Experiments in Competitive Product Positioning : Actual Behavior Compared to Nash Solutions

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Abstract

Almost all results on competitive product positioning derived in the literature so far are based on the hypothesis that static Nash equilibria of profit-maximizing competitors are accurate predictors of final market configurations. If the positioning behavior of firms differs from this assumption, it is questionable whether the corresponding propositions can be used in optimal product positioning. In this paper, we explore the validity of the Nash reaction hypothesis. We use a newly developed marketing simulation game, PRODSTRAT, to observe decisions of 240 advanced marketing students on product position, price, and marketing budget under various market conditions. We compare the players' final configurations to Nash equilibria under the assumption that all players attempt to maximize their profit. Our results show that pricing and budgeting decisions are very well described by Nash equilibria for fixed product positions, but that decisions on product positioning are significantly more competitive. The experiments lead to less differentiated market configurations. The result is increased pricing as well as budgeting competition, and significantly reduced profits. We develop and support the hypothesis that the more aggressive product positioning behavior observed here stems from attempts to reduce profit differences (asymmetry) relative to competitors. Since profit asymmetry occurs in many market settings, it is an important factor to consider in making product positioning decisions in a competitive environment.

1 Introduction[1]

Research on competitive product positioning has a long tradition and dates back to the classical paper by *Hotelling* (1929), who found that competition based on product positions in a joint attribute and preference space can lead to a clustering of product positions in the market (preference) center. Over the following decades, researchers asked under which market conditions this so-called "principle of minimum differentiation" holds. Many papers derive relationships between the final outcome of positioning competition, mostly modeled as profit-maximizing *Nash* equilibria, and market conditions[2].

Meanwhile, optimization approaches for competitive product positioning have been proposed by *Horsky/Nelson* (1992) and *Choi/DeSarbo/Harker* (1992, 1990). They use a joint-space map, which they obtain from a MDS procedure, as input. They provide optimization programs for determining an optimal entry position subject to competitive pricing and/or positioning reactions, again assuming (mostly) profit-maximizing *Nash* behavior.

The fundamental assumption of the research outlined above is that *Nash* behavior based on profit maximization is a good approximation of real competitors' behavior. However, there is recent empirical evidence showing that managers tend to overreact to competitive moves rather than follow profit-maximizing *Nash* behavior[3]. It is also not clear that a manager's objective is to maximize profit. *Armstrong and Collopy* (1996) find that to beat their competitors, managers will sacrifice parts of their achievable profit. Obviously, the managers are also driven by their relative position in comparison to competitors. Considerations of increasing sales or market share might also enter into their objectives. Therefore, the theoretically derived relationships between market

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1 The authors want to thank *Kerstin Schmitt* for her valuable help in carrying out the computations of the *Nash* equilibria. We also thank *Karen Gedenk*, *Manfred Krafft*, and *Bernd Skiera* for helpful comments.

2 See *Gabszewicz/Thisse* (1992), *Eiselt/Laporte* (1989) for a survey, and in the marketing literature especially *Ansari/Economides/Ghosh* (1994), *Carpenter* (1989), *Hauser* (1988), *Kumar/Sudharshan* (1988) and *Moorthy* (1988).

3 See *Leeflang/Wittink* (1996).

conditions and results of positioning competition reported in literature may not hold in the real world. Further, entry positions derived from optimization approaches based on profit-maximizing *Nash* reactions might be suboptimal. Managers must carefully investigate the validity of this key assumption if they want to prevent new product failure.

Many oligopoly experiments analyze the adequacy of modeling real competitors' decisions by means of *Nash* equilibria. These experiments cover a variety of completely different decision variables.[4] Although managers’ behavior sometimes appears to be either more cooperative[5] or more aggressive[6] than *Nash* behavior, most papers conclude that *Nash* equilibria are good approximations of real competitors' decisions.[7] However, researchers conduct these experiments with absolute profit maximization as the explicitly stated objective. They leave open the question of whether competitors follow profit maximization in reality.

Furthermore, none of these experiments is concerned with positioning behavior. Thus, it remains unclear whether the results can be generalized, since positioning differs considerably from other marketing instruments in its influence on competitors. For instruments like price, marketing budget, and R&D budget it is often profitable for competitors to follow one player's increased or decreased effort. On the one hand, one player's repositioning towards the market's ideal point makes it less attractive for others to do the same, because this would raise the degree of competitiveness when there is a higher similarity in products. On the other hand, leaving the market's ideal point to competitors might lead to a higher profit but weaken one's own relative market position. This conflict requests that researchers take great care when they generalize findings from the literature on experiments.

4 For surveys see *Holt* (1989), *Roth* (1988), *Plott* (1982).
5 E.g. *Beil* (1988).
6 E.g. *O'Neil* (1991), *Grether/Plott* (1984).
7 *Cooper/DeJong/Forsythe/Ross.* (1990), *Isaac/Reynolds* (1988), and *Alberts* (1984).

So far, only *Schenk* (1991) and *Brown-Kruse/Crenshaw/Schenk* (1993) have conducted experiments in the field of positioning competition. As long as communication between participants of the game is impossible, these authors observe competitive behavior close to *Nash* results. Unfortunately, the authors base their experiments on a market model in which the *Nash* and max-min-strategies are nearly identical. Hence, the experiments' results offer conclusions only on the level of cooperative behavior, not on competitiveness. Moreover, their research is limited to duopolistic experiments in only two different market settings, and the product position in a one-dimensional space is the only instrument.

In summary, previous empirical research does not provide conclusive results that profit-maximizing *Nash* behavior is an appropriate description of real positioning behavior. In order to explore the validity of the *Nash* hypothesis for positioning behavior, we have developed the new marketing game PRODSTRAT to obtain data on competitors' marketing decisions in varying experimental market settings. In order to make this oligopolistic game as realistic as possible the participants compete with the full marketing mix: they decide not only upon the product's position in a two-dimensional attribute space but also on the price and the overall marketing budget. The budget represents a composite of all other instruments, the use of which incurs initial costs before resulting in an increase in sales. As we operate with all marketing mix instruments, we can also investigate the interaction of product positioning decisions with other marketing instruments and its impact on competition. This results in a more complex situation with greater external validity but comes at the expense of less stringent internal validity. This is adequate because we want to explore what drives behavior rather than rigorously test hypotheses.

This paper is organized as follows. Section 2 describes the experiment as research method. We characterize the marketing game PRODSTRAT and its core element, the market model, and then discuss the experimental variation of market conditions. In Section 3, we specify our method for computing equilibria and analyze the data. We compare the observed outcome of our experiments with *Nash* equilibria of profit-maximizing competitors as well as with the industry optima. In Section 4, we hypothesize that the more aggressive product positioning observed in our experiments stems from attempts to reduce profit differences (asymmetry) relative to competitors. We show that asymmetry occurs in our market settings and is reduced by the players' decisions. We compare our final outcome with *Nash* equilibria based on competitors who not only maximize their absolute profit, but also minimize the profit difference to competitors to a certain degree. Our findings strongly indicate that profit asymmetries are the driving force in our experiment. This result is also supported by qualitative statements of the participants in the game. Conclusions are drawn in Section 5.

