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Integrated competition and customer analysis: Managing market share efficiently

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Abstract Like other types of executive, chief marketing officers are caught between opposing forces: driving long-term brand growth while making short-term sales targets. This paper proposes an integrated framework of analytics that is referred to as integrated competition models and consumer analysis, allowing readers to identify the drivers of brand choice and to understand which consumers are most likely to switch. These two types of insight help firms understand how to win or protect market share from competitors while staying true to the positioning of the brand and knowing who to target with what message. The framework also allows the identification of market structure maps that can be of help with more long-term business challenges, such as potential innovation or disruption areas.

KEYWORDS: competition analysis, switchable consumer, brand choice models, market structure analysis, loyalty and branding

INTRODUCTION

Chief marketing officers (CMOs) are caught, like other executives, between opposing forces: driving long-term brand growth while making the short-term numbers, driving sales but with less budget, and managing their brand while the category is being disrupted. No wonder many are focused on competitive benchmarking, since growth in most categories will come at the expense of competitors and, as a result, CMOs will need to know how to win market share and how to win it efficiently. Almost any CMO will at some point or another face one of the below five business problems:

1. Imagine you are the CMO of a big Fortune 500 company and have more than 50 per cent market share. Yet, something is nagging you. There is this small brand that has something that you do not. Do they have it in them to un-seat your brand? How can you identify if your market share is at risk?
2. Alternatively, you are the CMO of a small company with maybe 1 or 2 per cent market share. You are up against a few powerful and reputable firms. How do you survive, let alone grow? The business question is not only 'How can I win market share?', but also 'How can I win market share efficiently?', even if your marketing budget is not as high as the big guys.
3. Your brand is competing in a crowded market (think cars, credit cards, fast food chains, car insurance, kitchen appliances, beer, pet food, etc.). In these markets, your insights need to go further: you need to understand who you are competing with most directly so you can adequately position yourself against them. You need to understand which customers are at risk of defecting to which competitor, and which competitors you are most likely to attract customers from.
4. When you have lots of heterogeneous customers, some are going to be more valuable than others. You need to keep your most valuable customers. Likewise, you need to understand which new customers are going to be easiest to acquire.
5. Lastly, while you are managing your brand and are working on protecting or growing your market share, you need to understand if your market is ripe for disruption or has unfulfilled innovation opportunities.

The above five business challenges can be answered within an integrated framework of analytics that we refer to as competition models and customer analysis.

HOW TO WIN MARKET SHARE: COMPETE MODELS

Let us start with the first question: how can we win or defend market share? The insights needed to tackle this marketing challenge come from what we refer to as 'compete models'. A compete model[1] has the following components:

A. A measure of a consumer-preferred choice over an alternative choice. For example:
   - some consumers prefer Bank of America over Wells Fargo;
   - some IT professionals prefer Linux over Windows;
   - some mothers prefer Graco over Britax;
   - some people prefer Coors over Miller; and
   - some eat Mars bars more often than Hershey's bars.

B. A set of measures on which the competing brand alternatives can be compared.

So, the dependent measure is binary (ie yes or no, indicating preferred brand, for instance) and the independent measures are how the brands perform on some attributes. We first applied this approach in the enterprise software market where we were interested to understand if a juggernaut brand (more than 70 per cent market share) would have to take a small entry brand (less than 3 per cent market share) seriously. It turned out that the answer was Yes! In the first step of the compete model, consumer brand preference choices were modelled as a function of about 15 brand perceptions (using a logit model). Each of the two brands was rated on 15 perceptions, yielding a total initial set of 30 potential

COMPETE MODEL DRIVERS	PREDICTED CHANGE IN SHARE (as a result of getting the lagging brand to parity with leading brand on each attribute)
Training	**25%↓**
Features	4.6% ↓
Price	7.5%↑
Product Quality	4.7% ↑

Figure 1: Impact of simulated changes in key drivers

Note: The first column shows the drivers from the compete model: training, etc. The second column shows the change in predicted market share if we increase the entry brand's perception to the same level as the juggernaut brand. For Price and Product Quality the entry brand had a better average perception. Here we simulated what would happen if the juggernaut brand caught up with the entry brand.

driver variables (15 for each of the two brands). The result of this modelling exercise was that we found about six significant perception drivers. Next we did simulations: we simulated the impact on market share if one competitor could catch up with the other, on each of the six perception drivers. In Figure 1 we show simulations on four out of the six attributes.

