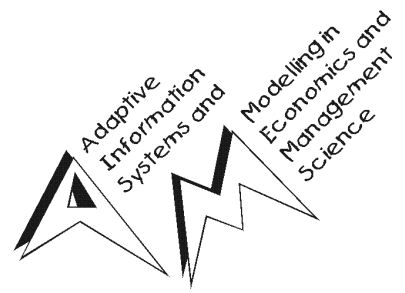


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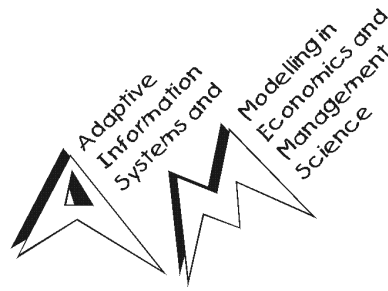


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Is Thinking Worthwhile?

A Comparison of Corporate Segment Choice Strategies

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Abstract

The field of strategic marketing has long been identified as fruitful ground for gaining competitive advantage. Ever since the market segmentation concept was introduced in the late sixties, research interest steadily increased, covering issues as e.g. which fundamental segmentation strategy is most appropriate, in which ways can segments be identified or constructed, which algorithm provides optimal data-driven segmentation solutions, which number of segments should be constructed etc.. Interestingly, the issue of segment evaluation and choice has not been emphasised very strongly in the past, although this is of primary interest as soon as it comes to practical implementation. This article tries to fill this gap in an experimental manner: the consequences of different corporate segment choice strategies based on different segment evaluation criteria are investigated under different environmental conditions formalised in a complex artificial consumer market. The results indicate that complex decision models for segment choice do not turn out to be superior in general. Both mass marketers and firms concentrating on particular segments based on an *a priori* logic can be just as successful under “favourable” market conditions, the most influential condition being the available advertising budget.

Keywords market segmentation, target segment choice

1 Introduction

Market segmentation has received a lot of attention among both practitioners and researchers during the last decades. The main reason might be the fact that superior market segmentation bears high potential of gaining competitive advantage. Typical fields of research in this context include comparative studies of different segmentation approaches and techniques (Punj

and Stewart (1983), Wedel and Kamakura (1998), Krieger and Green (1996), Mazanec and Strasser (2000)), evaluation of the usefulness of different segmentation bases (Haley (1968), Woodside and Pitts (1976), Abbey (1979), Davis et al. (1988), Gitelson and Kerstetter (1990)), and segmentation applications from various business contexts (an excellent review of almost 300 such applications is provided by Baumann (2000) with the latter dominating in terms of quantity).

A number of issues remain unsolved from a practitioner's point of view: Once segments have been defined, there are no commonly accepted and formalised evaluation criteria for market segments. Furthermore, apart from traditional portfolio methods there are no theoretical recommendations about the actual target market choice process. As this issue is strongly dependent on and interrelated with the real-world situation faced in the marketplace, simulation enables a systematic and fully controlled investigation of consequences of different target segment choice strategies and aims at causal understanding of effects. The aim of this study is to gain insight into the usefulness of different segment evaluation criteria as well as target segment choice procedures. This goal is achieved by conducting a controlled experiment in an artificial simulation environment with five competing companies following different target segment choice strategies.

The article is organised as follows: In the first section a brief review of literature focusing on segment evaluation criteria and target segment choice is provided. The experiment is outlined in the second chapter, containing information on the artificial consumer market used, the five companies (actors, agents) that are competing within the artificial world, the hypotheses that guide the entire experiment and the details on the experimental design. Finally, results are discussed followed by a conclusion.

2 Segment Evaluation and Target Segment Selection

The basis for formalising both the issue of segment evaluation as well as target segment choice is most systematically and comprehensively provided by Frank et al. (1972). Operational market segments must be (1) sufficiently different from one another in order to make disproportionate allocation of resources worthwhile and (2) reachable in an efficient manner through the available promotional vehicles. Thus, the distinctiveness and the reachability are considered to be central criteria for segment attractiveness assessment. A highly management-oriented approach is chosen by McDonald and Dunbar (1995). They list a wide variety of possible criteria that determine a segment's attractiveness, some of them include: growth rate of revenue spent by each segment, accessible segment size, profit potential, threat of substitutes, threat of new entrants, power of suppliers and power of customers. Wedel and Kamakura (1998) summarise the segment requirements by stating six relevant criteria: identifiability, substantiality, accessibility, stability, responsiveness and actionability.

