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Market Structure: The last thirty-five years

The aim of this document is to describe the development of market structure analysis (MSA) from the point of view of the practitioner rather than the academic. Although we make reference to the academic literature, the genesis of quantitative MSA began with the Hendry group who purposely kept the inner workings of their model a secret. After Hendry and up to the present, the fundamental story of MSA is one of research practice not keeping up with modern advances in the analysis of marketing data.

Broadly speaking, MSA describes the nature of competition among products in a market. This competition is fundamentally related to a product's attributes (e.g. flavor) with each attribute having various levels (e.g. strawberry, vanilla, etc). Competition may involve attributes that are shared among products (e.g. every food product has a calorie count) or the attributes may be innovations that may be found in only one product.

The basic assumption of MSA is that competition is directly related to the consumers' need-states or motivations. Consumers search for product attributes that satisfy a need, desire, motive, wish, or craving. The goal of much market structure work is to link competitive structure through the product attributes to human needs.

Data for the analysis of market structure usually consists of a series of consumer purchases from which we try to discern the patterns of loyalty and switching. Data may be a long series of individual purchases such as in Gaudagni & Little (1983), or a simple switching matrix where data are collected at two time points (Grover & Srinivasan, 1987), or the sum of many consecutive switches aggregated into a switching table (Rao & Sabavala, 1981). Most analysts assume a zero-order Markov process (switches occur from Brand A to Brand B) rather than assuming a higher order Markov process (switch from A to B to C).

The Hendry System

Many of the methods in use today are rooted in the original Hendry method that dates from about 1972. Since this method is credited as the genesis of MSA, it is worth describing in some detail, yet at the same time acknowledging that no in-depth description of the Hendry system has been published in any public forum. With this in mind, it is also worth noting that little has been published in the academic literature on the Hendry system in past 30 years.

One of the few published works on the Hendry system is the article by Kalwani and Morrison (1977). From a careful reading of this article, it is possible to derive some of the mechanics. The full theory of ***Hendrodynamics*** and its various extensions to new product forecasting, media spend optimization, assortment, distribution and price have not been made public.

The Hendry method involves a manually-created, stepwise procedure to decompose a superset of product attributes (e.g. brands, forms, flavors, etc) into the market hierarchy. Within each attribute are various levels such as the Brand set {Tide, All, Arm & Hammer, etc.}. Each step of the hierarchy from top to bottom corresponds to an attribute and defines a ***direct competing set***. The order of the hierarchy is determined by a measure of entropy called "Kw," which is calculated as the ratio of the observed number of non-loyal consumers at that step to the number of non-loyal consumers you would expect by chance. Kw ranges from zero to one, with zero reflecting maximum loyalty (no/little switching) and one reflecting switching from one product to another in proportion to marginal shares (random switching).

The trees that are subsequently built from this process have the attributes with maximum loyalty (i.e. Kw small) at the top of the tree and minimum loyalty at the bottom. Despite the scientific sounding background of the Hendry procedure, the exact order of the attributes is subject to considerable choice by the analyst. In mature markets using the Hendry procedure, about 80%-90% of the time the first split in the uppermost part of the tree is "brand," reflecting either a very high stickiness factor for brand equities or, more cynically, a desire by the analyst to show marketers that brands matter the most.

The Hendry system also includes a notion called ***par share,*** which is a measure of the vulnerability of a competitive set to the entry of a new product. The par share idea was later extended to include a way to estimate the media spending required to support a brand. Brands needed to spend more than average to gain share in a low par share (or highly loyal) set and to spend less than average in a high par share (switching) set. In short, inventing a new "brand" usually costs a lot, whereas introducing a new flavor of jelly costs much less.

While there was much that was brilliant about Hendry -- and the name certainly became synonymous with MSA in many CPG companies, it has key failings:

1. It is not based on a theory of consumer behavior.
2. Since it uses aggregate-level data, it does not take account of heterogeneity in consumer behavior, either at the level of a segment or the level of the individual.
3. It does not integrate distribution, price, promotion and advertising in the main model, but rather through add-on analyses.
4. It does not offer any direct insight into need-states, but rather requires that need-states be inferred after the construction of the tree.