This figure shows the following. The first column shows the drivers from the compete model: training, etc. Both the juggernaut brand and the entry brand have an average perception of these variables. On 'Training' and 'Features' the juggernaut brand had a better perception. The second column shows the change in predicted market share if we increase the entry brand's perception to the same level as the juggernaut brand. For 'Price' and 'Product' quality the entry brand had a better average perception. Here we simulated what would happen if the Juggernaut brand could catch up with the entry brand. The results were astounding in three ways:

1. No-one had suspected that the most important driver would have a significant impact, let alone the biggest impact. On this driver, the juggernaut performed much better than the incoming brand and so initially the juggernaut brand was not worried about this attribute;
2. Surprisingly, the results showed that the juggernaut brand stood to lose 25 per cent market share if the small brand could catch up on this most important attribute; and
3. We identified a trend that showed that, due to external factors in the environment, the performance of the small brand on this key driver would automatically improve up to a point that the juggernaut's advantage on this driver would decrease to nearly zero. We note that in order to get to this trend insight we had to look for data outside our survey. An exercise similar to a pestle analysis[2] was done after the survey insights were available. In this case the future professionals, who would be buying and using this product in the future and who were still in school (college), received training that would enable them to use the small entry brand. Hence, over time, the barrier that the entry brand was facing, ie the lack of adequate skills, would diminish. So the juggernaut brand determined that this small entry brand indeed represented a true future threat.

Initially the simulated scenarios were not believed by the management. Over a period of six months, however, we (1) replicated the result on a second dataset, and (2) were able to show that the initial choice model predicted market shares that were very close to reality. We had a second study that measured market shares. The two studies were done around the same time frame and were performed in a number of the same countries. This gave us a small number of data points (eg two waves of data, 15 countries, and two brands gave 60 data points), sufficient to look at the correlation between predicted market shares and the actual market shares. This showed a very high correlation and further added to the credibility of the model. These insights led to a full rethinking and redesign of a major advertising campaign and a structural rethinking of how to neutralise this new competitor. The model has been in use for over 10 years and over this period in certain regions the incoming brand achieved at times market shares between 20 and 30 per cent, validating the predictions and the approach. Most importantly, it allowed the juggernaut brand to maintain its dominant position.

HOW TO WIN MARKET SHARE EFFICIENTLY: THE SWITCHABLE CONSUMER

The next business question is: how can we win market share efficiently? The solution to this approach is nicely illustrated in the ABB Electric case study.[3] ABB found itself in a situation where they entered a declining market where they were up against three major competitors. So ABB set out on a programme to understand its customers and its competitors' customers better. What attributes did these customers use in their decision making and how did ABB perform on these attributes vis-à-vis their competitors? In an initial survey, consumers ranked and rated large sets of attributes. These attributes were subsequently factor analysed to identify key underlying dimensions. Next they selected one attribute for each dimension that heavily represented that dimension. In that way they ended up with 10 fairly independent attributes. Note that this approach is somewhat different from the previous example where we worked with all original survey attributes: ie in the previous example there was no factor analysis pre-step. There is some guidance in the literature as to when to use factor analysis as a pre-step.[4] Consumers also indicated their preferred suppliers. On these data a compete model (logit model) was estimated that indicated the key drivers. This first part is very similar to the 'How to win market share' scenario in the first section. The ABB team compared the market shares predicted from the choice model with the actual market shares and found the predictions to be very close to the actual numbers.