Although numerous - strongly convergent - criteria can be found in literature, there are very few endeavours to propose a systematic evaluation tool of segment attractiveness. Wedel and Kamakura recommend the use of standard portfolio analysis, McDonald and Dunbar (1995) also suggest the application of either the Boston Consulting Portfolio tool or the McKinsey multi-factor extension of this concept. In addition the authors present a simple step-by-step process for evaluation and choosing the optimally suited market segment that consists of the following stages: (1) Defining segment attractiveness criteria. (2) Weighting segment attractiveness criteria. (3) Setting segment scores for the criteria. (4) Calculating

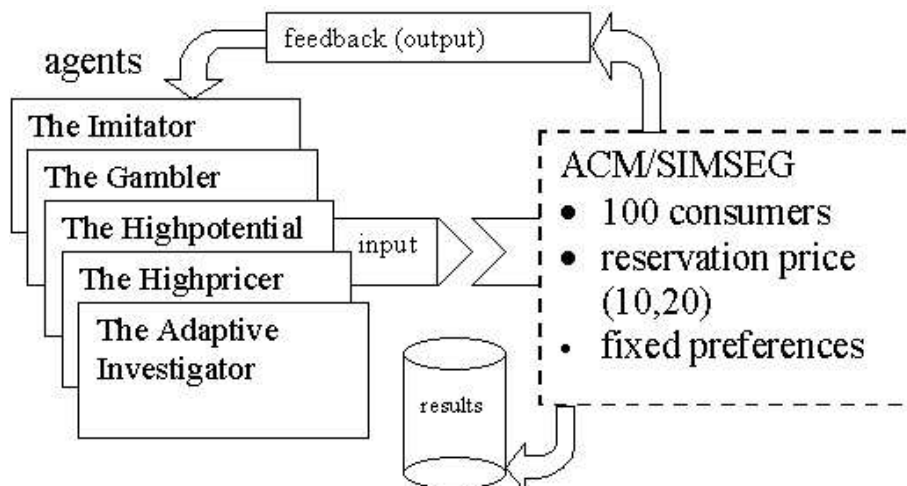
segment values. (5) Establishing the company’s ability to compete in each segment.

3 The Experiment

In the following subsections an overview is given about the simulation experiment which includes

- the artificial world
- the actors
- the hypotheses
- and the experimental design.

Figure 1 illustrates the combination of these elements to a logical cycle of simulation experiments



with the artificial world as a starting point.

3.1 The artificial world: ACM/SIMSEG

The simulations are based on an artificial consumer market simulation environment (Buchta and Mazanec (2001)). The main purpose of this environment is to provide a realistic framework which supports *ceteris paribus* experiments in order to gain insight on how successful certain corporate strategies are in a competitive marketplace. The central research question is thus formalised by constructing artificial actors that compete each other. In this article the main aim is to understand the influence of different segment choice strategies. Therefore actors make use of different decision rules. By simulating a long period of time within this artificial marketplace, insights can be gained about superiority and inferiority of particular strategies under given conditions. These conditions are defined a priori. For our experiment, the following setting is used:

- The product

The product consists of 12 attributes that can be perceived by a customer. They load on four hidden dimensions (factors), three attributes per dimension. Two dimensions (six items) represent information that is purely influenced by advertising action, the remaining two dimensions are based on technological features of the product. Thus, the success of advertising action in these variables is highly influenced by the actual technical profile of the product.

- The production

Underlying the 6 visible technical features is a 6-dimensional production process. There is a linear mapping from production process to features that is common to all agents because it is a characteristic of the world (“agents doing the same thing produce the same product”). Associated with the production process is a linear cost function with random coefficients drawn from a uniform distribution such that different elements of the production process yield different costs. This cost function is the same for all agents. Both the mapping from production to product attributes and from production to costs are subject to a small amount of additive noise, such that doing the same thing twice does not give exactly the same results. All agents use the same regression model to learn the production process and the associated cost function (starting with 20 samples and adding all products they produce to their respective set of samples).

