Health Care Manag Sci (2017) 20:419–432
DOI 10.1007/s10729-016-9362-6

Preferred supplier contracts in post-patent prescription drug markets

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Received: 30 July 2015 / Accepted: 10 February 2016 / Published online: 22 February 2016

Abstract In recent years, the expiration of patents for large drug classes has increased the importance of post-patent drug markets. However, previous research has focused solely on patent drug markets. In this study, the authors evaluate the influence of preferred supplier contracts, the German approach to tendering, in post-patent drug markets using a hierarchical market share attraction model. The authors find that preferred supplier contracts are a powerful strategic instrument for generic manufacturers in a highly competitive environment. They quantify the effects of signing a preferred supplier contract and show that brand-name manufacturers are vulnerable to tendering. Therefore, brand-name manufacturers should readjust their strategies and consider including preferred supplier contracts in their marketing mix. In addition, the authors employ a simulation to demonstrate that a first-mover advantage might be gained from signing a preferred supplier contract. Furthermore, their results can be used as a blueprint for decision makers in the pharmaceutical industry to assess the market share effects of different contracting strategies regarding preferred supplier contracts.

Keywords Generic drugs · Tendering · Strategic behavior · Pharmaceutical market · Market share attraction model · Rebate contract

1 Introduction

Pharmaceuticals are an important, rapidly growing market segment of the healthcare industry. Global sales are estimated to be US 1,100bn, with expected annual growth rates of 3–6 % through 2015 [1]. Patent drug markets (i.e., markets in which firms compete in the sales of therapeutically comparable substances) can be distinguished from post-patent – or generic – markets (i.e., markets in which firms compete in selling the same substance). Although most revenue is generated in patent drug markets, higher unit sales are found in post-patent drug markets. In the U.S., for example, the market share in terms of the revenue of generic drugs (i.e., identical copies of the original drugs) was 26 %, whereas their market share in terms of unit sales was 78 % in 2010 [2].

The importance of the post-patent market has increased over the years and is expected to increase further as a result of the expiration of patents for large drug classes, such as cardiovascular or hypertension drugs. In addition, increases in public pharmaceutical expenditures have fostered regulations that permit tendering in return for a certain degree of market exclusivity in nearly all European post-patent drug markets [3]. This has made managers to constantly rethink their marketing and sales strategy in post-patent drug markets. For example, investing in a company's brand strength might shield against competitors actions or signing a preferred supplier contract, the German approach to tendering, has the potential to increase market share. However, both actions come at the cost of a lower operating margin because of increased marketing expenses or a lower sales price. In addition, managers have to be aware of the competitive environment when signing a preferred supplier contract as first

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movers might have a strategic advantage compared to laggards [4]. While descriptive analysis of sales data may give a vague indication on the effect of signing a preferred supplier contract, it is not possible to analyze the interplay between brand strength and sequence of contracting. This paper has thus three aims:

(a) to quantify the effect of signing preferred supplier contracts on market shares at the brand level,
(b) to analyze whether branded generic manufacturers and original manufacturers – both usually not signing preferred supplier contracts – are to some extent able to shield their sales against other competitors that sign preferred supplier contracts, and
(c) to evaluate whether the sequence of contracting, e.g., being first mover, effects market shares in post-patent drug markets.

This paper is organized as follows. In the next section, we provide a brief overview of the literature on the use of marketing instruments in drug markets. We also explain the importance of differentiating between patent and post-patent drug markets. Next, we describe the methodological framework to estimate and predict market shares. We then present the results and discuss the findings with evidence from the existing literature. The final section concludes the paper and provides managerial implications.

1.1 Background on preferred supplier contracts

Drug markets differ from ordinary consumer good markets. In consumer good markets, consumers typically choose product brands, whereas in the prescription drug market, intermediaries (i.e., physicians and pharmacies) have a major influence on brand choice [5]. In patent drug markets, physicians implicitly choose brands by selecting (i.e., prescribing) chemical substances. Pharmacies must then dispense patented brand name drugs because no alternatives exist. However, in post-patent drug markets with generic competition, the prescription of a chemical substance (without specification of the brand) allows a pharmacy to choose between several brands of the same chemical substance. Only in special circumstances will a physician instruct a pharmacy to dispense a chemical substance of a specific brand.

Within patent drug markets, brands compete with different chemical substances for the same indication, e.g., genuine innovations (breakthrough drugs) or products with a similar therapeutic value (me-too drugs) [6]. Although these chemical substances are used for the same indication (e.g., hypertension), they differ in their efficacy or adverse effects. This enables brands to differentiate by highlighting individual product strengths. After patent expiry (i.e., in post-patent drug markets), original manufacturers compete with various new entrants (i.e., branded and unbranded generic manufacturers) that sell the same chemical substances in the same quality, dosage, and efficacy. Substitutability must be certified by federal agencies, such as the Food and Drug Administration in the U.S. or the European Medicines Agency in the EU. Thus, it is more difficult and more expensive for brands to differentiate.

Original manufacturers usually brand newly launched chemical substances with individual product names which can be characterized as offensive strategy designed to occupy the whole market [7], e.g., the chemical substance carbamazepine was branded by original manufacturer Novartis with the product brand name Tegretol®. After patent expiration, original manufacturers typically cease investment in individual product brands and begin to exploit physicians' accumulated stock of drug knowledge on the product [8, 9]. For generic manufacturers that enter into the post-patent market, 'classical' marketing instruments such as detailing, free drug sampling, and direct-to-consumer advertisements, are typically not cost-effective because of the low margins in markets with homogenous goods [8]. Thus, efficient drug marketing requires the use of different strategies for patent and post-patent markets. Unbranded generic manufacturers compete on price only [10], while branded generic manufacturers build strong brands using an umbrella branding strategy. Umbrella branding describes a branding strategy where a manufacturer uses the same brand name for a series of products to profit from economies of scale and therefore to profit from spillover effects [7, 11, 12]. For example, Hexal, a large branded generic manufacturer, follows an umbrella branding strategy and uses its brand name for a variety of chemical substances, e.g., 'SimvaHEXAL®' for generic simvastatin and 'AmbroHEXAL®' for generic ambroxol.

One type of tendering mechanism for drugs is the competitive bidding of post-patent drug manufacturers for a "preferred supplier status," which has been permitted in Germany since 2007. The contract can be on the chemical substance or at portfolio level [3]. If the status of a preferred supplier is granted to one or more brands by a health insurance, all German pharmacies are required by law to dispense a drug from a preferred supplier to enrolled individuals. Therefore, a preferred supplier contract theoretically shifts the freedom of choice among brands in the post-patent market from pharmacies to health insurance providers. When there are multiple preferred suppliers for the same chemical substance, pharmacies are allowed to choose among preferred brands. By law, pharmacies are allowed to dispense drugs from a non-preferred supplier only (a) if an attending physician explicitly prescribes a specific brand, (b) in situations of proven supply difficulties, or (c) if a patient pays the full price of a non-preferred drug [13]. However, since regulation is not fully enforced, pharmacies have some discretion in their dispensing. In addition, the patient who freely choses the physician as well as the pharmacy has some bargaining power towards both providers to obtain his favored brand. First, the patient may persuade his doctor to explicitly rule out generic substitution. Second, the patient may try to convince the pharmacy to stretch the legal

obligations [14]. Thus, the market shares of the bid-winning manufacturer(s) are well below 100 %.

2 Method

We estimated a hierarchical market share attraction model using drug volume data from a large health insurance company in Germany to quantify the influence of preferred supplier contracts on market share. Following the model specification and estimation, we simulated different scenarios to analyze the effects of the order in which manufacturers sign preferred supplier contracts. The estimation and simulation procedures were performed using the bootstrap method [15].