ABB Electric used this information to understand where they should make key improvements. They went further, however. They used the model to derive individual-level brand choice probabilities. Figure 2 shows what these brand choice probabilities look like for three hypothetical respondents.

The figure shows two hypothetical respondents in the rows. The second column indicates what the preferred brand of a respondent is as indicated in a survey. Columns 3–5 represent different brands. In the cells we show the individual-level brand choice probabilities as calculated from the brand choice model. As this table shows, respondent 3 has a fairly high brand choice probability for their preferred brand (as stated in the survey). The probability of choosing an alternative brand (as derived from the logit model) is rather low. On the other hand, respondent 1 prefers one brand (Westinghouse), but when we look at their brand choice probabilities then it is clear that they could easily tip over to another

Hypothetical Respondents		Individual Level Brand Choice Probabilities (%)		
	PREFERRED BRAND (As stated in survey)	BRAND 1 Westinghouse	BRAND 2 ABB	BRAND 3 GE
Respondent 1 A switchable consumer	Westinghouse	40%	35%	15%
Respondent 2 An at risk consumer	ABB	45%	50%	5%
Respondent 3 Lost cause consumer (for now)	GE	20%	15%	65%

Figure 2: The switchable consumer

Note: The figure shows three hypothetical respondents in the rows. The second column indicates what the preferred brand of a respondent is as indicated in a survey. Columns 3–5 represent different brands. In the cells we show the individual-level brand choice probabilities as calculated from the brand choice model.

brand (ABB) if such a brand were to make an appealing case. We call such consumers either a ‘switchable consumer’ or an ‘at-risk’ consumer, depending on whether it is being viewed from Westinghouse (in which case they would call this an ‘at-risk’ consumer) or ABB (in which case they would call this a switchable consumer). Note that in this application we used a logit modelling approach, although other methodologies can be used for this purpose. The logit approach has been shown to perform very well — in most cases, best.[5]

ABB Electric applied this methodology and identified these ‘switchable consumers’; next they figured out what was really important to these consumers. They compared the average ratings of the switchable consumers on these key drivers with the average ratings their competition had on these drivers. This information was used with razor focus to contact these switchable consumers, with messages that were all about the things that mattered to them and to highlight those drivers on which ABB was seen to have an advantage. The result: the market share of ABB grew from 2 per cent to 18 per cent over a 10-year period.[3,6] The authors and others[7] have successfully applied this methodology across different industries. Note that this approach is very similar to the churn models that are successfully applied by firms on transactional data, but applied inversely: rather than targeting customers to prevent them from defecting, they went after their competitor customers that were most likely to defect to them, and developed a marketing strategy specifically aimed at this switchable consumer.

HOW TO UNDERSTAND COMPETITION: A LOYALTY SEGMENTATION CASE STUDY

The following example is from a commercial project done in 2015. The category and the actual results have been disguised. In this example, a well-known food chain wanted to understand their customers better, especially consumers who said they went to this food chain most often. We note that this situation is slightly different from the previous examples. Whereas in the enterprise software and ABB example consumers typically made one brand choice (for the most part), this is obviously not the case for restaurants (and we expect will also not be the case for many CPG products). Consumers will always be likely to use a number of brands due to variety seeking or because different brands may be the best fit for a consumer-specific occasion (eg eating out with a family versus going out on a date versus going for a business lunch). Hence, the concept of brand choice is defined slightly differently: we use the concept of most often brand. Instead of asking 'what is your preferred brand', we ask what brand do you 'use most often'. From a data and modelling perspective, this situation is now identical to the previous two examples because we have a binary outcome variable: a brand is either a 'most often' brand or it is not.

The compete model (logit) was applied to explain the 'most often brand'. Respondents gave their opinion on a large set of brand attributes of food chains (only those they usually go to or consider going to). This large set of attributes was factor analysed and reduced to 32 factor drivers. These drivers were modelled against the most often brand using the logit model (similar to the model discussed in the second section). The result of this modelling exercise was 16 significant factor drivers.