2 Description of the Experiment

2.1 Need for Laboratory Experiments

The question of whether *Nash* behavior based on profit maximization is a good approximation of human behavior can only be answered empirically. To do so, we could calibrate a market model based on the marketing behavior and market outcome that we observe over time in real-world markets. We could then determine the *Nash* solution of the calibrated model and compare it to the actual behavior. However, the value of such empirical field research is limited by substantial noise in the data. In addition, it is impossible to manipulate market conditions. Thus, empirical findings almost never generalize beyond the individual case examined.

Control over the influencing variables and manipulation of the market setting can only be achieved in laboratory experiments. Therefore, we chose this empirical research technique for this project. In our experiment, we obtain the marketing behavior of the subjects by using the new marketing game PRODSTRAT, which we developed specifically for this purpose, since no other marketing game available was appropriate for our needs.

2.2 Development of the Marketing Game PRODSTRAT

PRODSTRAT is an interactive computer game. It uses a two-dimensional attribute space to focus on product positioning, pricing, and budgeting decisions in an oligopolistic market. The game's participants are each responsible for one single brand and compete against each other. They can perform market research and plan their marketing mix directly on the computer screen. After each player has entered his or her decisions, PRODSTRAT simulates the market results. The game is played over several periods. We collect data from 96 different games under experimentally altered market conditions. The experiments were conducted as follows:

Step 1: The experiment subjects were randomly assigned to experimental treatments. We selected a total of 240 graduate students from two German Business Schools majoring in marketing for 48 duopoly and 48 triopoly games. The participants remained anonymous.

Step 2: To create a reference situation, the game started with a display of the marketing mix and market results of the pioneer (duopoly) or two pioneers (triopoly). For the duopoly, this situation was constituted by the monopolistically optimal marketing mix for the established brand. For the triopoly, the starting configuration consisted of the duopolistic profit-maximizing *Nash* equilibrium.

Step 3: We simulated the market entry of the challenger. We fixed entry prices and budgets according to the market pioneer's monopolistically optimal values (duopoly) or the market average (triopoly). We experimentally altered the entry distance of the new product's position to the already established products.

Step 4: Each subject was required to independently fix the next period's position, price, and budget for his or her product. As in reality, we did not inform the players about the exact parameter values of the market model. However, we did provide them with a tool to conduct some market research in form of what-if analyses. By moving the cursor on the computer screen, subjects could explore the effect of changing product position, price and budget for given competitive marketing mixes. Thus, we could easily detect a good marketing mix.

To assess the impact of competitive actions, the participants could also undertake what-if analyses with different competitive marketing mixes. In addition, they could call up an archive of past decisions and results sorted by competitors or by periods. Through this market research tool, our participants obtained a little more information than could players in real markets. This tool compensated for the students' lack of experience and market knowledge that practitioners normally have when facing a marketing decision. Hence, the task of the participants is comparable to the respective task of managers. As soon as all competitors entered their actual marketing mix decisions in a certain period, the market results of this period were simulated and sent back to each computer terminal.

Step 5: Step 4 was repeated until subjects reached either a stable equilibrium or the limit of 13 periods. An equilibrium was reached when the last changes in price, budget, and position changes of all competitors were smaller than prespecified tolerances. The participants were not informed about termination criteria, so that no end-gaming effects could occur.

Step 6: After finishing the games, the participants answered a questionnaire on the computer screen in which they were asked to evaluate the game. In particular, they were asked to describe how they arrived at their marketing mix decisions.

Step 7: Finally, the participants were paid according to their "success". We intentionally left open which success measure - profit or sales, absolute or relative to competition - we applied. We believe that in practice, product managers are frequently evaluated on the basis of all of these success criteria, and that generally, the relative weight of each component will not be specified. With our approach, it is possible to test the validity of both components of the profit-maximizing *Nash* behavior. First, we can see clearly whether competitors really follow absolute profit maximization as their only goal, and second, whether they really do not anticipate competitors' future reactions.

2.3 Market Model

The core element of PRODSTRAT is its market model. To arrive at a realistic model with high external validity, we make the market volume a function of the marketing mixes of all players. The market share of each brand depends on its own marketing mix as given by product position, price, and marketing budget, all of which are relative to competition. To stay as close as possible in the positioning research tradition, we choose a disaggregated, static, deterministic model with a stochastic error term for this project. In the following description, we drop period indexes for the convenience of the reader. ß's denote various parameters.

Consumer utility. Similar to the model of *DePalma/Ginsburgh/Papageorgio/Thisse* (1985), in a two-dimensional joint space the utility u_{ki} of the k-th consumer buying the i-th product decreases linearly with price P_i and Euclidean distance D_{ki} between product position and the consumer's ideal point. We represent random influences on consumer utility by a *Weibull*-distributed error term ε. Similar functions have also been used by *Choi/DeSarbo/Harker* (1990). With *Carpenter* (1989) and several other authors, we further assume that consumers only tolerate a certain discrepancy D_{max} between the ideal point and product position. Formally:

$$u_{ki} = \begin{cases} \mathrm{Max}(0; ß_0 - ß_1 D_{ki} - ß_2 P_i + \varepsilon_{ki}) & \text{if} \quad D_{ki} < D_{max} \\ 0 & \text{otherwise} \end{cases} \qquad [k \in K, i \in I] \qquad (1)$$

where:

$$D_{ki} = \sqrt{\sum_{d \in \{1,2\}} (q_{dk} - Q_{di})^2} \qquad [k \in K, i \in I]$$

I : set of products,
K : set of consumers,
u_{ki} : utility of the k-th consumer [k∈K] buying the i-th product [i∈I],
D_{ki} : distance of the k-th consumer's ideal point [k∈K] to the i-th product position [i∈I],
P_i : price of the i-th product [i∈I],
Q_{di} : i-th product's coordinate [i∈I] in d-th dimension of the joint space [d∈{1,2}],
q_{dk} : coordinate of the k-th consumer's ideal point [k∈K] in d-th dimension of the joint
space [d∈{1,2}],
D_{max}: maximum quality tolerance of consumers,

ε_{ki} : *Weibull*-distributed stochastic error term of the k-th consumer's utility $[k \in K]$ for the i-th product $[i \in I]$.