2.1 Data

We obtained data on monthly prescription volumes from KKH-Allianz, a German public health insurance company that operates nationwide. The data cover 30 periods from January 2007 to July 2009 from approximately 760,000 insurees living in four federal states of Germany. In addition to list prices, the dataset includes data on monthly drug unit sales based on defined daily doses[1] (DDDs) and the preferred supplier status for each brand. However, because negotiated rebates are confidential, we are not aware of the amount of rebates granted. We calculated unit-based market shares for each market $M_{i,c,t}$ by dividing the number of DDDs sold from a brand i, $i = 1, \ldots, I$ in market c, $c = 1, \ldots, C$ and in period t, $t = 1, \ldots, T$ by the sum of all DDDs sold per market in month t.

We differentiated markets according to the Anatomical Therapeutic Chemical Classification System (ATC), which is defined by the WHO Collaborating Centre for Drug Statistics Methodology, and considered different chemical substances (fifth-level ATC) as different markets. We focused on large prescription-only post-patent markets in which chemical substances were available in tablet form. We chose chemical substances for the treatment of chronic diseases to ensure that – besides physicians and pharmacies also – patients are familiar with the different brands on the market. In addition, we required at least one brand to enter into a preferred supplier contract during the data period. We excluded drug markets in which chemical substances were also available as OTC drugs, as such brands may have considered spillover effects to the OTC market when contracting for preferred supplier status for the prescription formulations of their drugs. We further excluded drug markets with patent expiry after January 2007 because we expected distortions resulting from the subsequent entry of new generic brands and contracts for preferred supplier status. In addition, we excluded products that were available in different dosage forms and combinations of chemical substances because DDDs were not comparable for these products. After controlling for the above-mentioned criteria, we obtained a sample of 31 chemical substances (i.e., 31 different drug markets). On average about 20.8 (StD 5.6) different manufacturers competed within one market. Most of the preferred supplier contracts were signed during the period of June to October 2007.

Because of the limited variation across time and brands in signing a preferred supplier contract, we restricted the analysis to seven brands or groups of brands. The first three brands are generic brands that signed the most preferred supplier contracts in our dataset and competed in all markets: (a) the generic brand Aliud (PSC_1), (b) the generic brand Mylan (PSC_2), and (c) the generic brand Betapharm (PSC_3). These three generic manufacturers were responsible for more than 44.8 % of the market share in our sample at the end of the observation period (see Table 1) and are among the five most important unbranded generic manufacturers in the German outpatient pharmaceutical market in 2007 [16]. The fourth is a group of all other generic brands that signed preferred supplier contracts; for our analysis, we merged these brands into a single variable, 'PSC_4,' which represents the joint market shares of in total five brands. The remaining three groups did not sign preferred supplier contract within the observation period although, by law, they could have done so: the fifth is a group of three branded generic manufacturers in Germany (Hexal, Stada, and Ratiopharm); for our analysis, we merged these manufacturers into the single variable 'BrGEN', which contains the joint market shares of all three manufacturers. The sixth is the group of in total 22 manufacturers that sold the branded original; hence, the manufacturer behind this group differed between markets (ORIG). The seventh group merges all remaining generic brands that did not sign a preferred supplier contract into the single variable 'OthGEN,' which represents their joint market shares. PSC_1-4 and OthGEN reflect groups that primarily follow a low-price strategy and are comparable to private labels in consumer markets, whereas BrGEN and ORIG reflect groups that follow a different strategic approach in marketing. These brands are comparable to national brands in consumer markets.

2.2 Conceptualization using a market share attraction model

Following Bell's market share theorem [17], the market share $M_{i,c,t}$ of a specific brand i, $i = 1, \ldots, I$ in market c at time t, $t = 1, \ldots, T$ is equal to its attraction, $A_{i,c,t}$, relative to the sum of the attractions $A_{j,c,t}$ of all brands j, $j = 1, \ldots, I$.

$$M_{i,c,t} = \frac{A_{i,c,t}}{\sum_{j=1}^{I} A_{j,c,t}} \tag{1.0}$$

[1] According to the WHO, the defined daily dose is the assumed average maintenance dose per day for a drug that is used for its main indication by adults.

Table 1 Baseline characteristics across all 31 markets by brand

January 2007 (before preferred supplier contracts)					June 2009 (after preferred supplier contracts)			
Market share		95 % confidence interval		StD	Market share	95 % confidence interval		StD
Brand	(mean [%])	(lower/upper limit [%])			(mean [%])	(lower/upper limit [%])		
PSC_1	5.4	4.5	6.4	0.025	22.9	18.8	27.1	0.113
PSC_2	2.8	2.1	3.5	0.019	12.6	10.0	15.2	0.072
PSC_3	4.7	3.4	6.1	0.037	9.3	7.2	11.4	0.057
PSC_4	7.6	4.9	10.2	0.073	27.2	22.2	32.2	0.137
BrGEN	48.3	44.1	52.6	0.116	15.2	12.9	17.4	0.062
ORIG	10.6	7.8	13.5	0.078	4.3	2.8	5.9	0.043
OthGEN	20.5	18.0	23.1	0.071	8.5	6.7	10.2	0.048

To define $A_{i,c,t}$, we use a fully competitive interaction model (MCI) [18, 19]. Although there is no consensus regarding the superiority of market share attraction models compared to simple linear or multiplicative models [20–28], we value the logical consistency of market share attraction models; that is, market shares are by definition greater than zero and sum to unity [29].

In addition, market share attraction models have the advantage that the elasticity of a brand's market share depends on its size and its explanatory variables. This property ensures that it is more difficult to gain market share when large parts of the market are already under a brand's control, and it allows the market share elasticity to approach zero if explanatory variables are approaching infinity [30]. The multiplicative specification of the model ensures that market share elasticity monotonically declines as explanatory marketing efforts increase. In contrast with the multiplicative specification, the multinomial logit specification is not appropriate for the equilibrium analysis of marketing competition, as exponential properties do not allow for decreasing returns to scale for the marketing efforts for any brand with less than 50 % market share [31]. Therefore, we specify the attraction $A_{i,c,t}$ of brand i at time t in market c as follows:

$$A_{i,c,t} = \exp\left(\mu_i + \nu_{i,c} + \varepsilon_{i,c,t}\right) \prod_{j=1}^{I} \prod_{c=1}^{C} f\left(x_{j,c,t}\right)^{\beta_{j,i}} \prod_{p=1}^{P} \left(M_{j,c,t-p}^{\alpha_{p,j,i}} \cdot f\left(x_{j,c,t-p}\right)^{\beta_{p,j,i}}\right) \tag{2.0}$$

$x_{j,c,t}$ denotes the preferred supplier status, defined as one if there exists a preferred supplier contract for brand j in market c at time t, and zero otherwise.[2] $\beta_{j,i}$ denotes the coefficient estimates that measure the effect of the preferred supplier contract of brand j on brand i. Because the preferred generic status of a drug imposes the same requirements on patients in all markets, we estimate $\beta_{j,\ i}$ (i.e., the average effect of preferred supplier contracts) across all markets while controlling for differences in brand- and market-specific baseline attraction ($\mu_i + \nu_{i,c}$). $f(x_{j,c,t})$ denotes an exponential transformation of the preferred supplier status $f\left(x_{j,c,t}\right) = e^{\left(x_{j,c,t}\right)}$ to prevent the variable from being equal to zero [19].