- The customers

The world consists of hundred consumers. These customers have homogeneous preferences with regard to the 12 product attributes they perceive. All in all, six market segments are modelled, the preferences of which are given in Table 1. Every column represents one hidden dimension (factor), every row represents one segment. An 'I' indicates that the dimension is irrelevant to the segment described, whereas an 'R' stand for relevant. Thus, segment #1 does not care about the items that are purely advertisement based (e.g. associations like cool, sexy, funny, etc.), on the other hand the information that is based on the technical product profile is studied very carefully by this group of customers when they make a buying decision. The preferences remain fixed during the simulation. Each customer buys exactly one product in each period. The reservation prices of the customers are uniformly distributed between 10 and 20 monetary units.

- The competitors

Five one product companies compete in the marketplace. They are modelled as artificial actors or agents and described in detail in the section on 'The artificial actors: Corporate Segment Choice Strategies'.

One simulation period starts with input that is passed on from the actors to the artificial market environment. These inputs consist of the technical product features, the profile that is communicated to the customers by means of advertising, the price and the target segment chosen. After all computations within the artificial world are executed, the actors receive the results in form of output variables including consumer choices (who bought which product), an attractiveness ranking of all products for each consumer, the beliefs or perceptions of the customers on all 12 attributes and finally the ordinally scaled satisfaction level of the consumers with both the entire product as well as the single attribute dimensions.

Table 1: segment structure

segment	advertising dimensions		technology dimensions		size
segment 1:	I	I	R	R	(10%)
segment 2:	R	R	I	I	(10%)
segment 3:	R	I	R	I	(30%)
segment 4:	R	R	R	R	(10%)
segment 5:	I	I	I	I	(10%)
segment 6:	I	R	I	R	(30%)

3.2 The artificial actors: Corporate Segment Choice Strategies

As mentioned before, each of the five agents (actors) has its own philosophy of behaving in the marketplace with varying levels of sophistication. The requirements for designing agents were manifold: (1) each agent should follow a unique corporate strategy, (2) the corporate philosophies underlying the agents' behaviour should be reasonable and might be encountered in real world, (3) fundamentally differing segmentation strategies should be included and (4) one benchmark agent should enable testing against strategy-free behaviour. In the following paragraphs these corporate strategies are explained in detail. Basically, they can be grouped into four agents which segment the market and one mass marketer who applies marketing tools in an undifferentiated manner.

The rules that underly the operational marketing behaviour of these actors are identical (following the *ceteris paribus* requirement for controlled experiments). The only difference is caused by the fact that different customer groups are addressed.

Undifferentiated corporate strategy The first actor named *Imitator* is a very simplified version of a corporate strategy. He is the only one who does no partitioning of the consumer survey data available but tries to serve the entire market. The price for his product and its product attributes are imitated from the biggest competitor. The imitator modelled in this experiment thus represents a typical mass marketer who additionally follows a simple success strategy with regard to product attributes.

Concentrated corporate strategy The alternative to mass marketing is to construct homogeneous market segments, evaluate the attractiveness of each resulting segment and choose one such group for targeted marketing action. All remaining actors follow this fundamental principle and are described in the order of their rule sophistication starting with *The Gambler* followed by *The High Potential*, *The Highpricer* and the *The Adaptive Investigator*. The agents differ in their ways of choosing the best group of customers. The market analysis they require is conducted by each firm following the same algorithm. As a starting point market survey data is used, where all customers indicate their perceptions concerning every single of the 12 product attributes for every product (every firm) in the marketplace in a binary manner (three way data set with the dimensions customers, attributes and products). Ignoring the product dimension, the data set is partitioned into 5 groups (the rationale behind the number of clusters is that in a marketplace with 5 competitors, 5 groups should enable every firm to concentrate on one niche.). These groups represent different ways of perceiving this product and are addressed as "perceptual classes". The agents are provided the information

which product is perceived in which group by which consumer. In addition, the agents get the information, which product was actually bought by every single respondent. Thus, within every perceptual class there is a subset of perceptions that have actually been chosen. This subset is called “segment”. The sum of all such subsets is equal to the number of customers in the marketplace, as each person buys exactly one product per period (for details on this segmentation concept called PBMS - perceptions based market segmentation - see Mazanec and Strasser (2000) and Buchta et al. (2000)).

The Gambler primarily functions as benchmark for the other agents. The *Gambler’s* “behaviour” is to choose one segment at random (with evenly distributed chances), to set the price at random and the technical features as average of all chosen products in the cluster.