The model thus aims to understand how strong individual respondents' preferences were for their most frequently used brand, and therefore how likely they were to defect to competitor brands. Applying the estimates of the logit model, we calculated the probability for each brand to be 'the most often brand'. The probabilities are calculated as follows. The logit model is a regression model where the dependent variable is binary and it estimated across the entire sample: ie we have one aggregate-level brand choice model. The estimation of such a model usually takes places over several iterations until we find a model that is able to predict the stated brand preferences (very) well. Similar to standard linear regression we get a set of regression coefficients (or weights). Whereas linear regression predicts a numerical value, however, the logit model predicts a probability. Once we have a final model, we apply these regression weights to the individual-level brand factor values. Each respondent for each brand will have a value on these brand factors indicating the degree to which the respondents associate that factor with that brand. The calculated weighted sum of these brand factor scores weighted by the corresponding regression weights results in the individual-level brand choice probabilities and allows us to classify for each brand the size of each of the following groups:

1. *Loyal consumers* are the respondents for whom the estimated brand choice probability is the highest for the brand they indicated in the survey as the most often used brand.
2. *At-risk consumers*, if the predicted probability for the stated 'most often' brand is either not the highest predicted probability or if it has a similar predicted probability compared to the other brands the consumer rated.
3. *The switchable consumer*, if the stated 'most often' brand is at risk, and there is another brand that has the potential to replace it. In other words, there are brands that have a brand choice probability that is higher (or statistically) equal to the brand choice probability of the 'most often' brand they indicated in the survey.

Figure 3 shows these various groups, and is read in the same way as Figure 2 — only in this case it is based on real respondents. If we take consumer 1, his 'most often' brand (Applebee's) has a much higher probability than Culver's (75 per cent as opposed to 5 per cent). This means that this consumer is very loyal to Applebee's and this brand is not at risk of losing this consumer. On the other hand, look at consumer 2, who has the highest probability for Culver's. Culver's does not present a huge advantage over the other brands this consumer considers or usually eats at, however. This means

	Most often brand[1]	Applebee's	Culver's	Red Lobster
Respondent 1	Applebee's	75%[2]	5%	-
Respondent 2	Culver's	49%	50%	45%

Figure 3: Logit model probability

Notes: [1]Most often brand as indicated in the survey, eg 'Tell us what restaurant brand do you go to most often?'
[2]The individual brand choice probabilities — these are the result of multiplying the respondent's brand ratings with the compete model regression weights.

that this consumer is at risk for Culver's. Both Applebee's and Red Lobster have the potential to be his new 'most often' brand in the future. Based on this classification, we were able to calculate for each brand the percentage of their customers who are loyal or at risk, and the percentage of the other customers that are switchable to them (the 'potential' percentage).

In Figure 4 the percentages for loyal and at risk add up to 100 per cent because the base for these percentages are the brand's current customers ('most often' customers). For the potential, the base is all consumers for the brand that are currently *not* using the brand 'most often'. For example, Red Lobster has more loyal customers than Applebee's and it also appears as the brand with the higher percentage of switchable consumers among the fast food chains.

To understand competitive dynamics more deeply, we can also break down the at-risk customer group and see which

Restaurant Chain	Loyal	At Risk	BASE[1]	Brand Potential	BASE[2]
Applebee's	36%	64%	69	21%	710
Culver's	41%	59%	125	23%	640
Red Lobster	45%	55%	124	26%	900
P.F. Chang's China Bistro	59%	41%	522	26%	1258
Old Country Buffet	31%	69%	29	22%	324
Panera Bread	45%	55%	187	26%	774

Figure 4: Brand classification from the logit model

Notes: [1]The base in this column is the total number of loyal and at-risk customers. Hence the percentage numbers in columns 2 and 3 add up to 100%.
[2]The base in this column is the total number of respondents that are currently not the 'most often brand' customers and consumers. The brand potential column shows the percentage of the base that is switchable to the corresponding brand in the row.