μ_i (baseline attraction) is defined as a brand-specific fixed effect that accounts for different competitive strengths of brands and differences in the efficiency of using marketing instruments across markets because we expect differences in promotional efforts to be brand-specific [32, 33]. $\nu_{i,c}$ (market-specific baseline attraction) represents the differences in competitive strength and in the efficiency of using brand marketing instruments in different markets. Given that brands have specific reasons for choosing to adapt a particular strategy in forming or not forming preferred supplier contacts, we believe the brand effects to be correlated with our independent variable $x_{j,c,t}$. Therefore, we chose to model μ_i as fixed effects. Because we believe our sample of markets to be similar to a randomly drawn subsample of all post-patent drugs, we modeled $\nu_{i,c}$ as random effects and assumed a normal distribution with a zero mean and σ standard deviation.

To allow for time dependencies, i.e., carry-over effects, we include $p = 1, \ldots, P$ lagged market shares $M_{j,c,\ t-p}$ and lagged preferred supplier status $x_{j,c,t-p}$ with the vectors $\alpha_{p,j,i}$ and $\beta_{p,j,i}$ of the lagged parameter estimates, respectively. Different specifications of $M_{j,c,t-p}$ and $x_{j,c,t-p}$ were analyzed. $\varepsilon_{i,c,t}$ denotes a normally distributed error term with a zero mean and a standard variation of Σ.

[2] In the case of PSC_4, which represents in total five brands, $x_{j,c,t}$ is defined as one if a preferred supplier contract for at least one of the five brands exists and zero otherwise.

2.3 Specification of the market share attraction model

For the parameter estimation, we use the base brand approach that is described by Fok [19]. Therefore, we define OthGEN as the base brand I in our model. To estimate Eq. (2.0) for all brands $i = 1 \ldots I$, we divide $A_{i,c,t}$ by $A_{I,c,t}$ for all i except $i = I$, which leads to a system of $I-1$ Eq. (3.0).

$$\frac{M_{i,c,t}}{M_{I,c,t}} = \frac{\exp\left(\mu_i + \nu_{i,c} + \varepsilon_{i,c,t}\right)\prod_{j=1}^{I}\prod_{c=1}^{C} f\left(x_{j,c,t}\right)^{\beta_{j,i}}\prod_{p=1}^{P}\left(M_{j,c,t-p}^{\alpha_{p,j,i}} \cdot f\left(x_{j,c,t-p}\right)^{\beta_{p,j,i}}\right)}{\exp\left(\mu_I + \nu_{I,c} + \varepsilon_{I,c,t}\right)\prod_{j=1}^{I}\prod_{c=1}^{C} f\left(x_{j,c,t}\right)^{\beta_{j,I}}\prod_{p=1}^{P}\left(M_{j,c,t-p}^{\alpha_{p,j,I}} \cdot f\left(x_{j,c,t-p}\right)^{\beta_{p,j,I}}\right)} \tag{3.0}$$

If the log is taken on both sides, then this finding can be transformed as follows:

$$ln\left(\frac{M_{i,c,t}}{M_{I,c,t}}\right) = \mu_i - \mu_I + \nu_{i,c} - \nu_{I,c} + \varepsilon_{i,c,t} - \varepsilon_{I,c,t} + \sum_{j=1}^{I}\sum_{c=1}^{C}\left[\left(\beta_{j,i} - \beta_{j,I}\right)ln\left(f\left(x_{j,c,t}\right)\right) + \sum_{p=1}^{P}\left(\left(\alpha_{p,j,i} - \alpha_{p,j,I}\right)ln\left(M_{j,c,t-p}\right) + \left(\beta_{p,j,i} - \beta_{p,j,I}\right)ln\left(f\left(x_{j,c,t-p}\right)\right)\right)\right] \tag{3.1}$$

Let $\tilde{\mu}_i$ denote $\mu_i - \mu_I$, $\tilde{\nu}_{i,c}$ denote $\nu_{i,c} - \nu_{I,c}$, $\tilde{\varepsilon}_{i,c,t}$ denote $\varepsilon_{i,c,t} - \varepsilon_{I,c,t}$, $\tilde{\beta}_{j,i}$ denote $\beta_{j,i} - \beta_{j,I}$, $\tilde{\alpha}_{j,i}$ denote $\alpha_{p,j,i} - \alpha_{p,j,I}$, and $\tilde{\beta}_{p,j,i}$ denote $\beta_{p,j,i} - \beta_{p,j,I}$; thus, the equation to be estimated for $I-1$ brands is as follows:

$$ln\left(\frac{M_{i,c,t}}{M_{I,c,t}}\right) = \tilde{\mu}_i + \tilde{\nu}_{i,c} + \tilde{\varepsilon}_{i,c,t} + \sum_{j=1}^{I}\sum_{c=1}^{C}\left[\left(\tilde{\beta}_{j,i}\right)ln\left(f\left(x_{j,c,t}\right)\right) + \sum_{p=1}^{P}\left(\left(\tilde{\alpha}_{p,j,i}\right)ln\left(M_{j,c,t-p}\right) + \left(\tilde{\beta}_{p,j,i}\right)ln\left(f\left(x_{j,c,t-p}\right)\right)\right)\right] \tag{3.2}$$

For the estimation, we used a seemingly unrelated regression that allows for an efficient estimation if the error variables are correlated across equations [34]. We estimated the model with two lags of market share and one lag for preferred supplier status as this specification was superior to all reasonable alternatives according to the corrected Akaike information criterion (AIC_c) [35].

To ensure that the choice of markets did not affect the results, we resampled and re-estimated the model using the bootstrap method to assess the validity of the results and to test for statistical significance. We created 100 datasets by randomly drawing with replacement from the original dataset (i.e., the 31 drug markets). All estimation and test procedures were performed using PROC MIXED from SAS/STAT 9.2.

2.4 Retransformation of parameter estimates

The interpretation of the estimated 138 fixed and 186 random effects parameters and their significance is not straightforward because the baseline attraction $\tilde{\mu}_i$, the market-specific baseline attraction $\tilde{\nu}_{i,c}$, the non-lagged and lagged parameters for signing a preferred supplier contract $\tilde{\beta}_{j,i}$ and $\tilde{\beta}_{p,j,i}$, and the parameters for lagged market share $\tilde{\alpha}_{p,j,i}$ denote the difference in the magnitude of effects compared with the base brand I. Similar to the retransformation of market shares that is described by Fok [19], we retransformed the parameter estimates by dividing the i delogarithmized parameter by the sum of the I delogarithmized parameters (with the delogarithmized value of brand $I = 1$); this procedure resulted in 154 retransformed fixed effects parameters and 217 retransformed random effects parameters.

To facilitate the interpretation of the percentages, we divide the normalized values by the uniformly distributed average market shares of our seven brands analyzed (i.e., 14.29 %) and subtracted the result by 1. The retransformed parameter estimates can now be interpreted as measuring the positive or negative effect that would occur if all brands had the average market share (i.e., 14.29 %).

We explored whether brand strength has an influence on market shares by analyzing the baseline market shares that result from the baseline attraction μ_i. In the absence of other measures to differentiate products (i.e., all brands compete in the sales of the same substance with the same quality), μ_i represents differences in brand strength only. We expect that branded generic manufacturers (BrGEN) profit from their strong marketing effort in combination with umbrella branding. The umbrella branding catalyzes the marketing effort and thus increases brand strength because of spillover effects. Further, we expect that original manufacturers (ORIG) successfully exploit physicians' stock of drug knowledge that is

accumulated before the patent of a substance expires. Therefore, the baseline market shares of BrGEN and ORIG – i.e., the resulting market shares if all other explanatory variables, except for baseline attraction μ_i, are distributed 'on market average' [30] – must be significantly higher than the baseline market share of the other generic manufacturers. We used a one-way ANOVA with a Bonferroni correction for testing multiple comparisons and plotted the results.

