GLS-SUR estimation methods were employed. The OLS estimation provides consistent yet not efficient estimates. GLS accounts for the inefficiency of the variance.

Based on the results reported in the earlier section, the Attraction Model does not account for the changing market structure which results from a new brand entry to the market. The share of voice coefficient is not constant across the different model specifications. The market structure dummy variable is also statistically significant in the Attraction Model specifications and carries a large positive coefficient value. On the other hand, the Full-Factorial Attraction Model does capture the changing market structure. The impact of the share of voice variable remains unchanged across all model specifications. The market structure dummy variable is also statistically insignificant and carries a coefficient of value close to zero.

The test of constancy of the parameters of the marketing variables presents that the Attraction Model is more responsive to the market changes as compared to the Full-Factorial Attraction Model. It is important to mention that the impact of marketing variables should change when a new brand enters the market, so the differences in the pre- and post-estimates are in agreement with the economic theory. The standardized coefficients of the share of voice variable differ greatly between the pre- and post-new brand entry to the market for the Attraction Model. In the case of the Full-Factorial Attraction Model, the decrease in the standardized coefficients of the share of voice variable is less pronounced. Based on the presented results, it is simple to conclude that indeed the Full-Factorial Attraction Model accounts for the changing market structure as well as keeps the marketing variable parameters' values constant even when a new brand enters the market.

The above analysis is the first empirical test of the Full-Factorial Attraction Model proposed by Howie and Kleczyk (2007) and provides support for this model as a superior approach to brand market share modeling. The model can be applied in all market share related studies, including pharmaceutical, financial, and agricultural industries. The model allows researchers to resolve the problem of pooling data across brands and time-series when dealing with market structure changes by creating two-brand markets for all study participants. The innovative model framework results in better and more precise historical market evaluation.

The future research should focus on validating the Full-Factorial Attraction Model for a wider number of products, markets, and industries. In this study, only a two- and three-brand market for the pharmaceutical industry has been tested, so the superior behavior of the model over the Attraction Model requires exploration for a greater number of brands across different industries. The unique setup of the model also allows for applying the concept to studies with multiple markets characterized by different market structures. If proven superior to the Attraction Model, the Full-Factorial Attraction Model would allow for estimation and forecasting of market share that is far more precise in markets with dynamic market structure.

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Patrick J. Howie is a Vice President of New Product Development Group at TargetRx located in Horsham, Pa. and Ewa J. Kleczyk is a Senior Econometrician at TargetRx and a Ph.D. Candidate in Economics at Virginia Tech located in Blacksburg, Va.

Appendix 1: Tables

Table 1. Pooled Pre- and Post- New Brand Introduction Attraction Model (OLS Estimation)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	1.525	0.563	2.708	0.010
Log Share of Voice	1.548	0.419	3.694	0.001
R-squared	0.229	Mean dependent var		-0.483
Adjusted R-squared	0.212	S.D. dependent var		1.146
S.E. of regression	1.017	Akaike info criterion		2.912
Sum squared resid	47.568	Schwarz criterion		2.990
Log likelihood	-67.892	F-statistic		13.646
Durbin-Watson stat	0.039	Prob(F-statistic)		0.001

Table 2. Pooled Pre- and Post- New Brand Introduction Attraction Model with Market Structure Dummy Variable (OLS Estimation)

Variable	Coefficient	Std. Error	Std. Coefficient	t-Statistic	Prob.
Intercept	-1.072	0.052		-20.550	0.000
Log Share of Voice	0.230	0.035	0.071	6.488	0.000
Market Structure Dummy	2.239	0.025	0.966	88.369	0.000
R-squared	0.996	Mean dependent var			-0.483
Adjusted R-squared	0.995	S.D. dependent var			1.146
S.E. of regression	0.078	Akaike info criterion			-2.208
Sum squared resid	0.273	Schwarz criterion			-2.091
Log likelihood	55.999	F-statistic			5069.576
Durbin-Watson stat	0.298	Prob(F-statistic)			0.000

Table 3. Pooled Pre- and Post- New Brand Introduction Attraction Model with Share of Voice and Market Structure Dummy Variable Interaction (OLS Estimation)

Variable	Coefficient	Std. Error	Std. Coefficient	t-Statistic	Prob.
Intercept	-1.061	0.051		-20.872	0.000
Log Share of Voice	0.237	0.034	0.073	6.877	0.000
Log Share of Voice*			-0.294		
Market Structure Dummy	-0.609	0.307		-1.984	0.054
Market Structure Dummy	1.557	0.344	0.672	4.523	0.000
R-squared	0.996	Mean dependent var			-0.484
Adjusted R-squared	0.996	S.D. dependent var			1.146
S.E. of regression	0.075	Akaike info criterion			-2.252
Sum squared resid	0.250	Schwarz criterion			-2.096
Log likelihood	58.056	F-statistic			3601.557
Durbin-Watson stat	0.262	Prob(F-statistic)			0.000