Choice probability in the case of awareness and availability of all products. Following the popular multinomial logit model[8], we assume a utility-maximizing behavior of consumers and a *Weibull*-distributed error term ε in the utility function. The choice probability in the case of awareness and availability of all products is then given by:

$$\Pr(Ch \mid A \& A)_{ki} = \begin{cases} \dfrac{\exp[u_{ki}]}{\sum_{j \in J_k} \exp[u_{kj}]} & \text{if } u_{ki} > 0 \\ 0 & \text{otherwise} \end{cases} \qquad [k \in K, i \in I] \qquad (2)$$

J_k : $J_k \subseteq I$; set of products offering positive utility to the k-th consumer $[k \in K]$,
$\Pr(Ch|A\&A)_{ki}$: probability that the i-th product is bought by the k-th consumer $[k \in K]$ in the case of awareness and availability of all products.

Awareness and Availability Rate. The marketplace's awareness and the availability of products can only be achieved by spending some of the marketing budget. Therefore, we need a response function of the i-th product's awareness and availability rate $(A\&A)_i$, that reflects the firm's own marketing budget B_i and the sum of the competitors' budgets $\Sigma(j \in W)B_j$. To distinguish between the impact of our budget and theirs, we need two additional parameters. We choose the modified exponential function because this rate cannot exceed a value of 1:

$$(A \& A)_i = \text{Max}\{0; 1 - \exp[-ß_3 B_i + ß_4 \sum_{j \in W} B_j]\} \qquad [i \in I] \qquad (3)$$

Unconditional choice probability. We merge the conditional choice probability $\Pr(Ch|A\&A)_{ki}$ and the awareness and availability rate $(A\&A)_i$ into the unconditional

8 See McFadden (1974).

choice probability $Pr(Ch)_{ki}$. This merge is analogous to the popular MARKSTRAT game.[9]

$$Pr(Ch)_{ki} = \begin{cases} \dfrac{\exp[u_{ki}] \cdot (A \& A)_i}{\sum_{j \in J_k} \exp[u_{kj}] \cdot (A \& A)_j} & \text{if } u_{ki} > 0 \\ 0 & \text{otherwise} \end{cases} \qquad [k \in K, i \in I] \qquad (4)$$

W	: W=I\{i}; set of competitors' products,
B_i	: marketing budget of the i-th product [$i \in I$],
$(A\&A)_i$	: awareness and availability rate of the i-th product [$i \in I$],
$Pr(Ch)_{ki}$	: probability that the i-th product is bought by the k-th consumer [$k \in K$].

Consumers' consumption volumes. Besides obtaining market share by aggregating the choice probabilities over consumers, we need a function relating market volume to the attractiveness of the offered products and to the firm's efforts to make the product available and known to the consumers. This function is modeled by having consumption volumes of consumers v_{ki} depending on the i-th product's utility and the industry's total marketing budget. Hence, primary demand is variable.

$$v_{ki} = Max\{0; ß_5(1 - \exp[-ß_6 u_{ki} - ß_7 \sum_{j \in I} B_j])\} \qquad [k \in K, i \in I] \qquad (5)$$

Sales. By multiplying individual choice probabilities with consumption volumes and summing up over consumers, we arrive at sales of the i-th brand X_i (6):

$$X_i = \sum_{k \in K} Pr(Ch)_{ki} v_{ki} \qquad [i \in I] \qquad (6)$$

The structure of the whole market model is outlined in *figure 1*.

- Insert Figure 1 about here -

9 See Larréché, Gatignon (1977).

Revenue and Profit. Equation (7) calculates revenue U_i. To reach conclusions based on profit figures π_i we must also consider production costs. We use a marginal production cost function (9) with four parameters in which costs vary across the joint attribute space. Since the *Euclidean* distance creates isocurves in the solution space with equal revenue, we include β_{11} in the cost function to make the solution points unequal. Thus, no symmetric profit-maximizing *Nash* equilibria occur. In addition, this property facilitates the computation of unique *Nash* equilibria. We need the other parameters, β_8, $\beta_{9,}$ and $\beta_{10,}$ to influence the realized profit/revenue ratio which, in turn, influences the magnitude of profit:

$$U_i = X_i P_i \qquad [i \in I] \qquad (7)$$

$$\pi_i = U_i - B_i - \kappa_i X_i - K_{fix} \qquad [i \in I] \qquad (8)$$

where:

$$\kappa_i = ß_8 + \sum_{d \in \{1,2\}} \frac{ß_9}{1 + \exp[-ß_{10} - ß_{11} Q_{di}]} \qquad (9)$$

X_i	: i-th product's sales [$i \in I$],
v_{ki}	: k-th consumer's consumption volume [$k \in K$] of the i-th product [$i \in I$],
U_i	: i-th product's revenue [$i \in I$],
π_i	: i-th product's profit [$i \in I$],
κ_i	: i-th product's marginal production costs [$i \in I$].
K_{fix}	: fixed costs.

2.4 Experimental Design

To see if the observed behavior depends on the chosen conditions and to allow for a broader generalization, we conduct experiments under varying conditions. To see if the observed behavior occurs consistently in a specific way or only at random, we perform all experiments with replications.

The conditions in our experiment are described by the market model's 16 parameters, which we must specify. We systematically vary the seven influential parameter values $ß_1$-$ß_4$, $ß_6$, $ß_7$, and D_{max}. In addition, we want to know whether the results are the same for cases of two or three competitors (Î) and in the case of a unimodal or uniform distribution of ideal points of consumers (IPD).

This desire asks for two more factors that we vary. We disperse 400 ideal points (each representing 10,000 customers) in a rectangular attribute space in which we use two dimensions that range from 0 to 100 distance units. In the case of a unimodal dispersion, the highest density is at coordinate (50,50) and the distance between neighboring ideal points drops at a rate of 6/7 from 0 to 50 and from 100 to 50. We set the other seven parameters ($ß_0$, $ß_5$, $ß_8$-$ß_{11}$, and K_{fix}), which are more technical in nature, to a fixed value.

A full factorial design with 7+2=9 factors at two levels would require 2^9 = 512 experimental treatments, which is impracticable. Therefore, we use a fractional factorial design that comprises only 12 combinations and yet allows for the investigation of all main effects. Table 1, rows 1-9, shows the selected experimental factors and their levels. We chose combinations of factor levels according to an orthogonal main effects plan that guarantees that all experimental variables are uncorrelated.[10] However, this combination does not allow for the estimation of interaction effects. Table 2, rows 1-12, shows the fractional factorial design.

- Insert Tables 1 and 2 about here -

We implement the 12 different market conditions in PRODSTRAT by using a close and a far entry distance (*ED*) of the new product's position to the established competitors' product position(s). Thus, we are able to detect whether the asymmetry of the starting configuration affects behavior. As a result, we create 12·2=24 different treatments. We

10 E.g. *Addelman* (1962), p. 21.

replicate each of the treatments four times to allow for a measurement of reliability. Thus, we arrive at 24·4=96 experiments to be conducted.