	BRAND AT RISK		
BASE SIZE	44	74	68
Potential ↓	Applebee's	Culver's	Red Lobster
Applebee's	0%	15%	25%
Culver's	14%	0%	15%
Red Lobster	34%	22%	0%
P.F. Chang's China Bistro	59%	58%	74%
Old Country Buffet	11%	11%	7%
Panera Bread	36%	32%	18%

Figure 5: Potential brands for the brands at risk

brands would replace the most often brand. Figure 5 shows this analysis for three brands: Applebee's, Culver's and Red Lobster. In the columns we show the brands that have at-risk customers. In the rows we show the brands to which these at-risk customers would defect. For example, whenever Red Lobster is at risk, PF Chang's is the brand with the higher potential to replace it.

Since we classified consumers as loyal, at risk or ('potential') we can also cross-tabulate the whole questionnaire by these loyalty segments. One interesting finding was that the frequency of consumption at fast food chains showed an unexpected spike for the percentage of Culver's at-risk customers (see Figure 6). The figure shows that, as the frequency of eating at a chain goes up, the percentage of consumers who are at risk goes down. There is one exception, however: the group who eat out about four times a month. For some reason, the switchable consumer percentage suddenly jumps up before it goes down again. This is counter-intuitive and it would be valuable for the client to find out what is going on with this group: this is a high net profit group, with a relatively large proportion of consumers to defect.

If we can identify the important drivers for the potential consumers, we will be able to increase client sales. Since we collected the attribute performance for the fast food chain that consumers consider using or usually use, we were able to profile the brand performance on the drivers by the different loyalty groups. See Figure 7, where we have five profiles:

1. The total Culver's group: this includes all respondents who go to Culver's.
2. Most often brand (MOB): this is the group of respondents for whom Culver's is their most often brand.
3. Loyal: this is the group of respondents for whom Culver's is the most often brand and according to our compete model have a low likelihood of defecting to a competing brand.

	Total Sample[1]	CULVER'S At Risk[2]
Once a Month	30%	31%
Twice a Month	30%	26%
3 Times a Month	12%	10%
4 Times a Month / Every Week	22%	**30%**
5 times a month or more	6%	3%
Average (Monthly)	2.65	2.66

Figure 6: Frequency of consumption at fast food restaurant versus degree to which at risk (Culver's profile)
Notes: [1]This column shows the percentage of respondents that eat at a certain frequency at a fast food restaurant. For example, 30% of the sample eat once a month at a fast food restaurant.
[2]This column shows the percentage of the Culver's current 'most often brand' customers that are at risk.