2.5 Model fit

To test predictive performance, we estimated our model using the 21 randomly selected active ingredients and set aside 10 chemical substances that were defined as test markets. We then predicted market shares of the 10 test markets setting market-specific baseline attraction $\nu_{i,c}$ to zero as $\nu_{i,c}$ cannot be estimated for these markets using this setting. Predictive performance was benchmarked with two naïve models (*naïve model I*: $M_{i,c,t}=M_{i,c,t-1}$, *naïve model II*: $M_{i,c,t}=M_{i,c,t-1}+(M_{i,c,t-1}-M_{i,c,t-2})$) using the mean absolute error (MAE) and the mean squared error (MSE). In addition, when re-estimating the model based on the total sample of 31 ingredients to do the simulation, we plotted the two markets in which our model performance was the best and for which this performance was the poorest.

2.6 Simulation

To obtain absolute market shares, we divided the relative market shares that we obtained from the model by the sum of the relative market shares for all $i=1\ldots I$ brands (see Formula 5.0). After the forecasting for the first period was complete, the forecasts for period $t+1$ were iteratively simulated using the forecasted market shares from period t.

$$M_{i,c,t}=\frac{\left(\frac{M_{i,c,t}}{M_{I,c,t}}\right)}{\sum_{j=1}^{I}\left(\frac{M_{i,c,t}}{M_{I,c,t}}\right)} \tag{5.0}$$

We simulated two sets of scenarios. The first set of four different scenarios was used to analyze whether a first-mover advantage for signing a preferred supplier contract exists. The second set of scenarios was used to explore the effect of time being the only preferred supplier. For all of our scenarios, we used brand average market shares from January 2007 (see Table 1) and assumed that no preferred supplier contract had been signed. We forecasted market shares for 24 months in an average market; thus, the market-specific baseline attraction was set to zero.

As in reality, where followers reacted within a period of zero to 6 months, we defined one brand as the first mover with the remaining brands following 3 months later in each scenario of the first set: in scenario I, PSC_1 signs a preferred supplier contract in period 1, followed by PSC_2, PSC_3, and PSC_4 in period 4; in scenario II, PSC_2 signs a preferred supplier contract in period 1, followed by PSC_1, PSC_3, and PSC_4 in period 4; in scenario III, PSC_3 signs a preferred supplier contract in period 1, followed by PSC_1, PSC_2, and PSC_4 in period 4; and in scenario IV, PSC_4 signs a preferred supplier contract in period 1, followed by PSC_1, PSC_2, and PSC_3 in period 4. We hypothesize that a manufacturer that signed the first preferred supplier contract in a market will gain a higher market share compared to the market share the manufacturer would gain as a second mover. We therefore interpret the area between both market share developments as first mover advantage.

Within the second set of scenarios, we defined different lags between signing the first and the following preferred supplier contracts. Development of market share was analyzed for PSC_1-4 with a lag of zero, i.e., a scenario where PSC_1-4 sign preferred supplier contracts within the same month, and with lags of 1, 2, and 3 months, i.e., scenarios where one brand pioneers the preferred supplier contract while the other three brands follow within 1, 2, and 3 months, respectively. We hypothesize that the time between the first brand signing a preferred supplier contract and followers correlates with higher market shares.

For the analysis, we first plotted market share by brand. We then used the variation that resulted from bootstrapping to test differences between the market shares of being the first and of being the second mover. The prediction of market shares was performed using Matlab 7.10.

3 Results and discussion

The dataset included information on seven brands offering 31 chemical substances over a period of 30 months, i.e., the total sample size consisted of 6510 observations. As we have employed 2-lagged market shares, the estimation relied on in total 28 periods, seven brands, and 31 chemical substances, i.e., in total 6076 observations. The sample comprised 18 cardiovascular drugs, 10 central nervous system drugs and three diabetes drugs. In 2008, total average sales to patients of KKH-Allianz ranged from € 200,000 to € 6,000,000 per drug. The number of competitors by market was between 13 (bromazepam, ATC: N05BA08) and 45 (simvastatin, ATC: C10AA01). The average market shares across all markets are shown in Table 1. On average, 5.8 preferred supplier contracts were signed in each of the 31 markets. However, preferred supplier contracts were signed by unbranded generic manufacturers only, whereas brand name manufacturers (i.e., BrGEN and ORIG) did not sign contracts with the health insurance provider. Most of the 179 preferred supplier contracts were signed between June and October 2007.

The proposed model outperformed the predictive ability of the two naïve models for all 10 test markets over a period of 12 months (see Table 2). As we could not control for market-specific baseline attraction $\nu_{i,c}$ in the 10 test markets, the effective model performance is likely to be underestimated. According to the full model including 31 markets, the best

fit between raw and predicted series was found for the lisinopril market, whereas the worst model performance was identified for the paroxetine market. Plotted results are shown in Fig. 1. The good model performance in the lisinopril market may be attributable to the relatively stable market shares, while the bad model performance in the paroxetine market may be attributable to more erratic changes in market shares after preferred supplier contracts have been signed.

3.1 Parameter estimates and the influence of preferred supplier contracts

Table 3 shows the transformed parameter estimates for the baseline attraction μ_i, for signing a preferred supplier contract $\beta_{j,i}$ and $\beta_{p,j,i}$, and for lagged market shares $\alpha_{p,j,i}$. One might expect that signing a preferred supplier contract would have a positive effect on a brand's own market share and a negative effect on the market shares of competitors. In accordance with this expectation, we find that the parameter estimates for signing a preferred supplier contract $\beta_{j,i}$ are strongly positive for all brands that signed a preferred supplier contract (PSC_1-4), whereas the parameter estimates for the cross-effects show the expected negative sign in 19 of 24 cases. The five cross-effects showing the unexpected positive signs result from superimposition in the short time period in which most of the preferred supplier contracts were signed. Thus, this may have caused some confounding which can also be seen for the lisinopril and paroxetine markets illustrated in Fig. 1. Carry-over of the preferred supplier status, i.e., lagged preferred supplier status $\beta_{1,j,i}$, has a negative effect on the brand's market share that has signed a preferred supplier contract in the previous period. This lagged effect moderates the high impact of the (non-lagged) preferred supplier status $\beta_{j,i}$ in subsequent periods. This is within our expectations since the increase in market share is strong during the first period while it stabilizes in the following periods.

The effects of signing a preferred supplier contract on the market shares of BrGEN and ORIG are clearly negative. This result indicates that the group of branded generic manufacturers and the group of original manufacturers are unable to protect their market share through their strong brand. Although evidence from other consumer markets shows that cross-promotional effects are asymmetric (i.e., that the effects on weaker brands are disproportionately greater) [36], this finding does not appear to apply to post-patent drug markets, as BrGEN and ORIG are affected by the preferred supplier contracts of PSC_1 to PSC_4 to approximately the same extent as OthGEN.

Regarding the interpretation of lagged market shares, we can conclude that the post-patent drug market is highly competitive. The transformed parameter estimates of the 1-lagged market shares are positive for the own brand but negative for all competitor brands. The results for the 2-lagged market shares are smaller than the parameter estimates for the 1-lagged market shares. This finding indicates that the market share in previous periods has an influence on the market share in the current period but that this effect decreases rapidly over time. These results likely reflect the rapidly changing market environment in post-patent drug markets.