There are no empirically known values available to choose from in the selection of specific parameter values. Therefore, we work with parameter values as given in *table 3*, which produce plausible elasticities for the marketing instruments and market conditions [see *table 4*]. These elasticities are close to those reported in meta-analysis studies such as *Assmus/Farley/Lehmann* (1984) and *Tellis* (1988).

- Insert Tables 3 and 4 about here -

3 Description of Actual Behavior in Comparison to Profit-Maximizing *Nash* Equilibria and Industry Optima

3.1 Computation of Reference Configurations

Our goal is to test the adequacy of the profit-maximizing *Nash* equilibrium as a hypothesis for the outcome of real competitive product positioning behavior. More precisely, we want to test whether the static *Nash* equilibrium will describe final product positioning configurations that we obtain from a series of competitive reactions. Although there are methods from evolutionary game theory that better predict the adaptation process of competitive behavior over time, because of the prominence of the *Nash* equilibrium we restrict our analysis to this reference solution.

Since we do not have a closed-form solution, we numerically compute *Nash* equilibria by iteratively optimizing the marketing mix of one firm while holding the marketing mixes of the competitors constant. When we apply this method consecutively for all competitors, we reach a *Nash* equilibrium when none of the competitors can improve his solution.[11] *Choi/DeSarbo/Harker* (1990 and 1992) also use this “variational inequality approach“.

To optimize the marketing mix of one player for a given mix of all his competitors, we use a grid search procedure. We cover the attribute space with a grid of 100 by 100 points. For each point, we iteratively compute optimal prices and budgets until we achieve convergence. For computing both the conditionally optimal price and the budget (with the other variables fixed), we use a grid search with locally decreasing step length. In contrast to other optimization approaches, e.g. a gradient procedure, this method guarantees results sufficiently close to the global optimum. With other algorithms, there is a high risk of running into local optima, because the profit function for the given market model is discontinuous due to the discrete ideal point distribution and the quality tolerance D_{max}. We note that the grid applied was even finer than the number of pixels on the computer screen. Thus, the accuracy of the computed *Nash* equilibria exceeds the required accuracy.

Nash equilibria can be computed either simultaneously or sequentially. If the marketing mixes of the competitors are held constant at their current levels while optimizing one firm's mix, we assume that all players decide simultaneously on their next period’s strategy. Since this is the way the games are performed, we prefer this way of computing the equilibria.

Unfortunately, this algorithm only converges for nine out of 12 different market conditions. For the remaining three market conditions we compute *Nash* equilibria sequentially. Since we do not have closed-form solutions, it is not possible to guarantee that the detected equilibria are unique. However, for all 12 market conditions we arrive at the same equilibria using both starting configurations described in the experimental design.

11 See *Harker* (1984).

It is well known that positioning decisions exert strong influence on pricing and budgeting. The more homogeneous the products, i.e. the closer the product positions, the lower the *Nash* prices are.[12] *Carpenter* (1989) found a decrease of marketing budgets with a stronger homogeneity of the products, but budgeting wars might occur under different conditions. To derive a clear picture of the isolated competitive pricing and budgeting behavior, we simulate a *Nash* competition with prices and budgets only subject to the realized product positions in the experiments as a reference.

To facilitate the assessment of whether the observed behavior is guided by cooperative considerations, we also derive the market configurations that will optimize the global industry profit. Since this optimization problem, which includes up to 12 decision variables (price, budget and two product coordinates for up to three products), is too large for a grid search procedure, we apply a genetic algorithm. *Marks* (1994) presents the computational details.

3.2 Analysis of the Games' Final Configurations

In some oligopolistic games, researchers observe behavior in each period and compare it to the reference configurations. In other games, only the final period as a stable end of a learning process is considered. Which method is adequate depends on how much the players must learn about the market before they are able to select a conscious strategy. PRODSTRAT, like reality, is quite complex in comparison to oligopoly experiments that work with a single instrument and limited choice set where the structure of the game can easily be described by a payoff matrix. The participants in PRODSTRAT are not explicitly given a transparent payoff matrix, but they must form an idea about the payoff function during the game. However, with the market research and simulation tools described above, players are better and better able to infer the payoff structure during the game. Hence, we can expect that a learning process occurs over time, so we can concentrate on the analysis of final configurations.[13]

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12 E.g. *d'Aspremont/Gabszewicz/Thisse.* (1979) and *Hauser* (1988).

13 *Marks* (1994) conducts a process analysis of the development of configurations over periods.

Focusing on the final configurations is only justified if they are not random outcomes but close to a steady state that is unlikely to be changed by the players. We terminated 19 of the 96 experiments because stable equilibrium configurations (identified as negligible price, budget, and position changes over the last two periods) were reached. For all other experiments, we econometrically tested whether the competitive processes converged to steady states such that we could consider the final configurations as good approximations of equilibria.

A time series consisting of the T=13 periods for the *i*-th product and the r-th marketing instrument converges to a steady state Ω_{ir}^* if both the estimated first-order autocorrelation ρ_{ir1} and the second order autocorrelation ρ_{ir2} meet the following conditions: $|\rho_{ir1}|<1$, $|\rho_{ir2}|<1$ and $|\rho_{ir1}+\rho_{ir2}|<1$.[14] This is the case for more than 96% of the 240 time series (players) for all three marketing instruments. These numbers demonstrate the appropriateness of the interpretation of final configurations as equilibria.

Another indication that the outcome in the games' final configurations is not random, but follows a conscious pattern, is indicated by a reliability test. Since we conduct the experiment using four replications of each treatment, *Cronbach's* α can be calculated for all marketing instruments. This measure indicates a very high reliability, with 0.88 for product positions' distances to the market center, DMC_{iT}, 0.82 for prices P_{iT} , and 0.94 for budgets B_{iT}.

3.3 Results

Table 5 shows the results of the games, i.e. mean values of marketing instruments and the market outcome of final configurations in the game, profit-maximizing *Nash* equilibria (for the complete mix as well as for budgeting and pricing only) and the industry optima. Since our attribute space is described by two artificial dimensions of identical scale, the exact coordinates are meaningless. We therefore describe the positioning behavior as the distance to the market center DMC_{iT}, which is similar to *Carpenter's* (1989) approach. We define the market center as the profit-maximizing position of a monopolist.

- Insert Table 5 about here -

Surprisingly, the games' participants arrive at significantly more competitive configurations than their *Nash* counterparts. This result is shown by the parametric one-sample test or the non-parametric *Wilcoxon* signed ranks test. The average distance to the market center drops to 14.0 units, which is 21% below the *Nash* equilibria (17.8 units) and even 38% below the distances in the industry optimum (22.6 units).