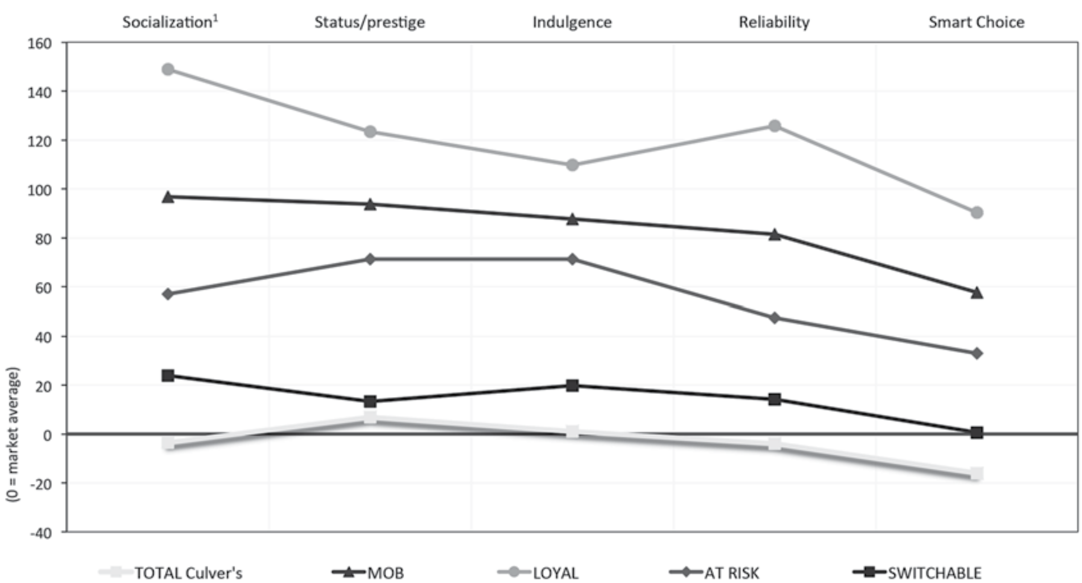

Figure 7: Culver's positioning on drivers for the different profiles (top five drivers)
Note: [1]Showing the average perception numbers for the five different loyalty groups on the top five drivers (socialisation, status/prestige, etc.

4. At risk: this is the group of respondents for whom currently Culver's is the most often brand but who according to our compete model are at risk of defecting to a competitor.
5. Switchable group: this is a group of respondents for whom Culver's is currently not the most often brand but who according to our compete model have a high likelihood of switching to Culver's.

For example, the difference in average perception between the loyal group and the at-risk group on socialisation (the most important driver) is higher than on any of the other attributes. This makes this attribute core for this category.

An interesting finding was the positioning of Culver's on the most important driver by these profiles. As we can see, the loyal consumers presented a higher gap for the positioning on this driver (compared to the other profiles): ie the difference between the highest socialisation score (for loyal) versus the lowest socialisation score (for total) is larger than the difference between the highest and the lowest scores on the other dimensions. This driver has to be improved by this chain. Besides the top driver, there is also an opportunity to work on the driver 'reliability'. We noticed that the most loyal consumers do think that Culver's is really strong on this driver. By improving these two drivers, Culver's will be able to:

a. avoid losing the 'at-risk' consumers;
b. convert potential ones into 'most often' brand users.

UNDERSTANDING THE STRATEGIC LANDSCAPE

Market structure analysis is a useful tool in understanding how consumers perceive the market. There are currently a number of approaches available to derive a market structure map, both derived and stated. Derived methods make use of perceived similarities between competing alternatives, for example, by showing respondents pairs of brands and asking how similar these brands are. Such similarity is then analysed using multi-dimensional scaling methods and/or hierarchical clustering methods. The disadvantage of this approach is that we have to collect such data, which is not always a trivial effort. Stated methods calculate similarities between brands based on these brands' ratings on a set of brand attributes.[8] We have deployed a third approach where market structure maps are derived from individual-level brand choice probabilities. We applied the Alscal[9] multi-dimensional scaling (MDS) approach because the similarity matrix that is derived from the individual-level brand choice probabilities is asymmetric. If we use a standard MDS approach the two similarities in the asymmetric matrix would be averaged and this would not be correct as it would assume that for any given set of two brands, the percentage switchable would be the same, which is clearly not true (see Figure 4). If we did not correct for this, the solution would most likely be uninformative or, worse, misleading. The distances between the brands (calculated from this MDS solution) are also analysed with a *k*-means analysis; this leads to the drawing of specific groups indicated by the colours on the map. Similar, though not identical approaches to market structure have been proposed for market share models estimated on store scanner data.[10]

Figure 8 shows the result of the Alscal/*k*-means analysis. The closer two brands are in the map, the more similar these brands are in terms of switching and hence are more likely to be substitutes. We can also try to interpret this at the dimension level. Going from the right side of the map to the left side, it seems we move from American-type food to non-American type food. The vertical dimension is harder to interpret, although it somewhat seems to represent a spectrum from basic burger-type food to more diverse food choices that are also of somewhat higher quality (eg as we move from Old Country Buffet, to Culver's, to Applebee's, to Red Lobster). As we have disguised the category and real results, we cannot reveal the real insights here. The purpose of this figure is to show that this type of analysis is feasible within the framework we presented here.