3.2 Baseline market share and branding strategy

The retransformed parameter estimates for the fixed effects are shown in Table 3. A negative sign for the parameter estimates for μ_i (baseline attraction) indicates lower brand strength, whereas a positive sign indicates above-average brand strength. To assess market-specific baseline attraction, one must consider the baseline attraction of the manufacturer, μ_i, and the market-specific baseline attraction, $\nu_{i,c}$. The parameter estimates, $\nu_{i,c}$, are reported in the Appendix. Similar to the interpretation of μ_i, values are to be interpreted as measuring the positive or

Table 2 Mean absolute error (MAE) and mean squared error (MSE) of randomly selected test markets

Active ingredient (ATC)	Proposed model		Naïve model I		Naïve model II	
	MAE	MSE	MAE	MSE	MAE	MSE
Glimeperide (A10BB12)	0.05	<0.01	0.13	0.02	0.17	0.07
Moxonidine (C02AC05)	0.07	0.01	0.14	0.03	0.15	0.03
Felodipine (C08CA02)	0.05	<0.01	0.15	0.04	0.16	0.03
Nitrendipine (C08CA08)	0.05	<0.01	0.15	0.04	0.20	0.07
Captopril (C09AA01)	0.06	0.01	0.12	0.03	0.16	0.05
Ramipril (C09AA05)	0.05	<0.01	0.10	0.02	0.16	0.03
Simvastatin (C10AA01)	0.07	0.01	0.13	0.03	0.16	0.05
Pravastatin (C10AA03)	0.05	<0.01	0.13	0.03	0.21	0.07
Fluoxetine (N06AB03)	0.06	0.01	0.08	0.01	0.37	0.30
Paroxetine (N06AB05)	0.11	0.02	0.13	0.03	0.27	0.10

MAE Mean absolute error, *MSE* Mean square error

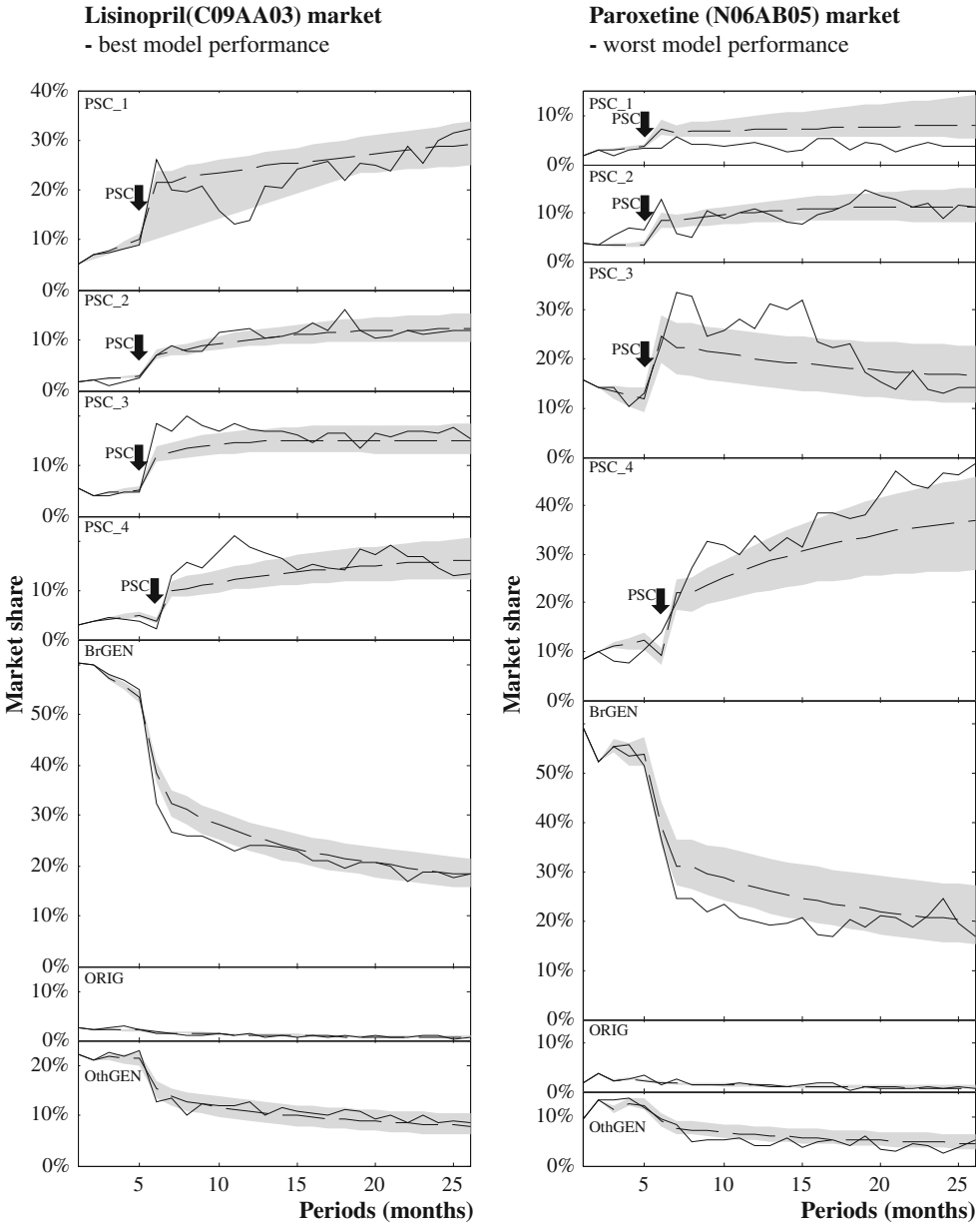

Fig. 1 Market share by brand: raw series (solid) vs. predicted values (dashed) with 10th and 90th percentiles of lisinopril and paroxetine after bootstrapping (100 replications)

negative effect on average market share (i.e., if all brands had the same market share of 14.29 %).

Essentially, we identified four groups of brands for which the baseline market share in the 31 drug markets differed significantly at the 5 % level (see Fig. 2). BrGEN has the highest brand strength, μ_i, resulting in a significantly higher baseline market share (17.0 %) compared with all other brands. The two brands OthGEN (15.8 %) and PSC_1 (15.6 %) showed significantly higher baseline market shares compared with PSC_4 (13.9 %), ORIG (13.4 %), and PSC_2 (13.0 %), and the lowest baseline market share was observed for PSC_3 (11.3 %). Interestingly, the baseline market share of BrGEN, the group of branded generic manufacturers, is significantly higher than that of all other brands, including ORIG ($p < 0.01$). Thus, we conclude that the group of branded generic manufacturers (BrGEN) has the highest brand strength and has successfully implemented their umbrella brand strategy. However, the baseline market share of the original manufacturers (ORIG) is significantly lower than that of the unbranded generic manufacturers PSC_1 and OthGEN and does not differ from the baseline market shares of PSC_4 and PSC_2. Therefore, we conclude that the original manufacturers are unable to successfully exploit physicians' accumulated stock of drug knowledge after generic entry.