Prices are also much more aggressive. At 5.66 they are 7% below the *Nash* level (6.11) and even 12% below the industry optimum (6.45). We note that these lower prices are primarily due to the lower differentiation of competitive products. This was to be expected from theory and it can clearly be seen in *table 5* by comparing the prices in *Nash* equilibria of the complete marketing mix (6.11) to those conditional on the realized product positions (5.76). The result is a difference of 5%. Corrected for this effect, observed prices (5.66) are only 2% below those of *Nash* players with fixed product positions (5.76), which still differs significantly from, but is sufficiently close to, theory for practical forecasting problems.

Observed budgets (4.736) are 7% lower than in the *Nash* equilibrium (5.068), 5% ((5.068-4.802) to 4.736) of which can be attributed to the higher degree of product homogeneity. This result confirms the finding of Carpenter (1989), that budgets are lowered when positioning competition increases. We perceive this to be simply an adaptation to lower profitability levels. Interestingly, the game's participants are underspending considerably in comparison to optimal budgets in the industry optimum (8.049). This behavior is obviously due to a kind of free-rider attitude, so that chances to stimulate primary demand are not utilized.

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14 See *Mason/Phillips/Nowell* (1992), p. 666.

The observed stronger competition in the game results in a drop in profit (8.770) by 38% in comparison to *Nash* equilibria (14.182). The profit achieved is less than half of that in the industry optimum (18.163). The profit decline is due to lower turnover (37.388), which is 18% smaller than *Nash* (45.491) and cannot be compensated by a cut in costs (26.618 to 31.309, i.e., -9% to *Nash*).

Surprisingly, the shortfall of turnover by 18% is caused only to a limited extent by decreased prices. Prices explain only 7%, but 11% lower sales (6.606 units) compared to *Nash* (7.445) are the main cause. This loss is due to a loss of customers (-12% to *Nash*), while the number of units bought by each customer remained nearly unchanged. The lower number of customers clearly indicates a suboptimal clustering of product positions in the market center, and that the firm is not serving niche customers on the market's periphery. The finding that the number of units sold per customer remains unchanged in spite of price cuts can be explained by the decreased marketing budgets and the suboptimal product positions. We note that the total utility aggregated over all consumers declines, such that the competitive outcome is also suboptimal from a welfare perspective.

In summary, the players in our game position their products closer to the market center than do their profit-maximizing *Nash* counterparts. Thus, they lose customers in differentiated market segments but they increase the competition in the market center. Increasing competition leads to decreasing prices, budgets, and profits, but also to lower economic welfare.

We also perform a dummy regression using the experimental factors as explanatory variables to check under which market conditions distances to market center are particularly low relative to the *Nash* equilibrium. The assumptions underlying the regression are met (residual normality cannot be rejected at the 0.07% significance level, heteroskedasticity can be rejected at the 0.96% level, and absence of multicollinearity is assured by design) and the equation is significant (F-statistic of 3.3, $p<0.001$). However, only 11% of the variance is explained. This result indicates the importance of other variables, such as personal characteristics in competitive behavior.

Only two experimental factors show a significant influence. First, in duopolistic markets the observed distance to the market center relative to the one realized by the *Nash* counterparts is lower by 21% (0.66 to 0.84) than it is in triopolies. Apparently the market center becomes less attractive if several competitors must divide the potential. Second, in markets with a unimodal ideal point distribution, the observed distance to the market center relative to the one realized by the *Nash* counterparts is by 30% (0.61 to 0.88) lower than in markets with uniformly dispersed preferences. This lower distance indicates that real players seem to overreact in comparison to *Nash* players if the market center is especially attractive. In markets with unimodal preferences, and also in duopolies, there is a payoff in absolute profit if at least one player remains differentiated from the market center. However, the differentiate player would have to leave the highly attractive market center and let the competitor have a higher market share and profitability. We believe that it was exactly this conflict that forced some of the human players, in contrast to their profit-maximizing *Nash* counterparts, to trade off part of their sales and profit against a lower difference to the better positioned market leader. We develop this hypothesis further in the following section.

4 Profit Differences to Competitors (Asymmetry) as the Driving Force

4.1 Alternative Explanations for the More Aggressive Competitive Behavior in our Experiment

The previous section has revealed the extremely competitive behavior of PRODSTRAT players in contrast to the experiences gathered in previously conducted oligopoly games. In the following, we explore three possible reasons why real game playing behavior may differ from profit-maximizing *Nash* behavior.

First, real players might not correctly perceive the market conditions and hence the decision problem. Since PRODSTRAT, with its three instrumental variables and its primary demand variability, is more complex than other games, perhaps the exact optimization of marketing mixes in the game was difficult. This difficulty might account for a slightly inferior outcome in comparison to the *Nash* equilibria determined with our algorithm. However, given the strong market research tools described in Section 2.2, it was easily possible to discover underlying response functions such that it is very unlikely that the games' participants have missed the decision problem. Our reasoning that the game-playing behavior is not driven by uncertainty, which would have led to a random outcome, is also supported by the facts reported in Section 3.2: The competitive processes generally follow a strict trend towards stable states. Further, the final outcome across all four replications of our treatments was highly reliable.

Second, it is possible that real players follow reaction expectations other than the non-reaction assumption of a *Nash* player. In our case, the players' more aggressive behavior might be due to the fear that a cooperative step would be answered by a threatening step. This scenario is not very likely, since this behavior has hardly ever been observed in other oligopoly experiments, as pointed out in the literature review in Section 1. On the other hand, many oligopoly experiments are designed to detect the extent to which cooperation is practiced. They do not allow for outcomes more competitive than *Nash* equilibria.[15] Thus, the literature could be biased.

We also cannot be sure that findings of the oligopoly literature generalize to positioning competition. In fact, there is some rationale for negative reaction expectations in the field of product positioning. If one competitor reduces the distance to the market center, he might be hoping that other players react by increasing their distance, since the market center would then become less attractive. However, if competitors are not willing to abandon the market center, players should learn this lesson immediately and the lesson should not lead to consistently negative reaction expectations.