Over the years, many companies have attempted to mimic or improve upon the Hendry system. This effort included the Hendry Company itself, which was bought by IRI, and Henry Rak's company that was bought by McKinsey. Some of these companies knew the inner workings of the Hendry process and continued them. Others took certain parts of the model and replaced it with something easier to produce. For instance, IRI replaced the stepwise entropy process with hierarchical clustering based on vectors of product attributes.

The tree representation was very useful for prioritizing the splits for managers but it also presented several limitations. Did the levels of the tree correspond to a hierarchy of needs – with major need-states at the top and mere preferences at the bottom? Was there always a strict order to the branches in the tree or were some attributes tied? How would a tie be represented? Could one tree capture all heterogeneity in a market?

In response to these ambiguities, Hendry and Henry Rak developed the notion of ***mixed modes*** – these were ways of "fuzzing up" the trees to allow more than one split to dominate. But ultimately, a method that based itself on an analogy of consumers to particles of energized gases achieving entropy through a series of heat transfers could not cope with the fact that the individual particles of gas might have separate wants and needs.

Other approaches to MSA

Probably the most common approach to MSA, outside of the Hendry model, utilizes hierarchical clustering applied to a matrix of product proximities. This matrix of proximities is typically created from a history of household purchases derived from panel data. The matrix is aggregated across purchase occasions, with rows representing "from" and the columns representing the switch "to." The main diagonal of this matrix represents the degree of loyalty in the market: switch from Brand A to Brand A.

The earliest academic paper in this tradition is the work by Rao and Sabavala (1981). These authors create a normalized aggregate symmetric switching matrix (A→B is equal to B→A) from household panel data. Note that the effects of market share are dampened through their normalization method. As another way to develop a tree-structure, the hand-crafted Hendry method is replaced by hierarchical clustering in this paper. Rao and Sabavala apply their method to the lower triangle of the switching matrix.

DeSarbo and De Soete (1984) improve upon this previous work by pointing out that the assumption of a symmetric switching matrix may be incorrect. In many markets, price reductions and promotions of higher quality goods will induce users of mainstream goods to trade up. Yet, those loyal to the higher quality goods are much less likely to trade down when mainstream products are promoted. In addition, the market may not be in equilibrium during the time that data are collected, nor is symmetry necessarily expected when aggregating over heterogeneous consumers who have different consideration sets. They first show that using the lower triangle of the switching matrix yields a different tree than either the upper triangle or an averaged upper-lower triangle. A new procedure to generate an aggregate asymmetric tree is then introduced, which can then be subjected to hierarchical clustering, or better yet, overlapping clustering.

However, like the Hendry system, hierarchical clustering has similar flaws:

1. It is not based on a theory of consumer behavior.
2. It uses aggregate- and not household-level data.
3. The marketing mix cannot affect the tree structure explicitly.
4. It does not offer any direct insight into need-states, which are imposed after the construction of the tree.

Newer Contributions

Over the years, several advances in the academic world have been made that have found surprisingly little traction in the applied CPG MSA world.

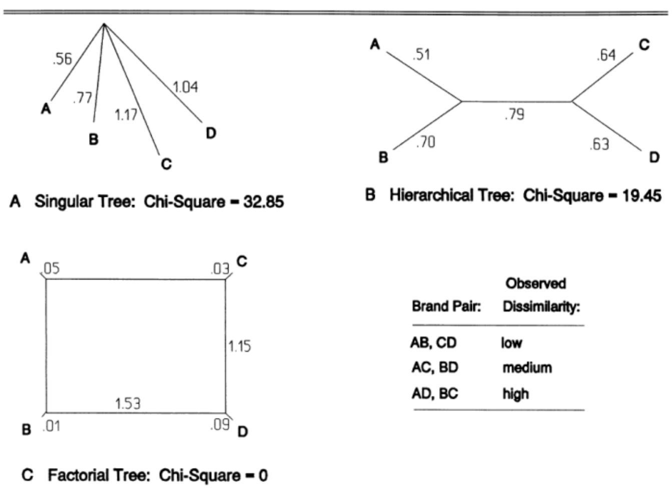
The main academic advances are in the area of understanding and modeling ***consumer heterogeneity***. The Hendry tree is delivered as a single and complete representation of the total heterogeneity in a market. However, there is no provision for consumer segments which might evidence very different trees. For instance, could there be a brand-first segment which switches between forms within each brand, and then also a form-first segment which was originally driven by a new innovation and then switched brands in order to buy the new form?