3.3 Forecasting and first mover advantage

The results of the first set of scenarios are shown in Fig. 3. All brands that signed preferred supplier contracts (PSC_1-4) were able to gain market share within the first months until their

Table 3 Parameter estimates for fixed effects (transformed)

		PSC_1	PSC_2	PSC_3	PSC_4	BrGEN	ORIG	OthGEN
Baseline attraction μ_i		0.066	−0.129	−0.230	−0.075	0.274	−0.049	0.144
Preferred supplier contract $\beta_{j,i}$		PSC_1	PSC_2	PSC_3	PSC_4	BrGEN	ORIG	OthGEN
	PSC_1	**0.630**	0.148	0.158	−0.290	−0.205	−0.146	−0.295
	PSC_2	0.062	**1.052**	−0.081	−0.245	−0.232	−0.275	−0.282
	PSC_3	−0.200	−0.242	**0.515**	0.002	−0.093	−0.030	0.048
	PSC_4	−0.166	−0.161	−0.116	**0.819**	−0.167	−0.097	−0.112
Lagged preferred supplier contract $\beta_{1,j,i}$	PSC_1	**−0.130**	−0.068	−0.035	0.226	−0.051	0.040	0.019
	PSC_2	−0.177	**−0.284**	−0.062	0.256	0.132	0.041	0.095
	PSC_3	−0.165	−0.144	**−0.346**	−0.105	0.278	0.245	0.237
	PSC_4	0.077	0.062	0.059	**−0.381**	0.119	0.016	0.048
1-lagged market share $\alpha_{1,j,i}$	PSC_1	**0.813**	−0.106	−0.122	−0.013	−0.186	−0.155	−0.230
	PSC_2	−0.127	**0.824**	−0.138	−0.051	−0.166	−0.189	−0.154
	PSC_3	−0.096	−0.105	**0.820**	−0.066	−0.170	−0.198	−0.186
	PSC_4	−0.161	−0.198	−0.160	**0.989**	−0.154	−0.150	−0.167
	BrGEN	−0.156	−0.105	−0.212	−0.092	**0.713**	−0.137	−0.011
	ORIG	−0.107	−0.115	−0.078	−0.041	−0.046	**0.461**	−0.073
	OthGEN	−0.107	−0.120	−0.093	−0.159	−0.032	−0.088	**0.600**
2-lagged market share $\alpha_{2,j,i}$	PSC_1	**0.180**	−0.043	−0.038	−0.173	0.019	−0.024	0.078
	PSC_2	−0.007	**0.125**	−0.047	−0.106	0.011	0.026	−0.001
	PSC_3	−0.092	−0.064	**0.126**	−0.083	0.044	0.025	0.045
	PSC_4	−0.028	0.015	−0.010	**0.031**	−0.005	0.002	−0.004
	BrGEN	0.012	−0.060	0.114	−0.076	**0.248**	−0.067	−0.171
	ORIG	−0.075	−0.057	−0.114	−0.111	−0.097	**0.517**	−0.064
	OthGEN	−0.041	0.019	−0.031	−0.026	−0.153	−0.062	**0.295**

Effect of the parameter estimates on the manufacturer's own market share are written in Bold

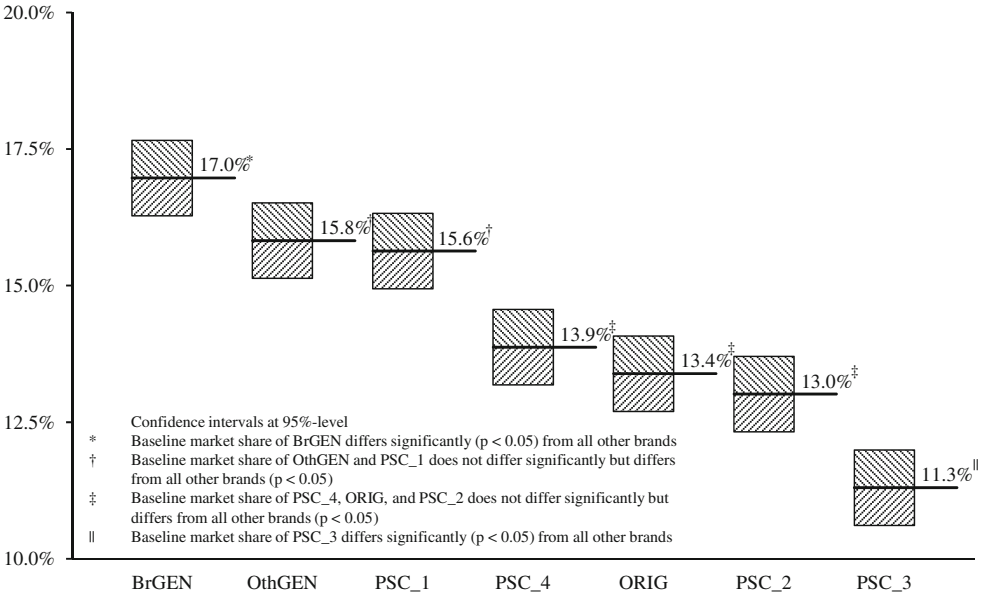

Fig. 2 Baseline market share with confidence intervals after bootstrapping (100 replications)

competitors also entered into contracts. In this situation, market shares stabilize, and each brand approaches a brand specific equilibrium market share. As defined in our model, the equilibrium market share depends (a) on brand strength, (b) on how much a brand can profit from carry-over effects, and (c) on the efficiency with which a brand implements preferred supplier contracts. However, all brands hold significantly higher market shares ($p < 0.001$), except for PSC_3, during the first 3 months after signing a preferred supplier contract compared with the alternative scenarios. PSC_3 is affected by confounding because this brand signs its preferred supplier contracts in most markets at the same time with one of the competitors. This limitation also induces an increase in market share as competitors sign preferred supplier contracts in month three. Besides for PSC_3, we find that the first-mover advantage persists over a period of 24 months but decreases asymptotically.

The second set of scenarios shows that time periods between signing the first and the following preferred supplier contracts positively affects market share gained although curves converge with time (see Fig. 4). The non-intuitive results of PSC_3 are potentially again produced by confounding.

Our findings are consistent with the findings of previous research from non-drug markets. Documenting the empirical association between the order of entry and market share, Robinson and Fornell [37] state that pioneering can lead to long-term consumer information advantages. In drug markets, such an advantage means that patients become familiar with the characteristics of the drug to which they switch, such as its