15 Such as the positioning experiment of *Schenk* (1991).

Third, it is possible that real players do not follow the goal of optimizing absolute profit. This could have occurred in our experiments, since we did not instruct the games' participants to follow a certain objective function (see Section 2.2). Real players might have deviated from optimizing absolute profit in three ways:

(1) Real players might follow a sales, rather than a profit, goal. This is not untypical for marketing managers, because they sometimes cannot influence costs. However, this does not seem to be the case in our experiments [see *table 5*], because the profit decline is largely due to a shortfall in turnover and sales rather than a cost explosion.
(2) Real players might also consider the risk of being hurt by competitive actions. This risk awareness would lead to max-min-behavior rather than *Nash* behavior, or to an optimization of some kind of (subjectively) expected profit. We know that such tradeoffs between profit and the risk of profit losses exist when managers misread competitors' behavior.[16] However, this risk awareness should favor more differentiated positions rather than the observed stronger degree of product homogeneity.
(3) Real players might also focus on their outcome relative to competitors, rather than on the absolute success. Evidence from experiments supports the hypothesis that players aspire to equal payoffs[17] and that asymmetry intensifies competition[18]. A game is asymmetric if the participants are "unequal", e.g. due to a different level of pre-experience, or if the game is "unfair". A game is unfair if rules offer a specific advantage to one participant.[19] Although formal asymmetry is not present in this experiment – all participants face exactly the same rules and chances – our equilibria are often characterized by one brand being positioned near the market center while the other brands follow a less profitable niche strategy. Thus, substantial profit asymmetry can and does occur, such that our players might have tried to reduce profit asymmetry at the expense of absolute profit. In the next two sections we show that this behavior has been indeed the driving force in the experiments.

16 E.g. *VanHuyck/Battalio/Beil* (1991), *Beckman* (1989).
17 See *Keser* (1991), p. 118, and *Selten* (1988), p. 269 ff..
18 See *Mason/Phillips/Nowell* (1992), *Prasnikar/Roth* (1992), *Weigelt/Dukerich/Schotter* (1989).
19 See *Weigelt/Dukerich/Schotter* (1989), p. 28.

4.2 Occurrence and Reduction of Profit Asymmetry in the Experiments

We can measure absolute profit asymmetry either by the standard deviation of competitors' profits or as the maximum profit difference between competitors. Relative profit asymmetry can be expressed by the variation coefficient of competitors' profits. *Table 6* reports the mean values of these three measures across the 96 experiments.

- Insert Table 6 about here -

Table 6 shows that strong profit asymmetries exist at the beginning of the game. The mean standard deviation of profit in the industry optimum amounts to $7.198M, which implies a mean variation coefficient of 44.3%. The most profitable product achieves an average profit advantage of $11.711M over the least profitable one. This asymmetry is already reduced by *Nash* competitors to a mean standard deviation of $1.878M, with a mean variation coefficient of 16.1%. Mean maximum profit differences are considerably reduced to $3.065M.

The profit asymmetry is largely due to the fact that one player often locates his product near to the market center. Thus, it becomes advantageous for the competitors' absolute profit to differentiate rather than to approach the market center, too. In the industry optimum, the profit of the central player (21.977) is 41% higher than that of the more differentiated competitors (15.621). In the *Nash* equilibrium this central player's advantage is reduced to 11% by locating products closer to each other (15.086 compared to 13.579).

We believe that this kind of profit asymmetry is not a rare, but rather a usual, occurrence in real markets. It appears to be typical for markets with unimodal and sufficiently concentrated distributions of preferences.[20] The reason for this occurrence is a kind of pioneer advantage which is different from the one studied by *Carpenter/Nakamoto* (1989, 1990). The profit asymmetry results from the sequential advantage that, once the

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20 See *Ansari/Economides/Ghosh* (1994).

first product is positioned in the market center, it is more profitable for followers to position their products differently outside the market center.

Extending *Ansari/Economides/Ghosh* (1994), we see that asymmetries in both profit and sales are likely to occur if, on one hand, preferences are strongly concentrated in the market center, but on the other hand are also sufficiently concentrated elsewhere (allowing for at least two profitable positions), and if costs decrease as distance to the market center increases. Then the market center will offer a highly profitable position for only one player while the others are better off choosing a differentiated position than a me-too position in the market center.

We have demonstrated that considerable asymmetry occurs in our market settings, and this is because there is a market leader who is closely positioned near the attractive market center, thus making it attractive for (absolute) profit-maximizing competitors to select a more differentiated position. *Table 7* shows that the followers react more competitive as can be seen from the observed higher degree of product homogeneity in our experiment in comparison to Nash equilibria. The distance to the market center of the differentiated players is on average 34.0% lower than that of their differentiated *Nash* counterparts, while that of the centrally positioned product is only 9.3% lower. Products close to the market center defend themselves by cutting prices more deeply than is efficient for *Nash* solutions. As a result, both groups lose profit. The central players face a significantly higher profit loss of -46.3% (in comparison to *Nash* outcome) than do the differentiated players with -35.7%.

- Insert Table 7 about here -

Our interpretation of this outcome is that the differentiated players are not willing to accept the level of superiority of the market leader and trade off some of their absolute profit to catch up with the dominating product. *Table 6* supports this interpretation. The profit difference between differentiated (8.602) and central players (9.023) is reduced to 5%. In comparison to the *Nash* outcome, absolute asymmetry is reduced by 21% if we measure it by the mean standard deviation of profits (1.491), and by 11% if we measure it by the mean maximum profit differences (2.600). We note that relative asymmetry could hardly be improved (mean variation coefficient 15.9% as compared to 16.1% for *Nash*), since the overall profit level (denominator) decreased strongly.

4.3 Motivation for Decreasing Profit Asymmetry in the Experiments

We conclude from Section 4.2 that absolute profit asymmetry was present and has been reduced in our experiments. We must still examine whether this was the players' intention, or if it was an outcome driven by other factors. Unfortunately, explicit statements of the players were not available. However, at the end of the experiment the players had the opportunity to describe how they arrived at their marketing mix decisions. By analyzing these qualitative statements, we classified each of the 240 participants according to their goal [see *table 8*].

- Insert Table 8 about here -

Table 8 shows that only 41% of the players specified their goal explicitly and completely. The others left their objective open. We note that these cases do not represent non-responses. Rather, an overwhelming majority of players provided detailed reports on the process of "optimization", but did so without saying what was optimized. Only 8% of the participants stated that they also considered other success criteria besides profit, primarily market share, which is a criterion relative to the competition. Even there, profit was the dominant part of the objective function. In total, 27% of the participants stated explicitly that they also considered their position relative to the competition. Profit asymmetry was explicitly mentioned as driving force by at least 17% of all players and 40% of those players stated their goal fully and completely.

Our second approach to examining whether reduction of profit asymmetry was the driving force of the results in our experiments is to compute modified *Nash* equilibria for a weighted objective based on absolute *and* relative profit maximization, and to study whether an increase of the weight for the relative part of the objective moves the

Nash equilibria in the direction of our observed game playing behavior. We do this with the same computational procedure as outlined in Section 3.1,[21] but with the following objective function:

$$z_i = w\,\pi_i + (1-w)\,(\pi_i - \pi_{\varnothing}) \qquad [i \in I;\ 0 < w \leq 1] \qquad (10)$$

π_i : i-th product's profit $[i \in I]$,
$\pi_{\varnothing}$: mean profit across the set of products I,
w : weight allocated to absolute profit versus profit differences.