This map gives several pieces of additional insight. First, let us see if the market structure map makes sense:

- We see a number of fairly basic restaurant chains on the right side. For the most part these are American-style semi fast-food chains.

Figure 8: Market structure map based on brand choice probabilities

Note: The various brands are plotted in a two-dimensional solution. The groups that came out of the *k*-means were used to colour code brands that fell into the same *k*-means cluster.

- Then more toward the middle we see non-American choices appear. These are still chains. The ones towards the top seem to be the somewhat less fancy chains.
- On the left we see two somewhat nicer/higher end type of restaurants.

It is clear from the market structure that in the ‘basic food’ area (the right side of the map), there are lots of alternatives, but in the more sophisticated area there are only two brands. So it seems that there might be a white space. There is no nicer ‘restaurant’ version for Fazoli’s (which is an Italian food chain). Likewise, there is also no fast food version of PF Chang’s. HuHot comes close, but HuHot is ‘all you can eat’, and hence is a very different type of restaurant. Such alternatives do exist in other parts of the world, so management of, for example, Fazoli’s should consider expanding in these areas and should be aware that a competitor might do this as well. Such expansions would also fit with two of the key drivers: socialisation and reliability. It could very well be that a nice, more upscale Italian restaurant that stands out on socialisation and reliability could hit a sweet spot.

CONCLUDING REMARKS

Over the past few years, we have successfully applied the compete models and switchable consumer analysis on credit card services, banking services, consumer products and fast-moving consumer goods, and we have found this to be a very versatile approach that can be applied as a market share dynamics[11] and targeted segmentation and customer analysis approach. It has been found now that this approach can predict future market shares well, as indicated by our enterprise software case study, the ABB case study and others.[12]

In addition to this, the general approach can also be applied in many other situations such as:

1. *Brand management*. The compete model switchable consumer analysis approach calculates the switchable consumers and

the at-risk consumers. From these we can calculate the market share percentages that a brand would gain if all switchable consumers were to come over to the brand and we can calculate the market share loss if all at-risk customers were to defect from the brand. The difference between the two numbers gives us a measure of net expected short-term brand growth potential. Figure 9 — where we use banks as an example — shows a hypothetical result. For two of the three brands this potential is positive but for the third brand this number is negative: ie they stand to lose market share if they do not act. For companies who do tracking research this can now be an attractive and actionable metric that can easily be tracked and would be very useful on a scorecard.

2. *Concept testing and discrete choice conjoint*. This approach can be nicely applied to concept testing. Imagine if we knew how our concept did with the switchable consumer? We could much more effectively market our new product. Alternatively, what if we could identify the optimal combination of features for the switchable consumer segment?

3. *Funnel analysis*. A third area where we can apply the switchable consumer analysis is the context of understanding movements through the funnel. Often brand analyses are done on those respondents who consider the brand. Brand consideration is a major, often under-utilised brand metric, however. Buick was ranked as high as Lexus in a J.D. Power dependability study, yet very few consumers considered Buick at that time.[13] Applying the switchable consumer framework to the funnel means we are trying to understand which respondents that are in a given stage in the funnel are switchable to the next stage. For example, we applied this concept in a marketing mix study. The mix model indicated that the marketing efficiency was unimpressive and we were asked to diagnose the root cause of this. We analysed survey data and we found that the percentage of consumers who were aware of the brand but were found to be switchable to consider the brand was only 50 per cent, whereas the percentage of consumers who would consider the brand and were switchable to prefer

	Bank of America	Wells Fargo	ING
Switchable to Brand[1]	14.0%	2.7%	8.0%
At Risk to defect brand[2]	8.7%	1.0%	14.3%
Short-Term Brand Growth Potential	**5.3%**	**1.6%**	**-6.3%**