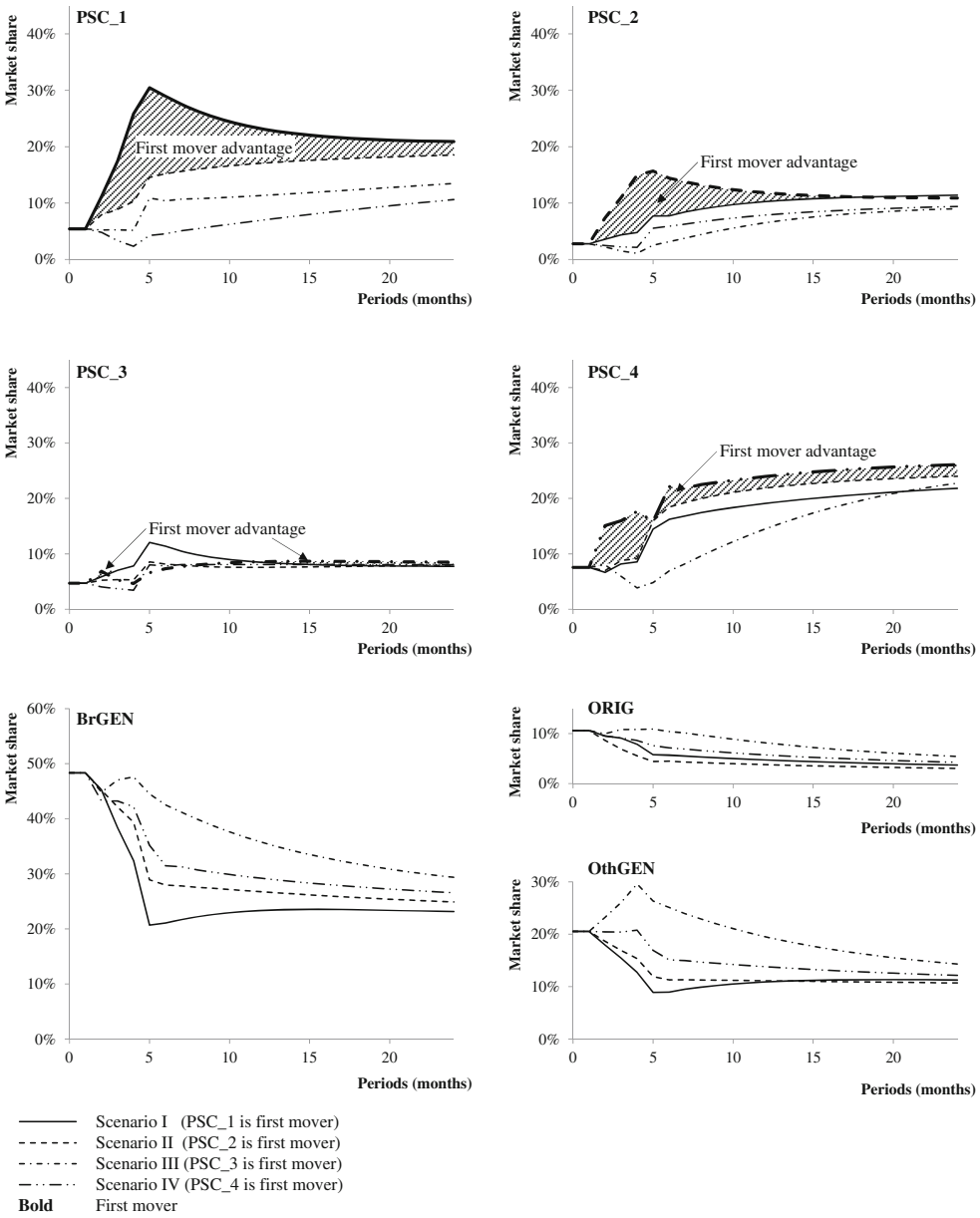

Fig. 3 First-mover advantage – the development of market share by scenario, grouped by brand

packaging, brand name, and color, and thus may remain with the first available choice. Similarly, Berndt et al. [38] and Grabowski and Vernon [39] find first-mover advantages for generic manufacturers after patent expiration.

According to our data, cumulative market shares of manufacturers that signed a preferred supplier contract increased from 20.5 to 72.0 % across all markets within the 30 months analyzed (see Table 1). This is in accordance with data from the AOK – the largest health insurer in Germany – that reported an increase of market share from 1.9 to 40 % for its preferred suppliers across all markets within 1 year [16]. As we observe a joint decision of physicians, pharmacies and patients, it is difficult to attribute findings to each group. Still, we can note that a substantial number of patients appear to accept a change in brand if imposed by their insurer. In addition, there appear to be only minor problems in compliance with the regulation from the physician's and the pharmacist's side. Hoffmann et al. [14] also found only a slight increase prescriptions that were explicitly for non-preferred brands after the introduction of preferred supplier contracts in Germany. Further, our analysis shows that the first-mover advantage, i.e., the hatched area between the market share of being the first and of being the second mover (Fig. 3), decreases over time. Since we only observe chronic conditions, we may conclude that pharmacies had no problems in switching between preferred brands a second time.

With the existence of preferred supplier contracts in post-patent markets, brand differentiation through the use of the 'traditional' marketing instruments of brand-name manufacturers appears to have become less effective in promoting high brand strength. Although we could show that the brand strength of branded generics is significantly higher than that of unbranded generic manufacturers, the business models of brand-name manufacturers appear to be vulnerable to preferred supplier contracts. At a minimum, market shares tend to stabilize after the introduction of preferred supplier contracts, but branded generic and original manufacturers should reconsider their strategy and consider the use of preferred supplier contracts in their marketing mix.

3.4 Limitations and future research

Because of limited data availability, preferred supplier status is the only marketing instrument that we evaluate. One could argue that other instruments, such as detailing, free drug samples or direct-to-consumer advertisements, also affect market shares. However, such an influence is unlikely for three reasons. First, marketing

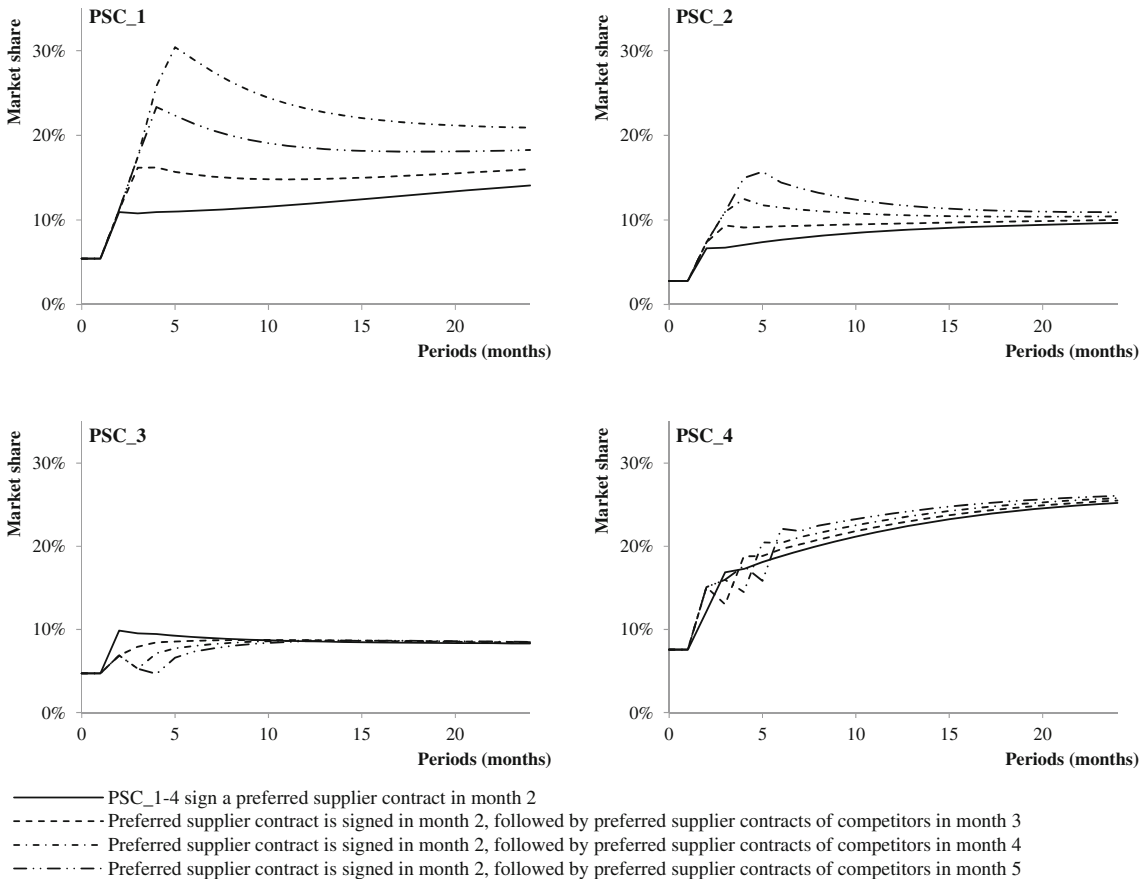

Fig. 4 Effects of time being the only preferred supplier

efforts at the product level in post-patent drug markets are generally low [40]. Second, the use of resources to form a strong brand is reflected by brand-specific intercepts and thus would not influence our results for preferred supplier status. Third, for a highly regulated post-patent drug market, such as Germany, empirical evidence indicates that the above-mentioned instruments have little or no effect. Leeflang and Wieringa [32] examined data from the Netherlands and showed that in a similarly regulated drug market, detailing, direct-to-consumer advertisements, and price have no effect on sales. Thus, our study takes the first step in exploring the role of preferred supplier contracts, also known as tendering, in post-patent drug markets. Therefore, future research should evaluate whether our results may be replicated for similar marketing instruments used in other countries with different regulatory environments.