If (w = 1), we compute the usual (absolute) profit-maximizing *Nash* equilibria. The lower the *w*, the higher the weight attributed to decreasing asymmetry. We select this functional form, which focuses on absolute rather than relative profit differences as measure of asymmetry, for three reasons. First, the key driver in our experiments is absolute asymmetry, since the relative asymmetry, as measured by the mean variation coefficient, remained nearly constant in our games (15.9) compared to *Nash* equilibria (16.1, see *table 6*). Second, the weighted objective is composed of terms with the same dimension [$]. Thus, we avoid using an artificial parameter to link two different scales ($ versus %). Third, it would be no alternative if we were to optimize only the ratio of our own and our competitors' profit, because only minimum differentiated or symmetric equilibria would then be possible. Otherwise, the competitor with the lower profit would select a me-too strategy.

We vary the parameter w between $0 < w \leq 1$. It turns out that we reach the same equilibria for $w \leq 0.9$. Under all six duopolistic market conditions, even a small weight for the profit difference will drive the follower into a minimum differentiated equilibrium closer to the market center.

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21 For 9 market conditions, we reached equilibria with the simultaneous approach, and for 2 conditions the sequential approach achieved convergence. Only in a single case was a stable equilibrium not reached. In this case, market configurations moved in a cycle. One configuration was superior in terms of absolute as well as relative profit for all competitors, which was therefore taken as the "equilibrium".

Table 9 presents the mean values of marketing mix variables and market results of the *Nash* equilibria containing profit asymmetry as part of the objective function. The values show that moving from profit-maximizing *Nash* outcomes to the game players' outcomes described in Section 3.3 has the same effect as increasing the weight for considering profit asymmetry in the objective function of *Nash* players. A preference weight of 10% for reducing profit asymmetry will achieve an even more competitive behavior than we observed in the experimental games. *Nash* players considering profit asymmetry price their products (5.40) significantly lower (by 5%) than do the actual game players (5.66). This happens because in reality, players tend to avoid price competition, probably in the expectation that competitors will react analogously. If this is the case, then the situation worsens for all of them.

We cannot simulate the exact outcome of our experiments, because we must assume homogeneous *Nash* behavior across all players while in our games, behavior is heterogeneous. However, the results clearly show that firms that are motivated to reduce profit asymmetry will move in the direction of our experimental outcome. Considering this, along with the fact that 17% of the game participants explicitly stated that they also tried to maximize their profit relative to competition, we are convinced that profit asymmetry is the major driving force in our experiment, and that it explains the more aggressive behavior in comparison to the popular assumption of (absolute) profit-maximizing *Nash* competitors.

- Insert Table 9 about here -

5 Conclusions

We designed this research project to test whether real competitors follow an absolute profit-maximizing *Nash* reaction, as often assumed for competitive product positioning. Using the marketing game PRODSTRAT, we observed the positioning, pricing, and budgeting decisions of 240 graduate marketing students in experimentally varied market situations, and compared our results to corresponding *Nash* equilibria. Surprisingly, real players in our game positioned their products much closer to the market center than did their profit-maximizing *Nash* counterparts, thus losing or poorly serving customers in differentiated market segments and increasing competition in the market center. This led to decreasing prices, budgets, and profits, and also to lower economic welfare. In contrast, we found that pure pricing and budgeting competition corrected by the effect of increased product homogeneity was well described by profit-maximizing *Nash* behavior.

We develop the hypothesis that the more aggressive product positioning observed in our experiment stems from attempts to reduce profit differences (asymmetry) with competitors. We show that absolute profit asymmetry was present and has been reduced – especially by differentiated and disadvantaged players – in the experiments. We also find strong evidence that profit asymmetry reduction was also the underlying motivation that drove the games' participants.

We observed particularly aggressive positioning behavior in duopolistic markets and also in markets with unimodal ideal point distributions, where substantial asymmetry does occur. Generally, asymmetry is likely to occur if preferences are concentrated in such a way that at least two profitable positions exist, and if costs decrease as the distance to the market center increases. Then, the market center offers a highly profitable position for only one player, while the others are better off choosing a differentiated position than a me-too position in the market center. Under these market conditions, which we perceive to be quite common in the real market place, product managers would do better not to fully rely on profit-maximizing *Nash* behavior to predict competitive positioning reactions.

Inevitably, this research project has its limitations. We did not examine the underlying motivation of games' participants comprehensively. Also, there were three major problems of external validity: First, our generalization of the results is limited by the mathematical market model. Although our model is already comparatively complex and many different market conditions have been investigated, we have not considered dynamic components such as repositioning costs and carry-over effects. Nor do we include product line decisions or examine simultaneous competition in several markets.. Second, we conducted the experiments using as subjects graduate students majoring in marketing. Although we can expect that their behavior comes close to that of product managers, we cannot prove it. Third, we must be aware that positioning decisions in a marketing game are different from decisions in business, which take into account time horizons, marketing research methods, and the people involved. Finally, we note that the *Nash* equilibrium is a static concept. It cannot be used for an analysis of the competitive reactions over time. Although we used a dynamic algorithm for numerically computing *Nash* solutions, these solutions can only serve as reference solutions for the final outcome of a game played over as many rounds as possible.

Keeping these limitations in mind, we conclude with the following research implications: Considering the relevance of our findings to the validity of the propositions of a long research tradition, we see that more research with alternative market models is needed. It would also be productive to analyze the influence of psychological aspects on competitive positioning behavior. Such an analysis might also lead to new insights into the extent to which students' behavior can be generalized. Dissimilarities to real problems can only be reduced by large-scale and innovative field research. Nevertheless, we hope that this paper will open up the discussion on how to model competitive behavior in product positioning problems.

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Table 1: Experimental Factors and Factor Levels

No	Experimental Factor	Equa-tion	Para-meter	Factor Level
1	Quality Effect	(1)	$ß_1$	strong, weak
2	Price Effect	(1)	$ß_2$	strong, weak
3	Budget Effect	(3)	$ß_3$	strong, weak
4	Competitive Budget Effect	(3)	$ß_4$	strong, weak
5	Utility Elasticity	(7)	$ß_6$	high, low
6	Industry Budget Elasticity	(7)	$ß_7$	high, low
7	Maximum Quality Tolerance	(1)	D_{max}	high, low
8	Number of Competitors		*Î*	two, three
9	Type of Ideal Point Distribution		*IPD*	unimodal, uniform
10	Entry Distance		*ED*	close, far