The High Potential evaluates the given segments according to the following criteria: First, the number of beliefs (number of perceptions in one homogeneous group) and the number of beliefs concerning the own product has to be higher than a predefined threshold value. Second, the perceptual class with the maximum number of choices (actual buying acts) is chosen. This agent represents a firm that does segment the market, but relies on the most fundamental criteria for creating segments (size). The price and technical features are the average of the products bought.

The Highpricer tries to find a segment which is willing to pay a high amount of money for his product and therefore chooses a partition with a minimum number of buyers, a high market share and a price level above average. The price is then set as average price of the products bought in the segment plus a standard deviation. The technical features corresponds to the technical features of the average product bought within this segment. The Highpricer thus represents a segmentation strategy that is focused on one central criterion (price). In real world this agent might mirror typical branding endeavours.

The *Adaptive Investigator* uses a combined segment evaluation strategy by weighting seven criteria (relative size in terms of perceptions and choices, profitability, feature similarity and difference, size as compared to competitors, change in share index). The weights are adapted over time according to a simple learning rule depending on market success (profit).

3.3 Thinking Makes a Difference: Research Questions

Based on the artificial world, the actors and the simulation design described in the previous sections, a number of hypotheses can be formulated:

- Is thinking worthwhile? Are companies that employ complex segment evaluation criteria for the purpose of choosing the target segment for marketing action more successful in the marketplace than companies that apply simple heuristic procedures?
- Does concentration lead to competitive advantage? Are companies that segment the marketplace and choose single segments for marketing action (concentrated segmentation strategy) more successful than companies that target all customers in the marketplace (undifferentiated segmentation strategy)?

- Isn't common sense better anyway? Are companies that construct data-driven market segments more successful than companies working with a priori defined customer groups?
- Does money matter? Does the height of advertising budget influence the optimal segmentation strategy choice decision?

3.4 Experimental design

The five companies described above compete against each other in the SIMSEG/ACM environment. Every simulation has a duration of 100 periods (with one period standing for one month of time).

The number of simulations is a result of the full factorial experimental design based on the following factors and factor levels:

Thinking Cycle: Companies do not necessarily have the opportunity to rethink their strategic segmentation decision every single period. But the frequency of reorientation opportunities might strongly interact with the success of the different segment evaluation and choice strategies. Thus, three factor levels are included in the design: thinking cycle of one period (meaning that the entire process of market segmentation and segment choice is repeated every single period of the simulation), thinking cycle of 10 (every tenth period) and 20.

Advertising Budget: In order to avoid situations where an initial starting solution favours one company by chance, this company is rewarded with high marketing budget and thus becomes “unwoundable” for the remaining 99 periods of the simulation, the marketing budgets are fixed and equal for all companies in the market. Two levels of marketing budgets are used: 100 and 300. The rationale behind changing the marketing budget over simulations is to make sure that mass marketers have a sufficient amount of budget in at least one condition.

Number of Segments: Obviously, the actual market structure strongly determines whether segmentation makes sense or not. In order to control for this market condition in the experiment, two different market structures are used: One third of the simulations are based on a setting where no groups of customers exist that have characteristic, homogeneous preferences concerning the product. The remaining simulations assume a world, where six such groups with very specific tastes (product preferences) do exist.

Size of Segments: Sizes of these groups of consumers with different preferences can also strongly influence the success of different segmentation strategies. Therefore two factor levels are included to control for this effect. In the first case, all customer groups (preference segments) have the same number of members, in the second case, the sizes differ.

As size of segments obviously has no effect when only one segment is present, the latter two design factors were merged into one: Scenario 1 contains six groups with different sizes, Scenario 2 six groups of the same size and Scenario 3 only one group.

3.5 Statistical Analysis

The simulation setting was evaluated using a full-factorial design and replicated three times, resulting in a total of 54 simulation runs. The success of the agents was evaluated using quantities (sold units), sales (sold units \times price), and profits (sales minus costs) accumulated over time.

As an example take profits in Scenario 1 as depicted by the boxplots in Figure 1: It can clearly be seen that for a thinking cycle of 1 and an advertising budget of 100 the imitator and highpricer perform significantly worse than the other three, while this effect is less pronounced for a higher budget and longer thinking cycles.