In the academic world, a more rigorous approach was being used to explain heterogeneity within the context of consumer psychology. Using a latent class model applied to two consecutive time periods of purchase data, Grover & Srinivasan (1987) divided consumers into several 100% loyal segments (bought the same product into the two time periods) and then allocated the remainder of consumers to several segments of switchers who did not purchase the same product at the two time periods. Attributes of the products preferred by each of the four switching segments revealed that different kinds of decision trees might be more appropriate for one segment versus another.

This work was later extended by Jain et al (1990) who developed a model that allowed for within-segment heterogeneity. This allowed for understanding the vulnerability and strength of each product, based on its attributes, within a segment and also allowed the size and composition of the loyal segments to be estimated in the same model as the switching segments.

Some later advances were made in producing representations of switching matrices that were not restricted to be trees. Novak (1993) used a regression approach to model the log-odds ratios of switching pairs using product attributes. The resulting market structures could be displayed in terms of loyalty components and shared attributes in cubes, trees, or combinations of the two. The cubes were essentially the interactions of two or more variables. This bypassed the need for a formal sequence of splits in the tree and allowed two or three attributes to share the top spot. This representation was similar to Grover & Srinivasan in that it separated the brand loyals from the switching segments who sought common attributes.

Figure 1
THREE TREE REPRESENTATIONS OF LOG-ODDS RATIOS



Other advances were occurring in the understanding of switching ***asymmetry***. Most analyses of switching, including Hendry, consider that there is no difference between "switching in" and "switching out." I may switch from strawberry flavor to raspberry flavor all I want, the key thing that a market structure analysis is trying to understand is whether my switching between flavors happens within one brand or whether I switch brands in order to make the flavor switch. The key assumption is that the system represented by the switching matrix is in ***equilibrium***. To the extent that new forms appear that only one or a few manufacturers can produce, or that ***trade-up*** options appear in the market where consumers will always switch into the trade-up product but never switch out of it, then all of the earlier methods described will break down.

Similarly, these attempts to develop a representation of market structure all ignore the role played, at least short term, by the marketing mix. Without taking the effects of marketing spend into account, an approach based purely on switching data misses the role of managerial actions on competitive structure. Thus, in this case, it may be that some of the observed structure can be attributed specifically to marketing interventions rather than being a result of consumer desires.

It is particularly ironic that Grover & Srinivasan (1987), Jain et al (1990) and Novak (1992) all use the standard IRI coffee data from the mid 1980's where the switching is dominated by caffeinated versus decaffeinated and ground coffee versus instant. The later arrivals of Starbucks coffee and of Keurig pods are both examples of asymmetries and innovations that these models would not handle well.

Current Frontier in Market Structure Analysis

For practitioners who are interested in representing market structure, there are now tools which overcome the weaknesses of the earlier tools. However, the graphics generated by MSA is not enough to investigate courses of action. The results of MSA must be married in a systematic way to both the need-states that drive loyalty and switching behavior and to the spending on marketing tactics that drive an ROI analysis.

The modern MSA should help the company decide on what markets to enter, what new products to launch, to forecast product volumes under competition, to formulate plans to reinforce loyalty, to create or change positionings, or modify the resources allocated to the marketing mix.

Hendry work did not consider the wider need-states and tended to assume that the reasons that products with certain attributes were chosen was self-evident. Later Hendry practitioners, like Henry Rak, attempted to draw associations between attributes in a tree and the need-states. However, these associations were almost always derived from a different data source and thus the linkages were based, at best, on face-validity and, at worst, were tenuous. The limitation of this approach is that it reflects the beliefs of the analyst, which may not be wrong, but which cannot lead to fresh insight such as the strength and variety of associations between attributes and the need-states.