Table 4. Pooled Pre- and Post- New Brand Introduction Attraction Model (GLS, SUR Estimation)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-0.186	0.043	-4.391	0.000
Log Share of Voice	0.230	0.0307	7.480	0.000
R-squared	0.996	Mean dependent var		-0.483
Adjusted R-squared	0.995	S.D. dependent var		1.146
S.E. of regression	0.078	Akaike info criterion		-2.208
Sum squared resid	0.273	Schwarz criterion		-2.091
Log likelihood	55.999	F-statistic		5069.576
Durbin-Watson stat	0.298	Prob(F-statistic)		0.000

Table 5. Full-Factorial Attraction Model (OLS Estimation)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	0.502	0.012	43.607	0.000
Share of Voice Gap	2.823	0.123	22.980	0.000
R-squared	0.764	Mean dependent var		0.503
Adjusted R-squared	0.763	S.D. dependent var		0.303
S.E. of regression	0.148	Akaike info criterion		-0.974
Sum squared resid	3.560	Schwarz criterion		-0.937
Log likelihood	82.369	F-statistic		528.058
Durbin-Watson stat	1.118	Prob(F-statistic)		0.000

Table 6. Full-Factorial Attraction Model with Market Structure Dummy Variable (OLS Estimation)

Variable	Coefficient	Std. Error	Std. Coefficient	t-Statistic	Prob.
Intercept	0.500	0.033		15.085	0.000
Share of Voice Gap	2.823	0.123	0.874	22.909	0.000
Market Structure Dummy	0.002	0.035	0.002	0.054	0.957
R-squared	0.764	Mean dependent var			0.503
Adjusted R-squared	0.761	S.D. dependent var			0.303
S.E. of regression	0.148	Akaike info criterion			-0.962
Sum squared resid	3.560	Schwarz criterion			-0.906
Log likelihood	82.370	F-statistic			262.416
Durbin-Watson stat	1.118	Prob(F-statistic)			0.000

Table 7. Full-Factorial Attraction Model with Share of Voice and Market Structure Dummy Variable Interaction (OLS Estimation)

Variable	Coefficient	Std. Error	Std. Coefficient	t-Statistic	Prob.
Intercept	0.500	0.028		17.644	0.000
Share of Voice Gap	1.710	0.178	0.540	9.630	0.000
Share of Voice Gap*			0.428		
Market Structure Dummy	1.718	0.221		7.786	0.000
Market Structure Dummy	0.002	0.030	0.002	0.056	0.956
R-squared	0.829	Mean dependent var			0.503
Adjusted R-squared	0.826	S.D. dependent var			0.303
S.E. of regression	0.128	Akaike info criterion			-1.270
Sum squared resid	2.586	Schwarz criterion			-1.194
Log likelihood	108.736	F-statistic			259.544
Durbin-Watson stat	1.162	Prob(F-statistic)			0.000

Table 8. Full-Factorial Attraction Model (GLS - SUR Estimation)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	0.502	0.011	43.608	0.000
Share of Voice Gap	2.823	0.139	20.264	0.000
R-squared	0.764	Mean dependent var		0.503
Adjusted R-squared	0.763	S.D. dependent var		0.303
S.E. of regression	0.148	Akaike info criterion		-0.974
Sum squared resid	3.560	Schwarz criterion		-0.937
Log likelihood	82.368	F-statistic		528.058
Durbin-Watson stat	1.118	Prob(F-statistic)		0.000

Table 9. Full-Factorial Attraction Model with Market Structure Dummy Variable (GLS - SUR Estimation)

Variable	Coefficient	Std. Error	Std. Coefficient	t-Statistic	Prob.
Intercept	0.500	0.042		11.799	0.000
Share of Voice Gap	2.823	0.140	0.874	20.201	0.000
Market Structure Dummy	0.002	0.044	0.020	0.043	0.966
R-squared	0.764	Mean dependent var			0.503
Adjusted R-squared	0.761	S.D. dependent var			0.303
S.E. of regression	0.148	Akaike info criterion			-0.962
Sum squared resid	3.560	Schwarz criterion			-0.906
Log likelihood	82.370	F-statistic			262.416
Durbin-Watson stat	1.118	Prob(F-statistic)			0.000

Table 10. Full-Factorial Attraction Model with Share of Voice and Market Structure Dummy Variable Interaction (GLS - SUR Estimation)

Variable	Coefficient	Std. Error	Std. Coefficient	t-Statistic	Prob.
Intercept	0.500	0.014		36.233	0.000
Share of Voice Gap	1.709	0.068	0.540	25.135	0.000
Share of Voice Gap*			0.428		
Market Structure Dummy	1.717	0.174		9.873	0.000
Market Structure Dummy	0.002	0.018	0.002	0.095	0.924
R-squared	0.829	Mean dependent var			0.503
Adjusted R-squared	0.825	S.D. dependent var			0.303
S.E. of regression	0.127	Akaike info criterion			-1.269
Sum squared resid	2.586	Schwarz criterion			-1.194
Log likelihood	108.736	F-statistic			259.544
Durbin-Watson stat	1.162	Prob(F-statistic)			0.000