Linear models were fitted for an analysis of variance, using first order terms for all independent variables and second order interaction terms between budget and agent type. Models with more interaction terms were discarded because they gave no more significant parameter estimates and had larger AIC values. The output for the models is the usual table for linear regression models with parameter estimates in the first column, followed by the respective standard deviations, t -statistics and p -values in columns 2–4. Significant p -values are marked by stars. Finally several statistics on the goodness of fit of the model (like residual standard error or R^2) are given.

The model for quantities is:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	2.440e+03	7.052e+01	34.599	< 2e-16	***
think10	6.464e-15	4.617e+01	1.40e-16	1.000000	
think20	1.261e-14	4.617e+01	2.73e-16	1.000000	
budget300	-4.404e+01	8.429e+01	-0.522	0.601816	
agentimitator	-1.836e+03	8.429e+01	-21.782	< 2e-16	***
agenthighpotential	1.231e+02	8.429e+01	1.460	0.145487	
agenthighpricer	-4.694e+02	8.429e+01	-5.569	6.46e-08	***
agentinvestigator	8.237e+01	8.429e+01	0.977	0.329386	
scenario2	1.378e-14	4.617e+01	2.99e-16	1.000000	
scenario3	1.108e-14	4.617e+01	2.40e-16	1.000000	
budget300:agentimitator	9.241e+02	1.192e+02	7.753	2.13e-13	***
budget300:agenthighpotential	-4.011e+02	1.192e+02	-3.365	0.000882	***
budget300:agenthighpricer	-1.219e+01	1.192e+02	-0.102	0.918662	
budget300:agentinvestigator	-2.906e+02	1.192e+02	-2.438	0.015447	*

 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 309.7 on 256 degrees of freedom
 Multiple R-Squared: 0.7792, Adjusted R-squared: 0.7679
 F-statistic: 69.48 on 13 and 256 DF, p-value: 0

The intercept is for the baseline combination of think=1, budget=100, Scenario 1 and the gambler. The remaining coefficients should be seen as differences to this baseline. E.g., the line `budget300` gives the effect of a budget of 300 as compared to a budget of 100 *common to all agents*. In our case the agents sell on average 44 units less when the advertising budget is higher, however this estimate is not significantly different from zero (p -value of 0.6018). The

last four rows of the table give the interaction terms between budget and agent type, and one can easily see that three of these are significantly different from zero.

The imitator sells significantly less units than the gambler for a budget of 100, this effect is reduced if the budget is higher. The highpricer sells less units for all combinations, while highpotential sells significantly less units only when the budget is high. The various scenarios have no significant influence.

For sales the results are:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	25378.0	1022.6	24.816	< 2e-16	***
think10	156.4	669.5	0.234	0.81552	
think20	-1276.1	669.5	-1.906	0.05775	.
budget300	-3493.9	1222.3	-2.859	0.00461	**
agentimitator	-19642.3	1222.3	-16.070	< 2e-16	***
agenthighpotential	2221.4	1222.3	1.817	0.07032	.
agenthighpricer	-2297.8	1222.3	-1.880	0.06126	.
agentinvestigator	1711.6	1222.3	1.400	0.16263	
scenario2	-866.8	669.5	-1.295	0.19656	
scenario3	3225.2	669.5	4.818	2.49e-06	***
budget300:agentimitator	11357.1	1728.6	6.570	2.79e-10	***
budget300:agenthighpotential	-4276.4	1728.6	-2.474	0.01401	*
budget300:agenthighpricer	-481.3	1728.6	-0.278	0.78089	
budget300:agentinvestigator	-3043.0	1728.6	-1.760	0.07953	.

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 4491 on 256 degrees of freedom
 Multiple R-Squared: 0.6918, Adjusted R-squared: 0.6761
 F-statistic: 44.2 on 13 and 256 DF, p-value: 0

Results are similar, the biggest difference is that the parameter for Scenario 3 now is highly significant, i.e., sales are higher on average if only one group of consumers is present.