While the amount of the negotiated discount for the preferred supplier status remains confidential to physicians, pharmacists, and patients and therefore cannot influence dispensing decisions, one might argue that information on list prices should be included into our model. However, incentives to act price-sensitive for physicians, pharmacists, and patients in the low-price segment of post-patent pharmaceuticals are very limited in the German context. Consequently, including list prices in our model did not improve model fit according to AIC_c.

By using a market share attraction model, we do not differentiate between market growth and competitive stealing effects. However, market growth is primarily observed in patented drug markets, whereas we expect competitive stealing effects in post-patent markets. As a sensitivity analysis, we assessed whether there were changes in the size of the 31 markets during the period under observation. We did not find any evidence of substantial market growth or market shrinkage. Thus, the existence of preferred supplier contracts may slow the switch from post-patent drugs to therapeutically comparable drugs that remain under patent protection. Future researchers should focus on these cross-product spillovers.

Because of data limitations, we were also unable to control for spillover effects from the OTC market to the prescription market. This factor may be relevant, as most brands that apply an umbrella brand strategy are active in both the prescription and OTC markets. Although this phenomenon has been analyzed for firms competing in the sales of the same chemical substances [41], it would be interesting to examine whether this effect also persists across assortments of drugs.

As most of the contracting and thus our variation take place during the first 6 months of our panel, one could argue that our results are biased by serial correlation and overfitting; in particular, given the total number 324 parameter estimates. However, with 6076 observations used to fit models, we are in accordance with the rule of thumbs postulated by Harris [42] and Green [43] for $N \geq 50 + m$ and $N \geq 50 + 8m$, respectively, where N is defined as the minimum number of observations and m represents the number of independent variables. In addition, extensive testing has shown the model's predictive power. Nevertheless, there is no doubt that future research would take advantage of a longer panel with more variation over time.

4 Conclusion

With our analysis, we provided insight into the underresearched area of post-patent drug markets by exploring the influence of preferred supplier contracts in a market of increasing importance for the pharmaceutical industry. We quantified the impact of signing a preferred supplier contract and its interplay with brand strength and sequence of contracting on the manufacturer's and its competitors' market share. Further, we demonstrated that brand-name manufacturers are highly vulnerable to preferred supplier contracts, although they typically profit from brand shielding against the sales activities of other brands. Finally, we provided evidence that first movers profit from a higher market share compared to laggards. This gain increases with the time the first mover was the only preferred supplier. Therefore, the results demonstrate the strong impact of preferred supplier contracts in post-patent drug markets. As the use of tendering – a subordinate concept of preferred supplier contracts – has greatly increased during the last years [3, 44, 45], brand-name manufacturers should prepare to strategically use this instrument in their own marketing mix.

Furthermore, we have outlined a helpful blueprint for decision makers in the pharmaceutical industry to assess the influence of different strategies with regard to preferred supplier contracts on market share. If a brand does decide to sign a preferred supplier contract with a health insurance provider, then this decision should be made rapidly to profit from first-mover advantages. If a brand enters late into a contract, then patients, physicians, and pharmacies may partly already be constrained by 'habits' and thus choose to remain with their initially chosen preferred brands. However, although we show that brands may increase their market share by bidding for preferred supplier contracts, decision makers should be aware that the granted discounts may exceed the value of the contract. Thus they should consider that the anticipated gains might be too optimistic, i.e., they should be aware of the winner's curse, a phenomenon that typically occurs in bidding processes [46].

Acknowledgments Financial support for this study was provided entirely by a grant from the Federal Ministry for Research and Education in Germany (grant number: BMBF 01EH1101A). The funding agreement ensured the authors' independence in designing the study, interpreting the data, and writing and publishing the report.

Appendix

Table 4 Parameter estimates for random effects (transformed)

$\nu_{i,c}$	Metformin	Glibenclamide	Glimeperid	Molsidomin	Moxonidin	Doxazosin	Spironolacton	Metoprolol	Atenolol	Bisoprolol	Carvedilol
	A10BA02	A10BB01	A10BB12	C01DX12	C02AC05	C02CA04	C03DA01	C07AB02	C07AB03	C07AB07	C07AG02
PSC_1	0.041	0.008	−0.006	0.048	0.006	0.021	−0.023	0.025	0.062	−0.014	−0.001
PSC_2	0.021	0.004	−0.054	−0.088	−0.017	0.094	−0.056	0.044	−0.044	0.040	−0.032
PSC_3	−0.034	0.016	−0.005	0.034	0.022	0.030	−0.049	0.025	0.007	0.093	−0.024
PSC_4	0.059	−0.116	−0.037	−0.031	−0.060	−0.062	−0.058	0.041	0.044	−0.040	−0.007
BrGEN	−0.027	0.008	0.027	−0.002	0.007	−0.032	0.079	−0.055	−0.033	−0.034	0.054
ORIG	−0.041	0.060	0.028	0.066	0.048	0.020	−0.044	0.010	0.020	0.008	−0.020
OthGEN	−0.019	0.019	0.048	−0.026	−0.005	−0.071	0.151	−0.090	−0.056	−0.052	0.031
$\nu_{i,c}$	Amlodipin	Felodipin	Nifedipin	Nitrendipin	Captopril	Enalapril	Lisinopril	Ramipril	Simvastatin	Pravastatin	
	C08CA01	C08CA02	C08CA05	C08CA08	C09AA01	C09AA02	C09AA03	C09AA05	C10AA01	C10AA03	
PSC_1	−0.053	0.035	−0.009	0.040	0.021	−0.037	0.011	−0.012	0.014	−0.057	
PSC_2	−0.020	0.071	0.040	−0.051	−0.086	0.092	0.003	−0.059	0.027	0.034	
PSC_3	−0.061	0.066	−0.123	−0.028	0.028	0.069	0.038	−0.002	0.063	−0.109	
PSC_4	0.008	−0.022	0.059	0.044	−0.008	−0.050	−0.006	−0.043	0.039	0.021	
BrGEN	0.072	−0.065	0.029	−0.004	0.008	−0.024	−0.008	0.038	−0.035	0.076	
ORIG	−0.022	0.011	0.008	−0.003	0.000	−0.020	−0.045	0.039	−0.078	−0.020	
OthGEN	0.077	−0.096	−0.004	0.002	0.037	−0.029	0.007	0.039	−0.030	0.054	
$\nu_{i,c}$	Carbamazepin	Gabapentin	Bromazepam	Zopiclon	Opipramol	Fluoxetin	Citalopram	Paroxetin	Sertralin	Mirtazapin	
	N03AF01	N03AX12	N05BA08	N05CF01	N06AA05	N06AB03	N06AB04	N06AB05	N06AB06	N06AX11	
PSC_1	−0.064	−0.031	−0.024	0.039	0.021	−0.003	−0.016	−0.018	−0.019	−0.022	
PSC_2	0.003	−0.092	0.076	0.083	−0.001	−0.059	0.019	0.089	−0.020	−0.044	
PSC_3	−0.046	−0.027	−0.035	−0.007	0.031	−0.006	−0.013	0.084	−0.002	−0.025	
PSC_4	−0.019	0.063	0.009	0.024	0.022	0.012	0.059	0.032	0.011	0.011	
BrGEN	0.022	0.039	−0.013	−0.045	−0.038	0.023	−0.038	−0.059	0.005	0.019	
ORIG	0.031	−0.021	0.001	0.001	0.013	0.017	−0.035	−0.046	−0.013	0.013	
OthGEN	0.074	0.070	−0.015	−0.094	−0.048	0.015	0.023	−0.081	0.039	0.048	

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