Table 2: Design of Experimental Treatments

Treat-ment	**Experimental Factors**									
	$ß_1$	$ß_2$	$ß_3$	$ß_4$	$ß_6$	$ß_7$	D_{max}	$\hat{I}$	*IPD*	*ED*
1	0	0	1	0	1	1	0	2	um	0
2	1	1	0	1	1	0	0	2	uf	0
3	0	1	1	1	0	0	1	2	um	0
4	1	1	0	0	0	1	1	2	um	0
5	0	1	1	0	1	1	1	3	uf	0
6	1	0	1	1	1	0	1	2	uf	0
7	1	0	0	0	1	0	1	3	um	0
8	1	1	1	0	0	0	0	3	uf	0
9	0	0	0	0	0	0	0	2	uf	0
10	0	1	0	1	1	0	0	3	um	0
11	1	0	1	1	0	1	0	3	um	0
12	0	0	0	1	0	1	1	3	uf	0
13	0	0	1	0	1	1	0	2	um	1
...	...	...	...	...	...	...	...	...	...	...
24	0	0	0	1	0	1	1	3	uf	1

IPD type of ideal point distribution (um=unimodal, uf=uniform)
ED average entry distance to established product positions
1: high factor value
0: low factor value

Table 3: Chosen Values for Factor Levels

Factor Levels	**Experimental Factors**							
	$ß_1$	$ß_2$	$ß_3$	$ß_4$	$ß_6$	$ß_7$	D_{max}	ED
low	0.022	0.072	0.55	0.03	2.4	0.02	50.0	20.0
high	0.028	0.085	0.75	0.07	3.6	0.04	70.0	40.0
Other, non-experimental parameters: $ß_0$=1.0, $ß_5$=20.0, $ß_8$=2.0, $ß_9$=1.0, $ß_{10}$=-4.0, $ß_{11}$=0.08, K_{fix}=6 Mio. $								

Table 4: Distribution of Key Ratios and Elasticities Characterizing the Experimental Markets

Characteristics	Mean	Std. Deviation	Minimum	Maximum
Profit/Revenue-Ratio	19.81%	12.69%	-44.25%	45.53%
Budget/Revenue-Ratio	13.86%	4.85%	5.49%	51.29%
Price-Elasticity	-2.29	0.92	-6.39	-0.52
Cross-price-Elasticity	0.47	0.56	0.00	3.83
Budget-Elasticity	0.26	0.07	0.14	0.45
Cross-budget-Elasticity	0.05	0.05	-0.10	0.18

Table 5: Means of Marketing Mixes and Market Results in Final and Reference Configurations

N=240	Industry Optimum	Nash Full Marketing Mix (NFMM)	Nash Position Fixed (NPF)	Game Final Configuration (FC)	Significance Difference FC to NFMM
DMC [units]	22.6	17.8	14.0	14.0	0.000[b]
Price [$]	6.45	6.11	5.76	5.66	0.000[a]
Profit Contribution [$]	3.76	3.40	3.08	2.98	0.000[a]
Budget [Mill. $]	8.049	5.068	4.802	4.736	0.000[a]
Profit [Mill. $]	18.163	14.182	9.385	8.770	0.000[b]
Turnover [Mill. $]	55.226	45.491	37.845	37.388	0.000[a]
Sales [Mill. units]	8.562	7.445	6.572	6.606	0.000[a]
Cost [Mill. $]	37.063	31.309	28.460	28.618	0.000[a]
Customers [tsd.]	655	660	580	582	0.000[a]
Sales per Customer	13	11	11	11	0.497[b]
Turnover per Customer [$]	84	69	65	64	0.000[a]
Utility [units]	157	155	143	149	0.060[a]

a Two-tailed one sample test

b Non-parametric *Wilcoxon* signed ranks test because assumption of normally distributed differences had to be rejected with $p < 0.05$

Table 6: Different Measures of Profit Asymmetry in Final and Reference Configurations

N=96 Profit Measures [Mill. $]	Industry Optimum	Nash Full Marketing Mix (NFMM)	Game Final Configuration (FC)	Significance[a] Difference FC to NFMM
Mean				
- Total	18.163	14.182	8.770	0.000
- Central Product	21.977	15.086	9.023	0.000
- Differentiated Product	15.621	13.579	8.602	0.000
Mean Standard Deviation	7.198	1.878	1.491	0.000
Mean Maximum Difference	11.711	3.065	2.600	0.000
Mean Variation Coefficient	44.3%	16.1%	15.9%	0.569

a Non-parametric *Wilcoxon* signed ranks test because assumption of normally distributed differences had to be rejected with $p < 0.05$

Table 7: Influence of Product Position's Centralization on Relative Deviations

Characteristics	Mean of ... Products		t-Stat.	df	Signif.[a]
	Differentiated	Central			
DMC in % to Nash	-34.0 %	-9.3 %	-4.67	231.25	0.000
Price in % to Nash	-5.7 %	-9.2 %	3.31	182.66	0.001
Budget in % to Nash	-5.0 %	-8.7 %	2.59	212.54	0.010
Profit in % to Nash	-35.7 %	-46.3 %	2.45	166.08	0.015

a Two-tailed t-test with separate variance estimate; significance levels confirmed by nonparametric Kruskal-Wallis-Test

Table 8: Number of Game Participants' Goals based on their Qualitative Statements (N=240)

Goal Extent Success Criterium	Absolute	Also Relative to Competition	No explicit information	Total
Profit	18%	17%	6%	41%
Also Turnover, Sales, Customers etc.	1%	5%	2%	8%
No explicit information	0%	5%	46%	51%
Total	19%	27%	54%	100%

Table 9: Means of Marketing-Mixes and Market Results of Nash Equilibria considering Profit Differences vs. Game and Reference Configurations

N=240	Industry Optimum	Nash for Absolute Profit (NAP)	Game Final Con-figuration (FC)	Nash for Absolute Profit and Difference to Competition (NAPDC)	Significance of Difference FC to NAPDC
DMC [units]	22.6	17.8	14.0	10.9	0.693[b]
Price [$]	6.45	6.11	5.66	5.40	0.000[a]
Profit Contribution [$]	3.76	3.40	2.98	2.74	0.000[a]
Budget [Mill. $]	8.049	5.068	4.736	4.318	0.000[a]
Profit [Mill. $]	18.163	14.182	8.770	7.597	0.460[b]
Turnover [Mill. $]	55.226	45.491	37.388	35.288	0.021[a]
Sales [Mill.]	8.562	7.445	6.606	6.535	0.906[a]
Cost [Mill. $]	37.063	31.309	28.618	27.691	0.060[a]
Customers [tsd.]	655	660	582	591	0.324[a]
Sales per Customer	13	11	11	11	0.318[b]
Turnover per Cust. [$]	84	69	64	60	0.000[a]
Utility [units]	157	155	149	150	0.687[a]

a Two-tailed one sample test

b Non-parametric *Wilcoxon* signed ranks test because assumption of normally distributed differences had to be rejected with $p < 0.05$

Figure 1: Structure of the market model