Finally, the linear model for the profits yields:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	13851.6	1114.3	12.430	< 2e-16	***
think10	466.1	729.5	0.639	0.5235	
think20	-1044.1	729.5	-1.431	0.1536	
budget300	-19730.2	1331.9	-14.814	< 2e-16	***
agentimitator	-19615.4	1331.9	-14.728	< 2e-16	***
agenthighpotential	2352.5	1331.9	1.766	0.0785	.
agenthighpricer	-2249.2	1331.9	-1.689	0.0925	.
agentinvestigator	1788.8	1331.9	1.343	0.1804	
scenario2	-892.3	729.5	-1.223	0.2224	
scenario3	2984.8	729.5	4.092	5.75e-05	***
budget300:agentimitator	14521.2	1883.6	7.709	2.80e-13	***
budget300:agenthighpotential	-2731.8	1883.6	-1.450	0.1482	
budget300:agenthighpricer	267.5	1883.6	0.142	0.8872	

```
budget300:agentinvestigator    -2625.4    1883.6   -1.394    0.1646
```

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```

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Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Residual standard error: 4894 on 256 degrees of freedom

Multiple R-Squared: 0.8386, Adjusted R-squared: 0.8305

F-statistic: 102.4 on 13 and 256 DF, p-value: 0

with a similar pattern of effects as for sales. A detailed interpretation and comparison of these results follows below.

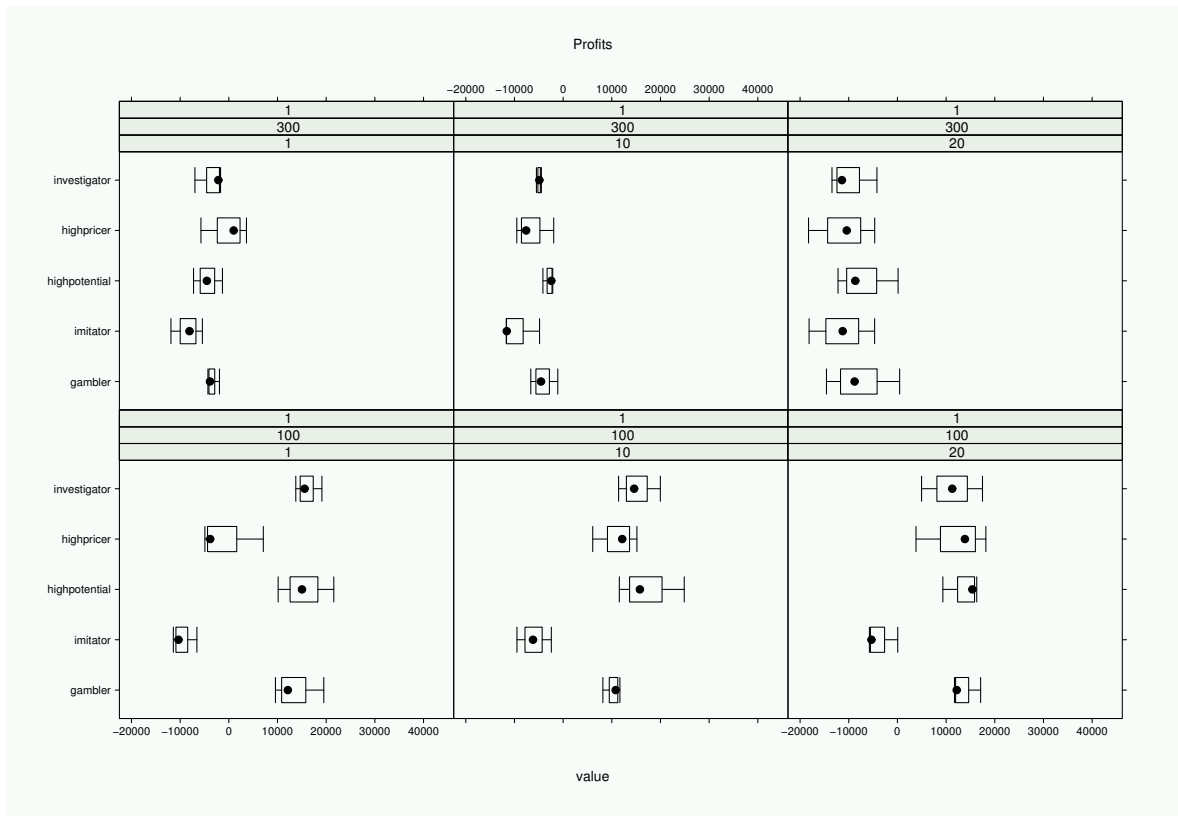


Figure 1: Boxplots of profits depending on agent, budget and thinking cycle for Scenario 1.