This ad hoc approach cannot also lead to a systematic understanding of what constitutes "loyalty." Is it an active pursuit of the brand and a confirmation of the attributes that persistently satisfy need-states? Is it merely the result of the scale of a product and the self-reinforcing logistics of ubiquitous brands? Is loyalty an unconscious habit? Is it a pursuit of the merely "good enough" and less mentally taxing on the consumer than switching?

It is clear that both the product switching that is driven by the active satisfaction of wants and needs and the purchase stickiness called "loyalty" must be understood as the direct effect of purchase motives that are manifested as the switching patterns in individual household data.

Finally, switching models need to incorporate the marketing mix. As stated, the Hendry model used the notion of par share to get estimates of the right amount of media spending required to launch a brand. Later, the Hendry group sought to provide the same sort of add-on services to deal with distribution and pricing. However, this was done before the advent of the modern sales response model with its finely calibrated measurement of the impacts of both short and long term drivers of the marketing mix.

The incorporation of marketing mix factors into MSA requires that we leave the convenience and comfort of aggregate switching matrices and adopt a disaggregate approach. Only in this way can the observed market spend data and need-state data be matched to align with the household panel purchases. It is in this context that we now offer the following potential solutions.

Our Solutions

We take as our fundamentals the following components:

1. We assume that household purchasing follows a zero order Markov process. This assumption has been shown many times to hold in household panel data.
2. Product choice is influenced by the marketing mix. To understand "true" switching, these effects must be parceled out and controlled for.
3. Households have different purchase rates and preferences. This heterogeneity must be explicitly modeled and accounted for.

4. Market segments probably exist, where members of a segment purchase similar products to fulfill similar needs/wants.
5. Needs and wants can be, in circumstances to be discussed, an explicit part of the MSA model.
6. While trees are a clever way of displaying market structure, a method such as hierarchical clustering that produces a tree should not be driving the analysis. Trees can be displayed after a comprehensive method generates a likely structure.
7. Finally, robust goodness-of-fit tests should supplement the analyst-only judgment applied in the Hendry model and these tests should supplant the weak tests for structure that are found in hierarchical clustering.

Our approach applies the following steps.

- For each household panel purchase, we create a choice set of both the chosen (purchased) item and considered-yet-not-purchased items (Erdem et al, 1999). Each and every purchase by the household contributes one such choice set to the overall analytic database.
- We employ hierarchical Bayesian estimation to the data, which permits us to estimate the direct effects of marketing tactics and product attributes, while at the same time, estimating the interactions of household characteristics and these other variables. This permits us to understand, for example, if higher or lower income households are more or less price sensitive in this category of interest.
- While the magnitude of these predictors are interesting in and of themselves, the reason that we include them in our model is so that we can generate a more "pure" estimate of the switching probabilities after we have controlled for marketing mix effects and for between household differences.
- We also impose a Latent Class structure on the households, so that we discover segments of consumers who have similar switching behaviors (Jain et al, 1990).
- From the resulting coefficients, which are estimated for every individual household, we can then create a switching matrix in total and for each derived segment. Since we are now operating at the household level, we have also effectively controlled for brand size.
- Several different modeling procedures can be applied to these new switching data, from hierarchical clustering to more advanced psychometric procedures.

The point of this step is to generate a graphical representation of the market that be easily understood by management.

- If there is interest, motives and need-states can be included in the analysis by fusing the household panel data with a targeted consumer survey (Swait and Andrews, 2003). In this survey, we would present respondents with a simulated shelf set and ask them to make choices within the context of the need state that drives the purchase. This part of the model employs the procedures outlined in Yang et al (2002) for connecting motives to product attributes to product choice. Swait and Andrews show that this data fusion exercise yields the best of both worlds: the effects due to the marketing mix and household purchase dynamics and the in-depth attitudinal and motivational understanding available through survey research.
- We then imbed the results of the MSA in a simulation tool which can be used by managers to understand the competitive landscape, to diagnose white space opportunities, to forecast product volumes under competition, and so on.

Conclusion

The field of market structure analysis has advanced far beyond the simple and incomplete methods introduced by the Hendry system or delivered by simple aggregate switching matrices analyzed with hierarchical clustering.

As leaders in the field of advanced marketing analytics, in4mation insights applies the most theoretically and scientifically sound methods, so that all relevant influences on market structure are included in a complete model of household purchasing behavior.

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