CONCLUSION	
Bank of America	ING
Likely to Grow	**Likely to Loose Market Share**

Figure 9: Short-term brand growth potential

Notes: [1]The numbers in this row indicate the percentage market share the brand in the column (Bank of America) stands to gain if all switchable consumers were won over.
[2]The numbers in this row indicate the percentage market share that the brand stands to lose if all at-risk customers defect.

the brand was 80 per cent. Clearly, from a marketing communication perspective, it would pay off to target direct marketing towards consumers who were already considering the brand, versus trying to reach everybody.

In sum: competition and customer analysis framework is a powerful analysis and general framework that can successfully work for a variety of marketing problems. In one approach we get five strategic outcomes:

1. drivers of brand choice (proxy for market share);
2. the identification of those consumers most likely to switch;
3. an identification of the brands that are going to be the most likely competitors;
4. an early warning system that can tell where the brand is currently headed; and
5. outcomes that can be used to create a strategic market structure map.

These five types of insights allow the marketer to address both short-term and longer term objectives and can help to make sure that decisions taken to drive short-term sales do not undermine long-term brand building and also fit with more strategic brand portfolio decisions (eg as to what area to expand). On top of that, we have identified several other areas where this approach can amplify the actionability of the insights (eg brand management, concept testing and funnel analysis).

References

1. Gensch, D. (1984) 'Targeting the switchable consumer', *Marketing Science*, Vol. 3, No. 1, pp. 41–54.
2. Paul, D., Cadle, J. and Yeates, D. (2010) 'Business Analysis', British Informatics Society Publishing, Swindon.
3. Gensch, D., Aversa, N. and Moore, S. P. (1990) 'A choice-modeling market information system that enabled ABB Electric to expand its market', *Interfaces*, Vol. 20, No. 1, pp. 6–25.
4. Gensch, D. and Ghose, S. (1992) 'A dimensional versus attribute approach for disaggregate choice models', *Marketing Letters*, Vol. 3, No. 1, pp. 27–37.
5. Neslin, S., Gupta, S., Kamakura, W., Lu, J. and Mason, C. (2006) 'Defection detection: Measuring and understanding the predictive accuracy of customer churn models', *Journal of Marketing Research*, Vol. XLIII, May, pp. 204–211.
6. Slywotzky, A. and Shapiro, B. P. (1993) 'Leveraging to beat the odds: The new marketing mind-set, *Harvard Business Review*, Vol. 71, No. 5, pp. 97–107.
7. Young, M. (2002) 'Choice-based segmentation and targeting the switchable consumer', *Marketing Management Journal*, Vol. 12, No. 1, pp. 98–106.
8. For a recent overview, see Elrod, T., Russell, G., Shocker, A. D., *et al*. (2002) 'Inferring market structure from customer response to competing and complementary products', *Marketing Letters*, Vol. 13, No. 3, pp. 219–230.
9. Takane, Y., Young, F. W. and DeLeeuw, J. (1977) 'Nonmetric individual differences scaling: An alternating least squares method with optimal scaling features', *Psychometrika*, Vol. 42, pp. 7–67.
10. Cooper, L. G. (1988) 'Competitive maps: The structure underlying asymmetric cross-elasticities', *Management Science*, Vol. 34, No. 6, pp. 707–723.
11. Vriens, M. (2012) 'The Insights Advantage: Knowing How to Win', i-Universe Publishing, Bloomington, IN.
12. Quagrainie, K. K. (2004) 'Forecasting market share using a flexible logistic model', Paper presented at the Southern Agricultural Economics Association, Tulsa, OK.
13. Hauser, J. R., Din, M. and Gaskin, S. P. (2009) 'Non-compensatory (and compensatory) models of consideration set decisions', *Proceedings of the Sawtooth Software Conference*, Delray Beach, FL, 23rd–27th March.