4 Results

4.1 Is thinking worthwhile?

The unexpected result is, that complex decision algorithms are not superior to the simplest choice rules for subgroups. The Gambler is not significantly less successful than the competitors. The main reason for this is that there is no cost for product modification. The Gambler thus takes advantage of the fact, that a smaller group is addressed that allows successful

advertising even in times with budget restrictions and is not punished for possibly completely changing the product that is offered in the marketplace.

The fact that The Adaptive Investigator does not turn out to be superior among these competitors can be attributed to two factors: first, the goals that implicitly underly the segment choice criteria of the Adaptive Investigator represent very different kinds of marketing goals and thus might function in a cannibalising manner. Second, the strength of the Adaptive Investigator lies in her ability to learn the importance by evaluating market response. Even if the segment decision is made in every single period, the Adaptive Investigator only gets 100 opportunities to learn. This number of learning steps might not be sufficient to take advantage of the learning competence.

The influence of the thinking cycle turns out to be insignificant. Two possible explanations can be provided: first, changing the segment decision is cost-free for the firms in the marketplace which consequently means that there are no sanctions for being inconsistent in terms of long-term target segment choice. Second, the preferences of the individuals remain unchanged throughout the simulation runs. Even if the segment choice is changed every single period, the individuals addressed do not change very strongly (except for the Gambler) as the choice rules remain the same.

4.2 Does concentration lead to competitive advantage?

The results indicate that addressing the mass market renders equally good results if the budget is high enough to enable The Imitator to advertise sufficiently. If there are budget constraints that dramatically decrease the advertising effect per person, The Imitator turns out to be significantly less successful than the competitors that focus on one segment only and thus can effectively communicate with the group of customers chosen as target segment. It can thus be concluded that the concentrated segmentation strategy does lead to competitive advantage, especially when budget restrictions hinder the mass marketer to communicate with the market in a sufficient manner.

4.3 Isn't common sense better anyway?

Common sense seems to be an excellent basis for corporate success, as long as the criteria are general enough. Among the agents that follow such an *a priori* logic, the High Potential agent does very well in the marketplace using minimal criteria based on the size argument primarily. The Highpricer on the contrary is not as successful. The Highpricer does not have an inferior strategy or weak rationale *per se*. In the simulation conducted it turned out that the competitive environment was not favourable for the Highpricer as both The Gambler and The Imitator can undermine his idea. The Gambler can incidentally choose a similar subgroup of customers and offer a similar product at a lower price and the Imitator will copy The Highpricer's strategy as soon as it turns out to be successful. When copying the strategy The Imitator does not calculate an add-on to the average segment price as The Highpricer does and therefore alienates the customers from the latter.

4.4 Does money matter?

As already mentioned above, budget strongly interacts with the segmentation strategy chosen. If the budget is high enough for unselective market communication, no significant differences can be detected between the agents that focus on target groups and the mass marketer. If

budget constraints do exist, firms that concentrate on a smaller group of consumers are more successful.

5 Conclusions

A simulation study was conducted in order to investigate the success of different segment choice strategies in an artificial market environment. Five different types of agents with varying degrees of sophistication compete against each other under 18 different market conditions. The results of the simulation are evaluated by analysing three performance criteria: sales, profit and quantities sold; all accumulated over time.

Following central conclusions can be drawn from the simulation: (1) market response based optimisation of the selection criteria (as conducted by the Adaptive Investigator) is not the most superior strategy *per se*, (2) following a mass marketing strategy can be sufficient to survive in a competitive marketplace with other companies focusing on target groups, but turns out to be very sensitive to advertising budget restrictions, (3) all agents following a concentrated segmentation strategy are less affected by advertising budget decreased and (4) *a priori* segment selection approaches are not inferior to entirely data driven approaches in general, they can turn out to be worse if the focus of attention is too narrow, as it is the case for The Highpricer.

The results of our simulation should be taken rather indicative than conclusive. Simulation studies always imply a tradeoff between realistic modeling and uncontrollable complexity. However, empirical investigation is hardly feasible because real world data is not available if measurable at all. In addition it would be impossible to control for the intervening variables. Thus, further empirical research regarding that issue should emphasize on singular stylized facts which can be used to assess compliance between models designed and reality.

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