Market modelling

Classifying market models

By Chuck Chakrapani

Varieties of market models

In the last article we defined a model as someone's idea of how things work. This is a reasonable definition, but it is too broad. As Lunn et al. point out in the *Consumer Market Research Handbook*, a model can be macro or micro, statistical or behavioural, attitude-oriented or behaviour-oriented, explanatory or predictive.

Micro vs. Macro

A *macro* model models a system. For instance, when we look at the market as a whole and model how it works, we are working with a macro model. Such a macro model can be based on theory or on empirical data. A large scale econometric model may be considered a macro model.

A *micro* model, on the other hand, models components of a system. For instance, we can model individual consumers in different segments of the market and attempt to predict their aggregate effect on the market. Such a model would be considered a micro model.

Whether one wants to build a micro or a macro model will depend on the context. Most marketing research and data based models tend to be micro models. Macro models (if they are supported by empirical findings) may be useful in developing an understanding of the system as a whole.

Behavioural vs. Statistical

In modelling the market, we are faced with two questions: How and Why. *How* do consumers behave? *Why* do they behave the way they do?

Behavioural models attempt to answer the question why. Why do some consumers buy higher priced goods and services while other consumers buy lower priced goods and services? Why are customers loyal to some brands and not to others? Why is negative advertising successful? Such behavioural models are often based on (proven and unproven) psychological and sociological theories.

In contrast, *Statistical* models attempt to answer the question How. What proportion of consumers buys higher priced goods and services? What proportion buys lower priced goods and services? To what extent are customers loyal to a given brand? How successful are negative advertisements?

Behavioural models have intuitive appeal because they attempt to satisfy our curiosity as to why things happen the way they do. Implied in them is the promise that one can extend the current model and build new ones as we understand the underlying mechanism.

In reality, however, many behavioural models are simply theories. To the extent that they are supported only be sparse empirical data, they can present a misleading view of the world.

Robust statistical models, on the other hand, can be used to great advantage even if we only vaguely understand the behavioural underpinnings. For instance, statistical models can show a strong and consistent relationship between affluence and generic brand buying. One does not have to have a behavioural model to benefit from this observed relationship, although a sound theory would enable us to be more confident about the relationship.

Pure statistical models are often criticized because they are 'black box' models i.e. we do not know why certain things are related in a certain way. Behavioural models are assumed to illustrate the black box. Paradoxically, what will illuminate the black box is the empirical data and consistent relationships provided by statistical models. Without this input, the validity of a behavioural model may never be known. It may not be an exaggeration to state that many behavioural models are based on a less-than-solid observed statistical relationship. As a result, they tend to be less valuable than statistical models. Despite these comments, these two classes of models should not be pitted against one another. Rather they should be considered complementary to each other.

Attitudinal vs. Behavioural

We can use either attitudes or behaviours to predict behaviour. When we use a number of *attitudinal* questions such as consumer's likes and dislikes, to predict their brand usage, we are using an attitudinal model to predict behaviour.

As an alternative to this approach, we can use *behavioural* measures, such as the number of times the brand was bought in the past 12 months, to predict future brand buying behaviour. Our model in this case is behavioural.

Whether we hypothesize that behaviour is primarily the result of attitudes,as given below:

Behaviour = f (attitudes)

or assume that attitudes are primarily the result of behaviour, as given below

Attitudes = f (behaviour)

it is generally accepted that attitudes and behaviour influence each other. As a corollary to this, attitudes influence other attitudes and behaviour influences other behaviours.

Given this interdependence, which class of models - attitudinal or behavioural - should we use? The answer to this question is based on pragmatic rather than theoretical considerations. Behavioural measures are more objective than attitudinal measures.

For instance, *number of cigarettes smoked yesterday* (a behavioural measure) will have the same meaning to all consumers while the *extent of agreement to an attitudinal statement on a 10-point scale* (attitudinal) may mean different things to different consumers. Some consumers may consider a rating of 7 to be 'good' while others may consider it to be 'a little above the average'.

Furthermore, databases increasingly provide reliable behavioural information. For these reasons, where possible, behavioural models are preferred over attitudinal models.

Hybrid models
The above classification is useful in understanding the broad range of activities that come under the general heading ‘market modelling’. However, now that marketing information and analytic systems incorporate data from a variety of sources (such as data bases, geodemographic information, marketing research data, statistical tools). The distinction among these different types of models has become less clear cut. Many marketing models tend to be ‘hybrid models’. Trends in information technology indicate that hybrid models are likely to be the norm in the future.

Resourcess for building marketing models
One can build models to any aspect of marketing.
- How can we identify the influence of different variables in our customer database to effectively build a relationship with our customers?
- How can we relate customer demographics and other attributes and relate them to advertising so we can relate advertising expenditure to the sales generated by advertising?
- How can we identify the differential effect of price and advertising on customer loyalty and brand switching?
- How do economic conditions affect purchase of luxury cars?

Such questions can be multiplied endlessly.

When we look at the list of examples, it is obvious that the nature of the questions have not changed over the years. But, as we discussed earlier, we have two new resources available to us: extensive database information and almost limitless computing power. These two developments have made it possible to define the test models that are *formal* (i.e. the terms of the models are clearly defined from an operational point of view) and *quantitative* (i.e. the results of the model can be expressed numerically). We will explore both theoretical and empirical models.

Predictive models vs. structural models
the availability of sophisticated databases and our ability to handle them with relative ease have not changed the basic structure of the problems we face.

All marketing models are designed to answer - directly or indirectly - one single question: How to maximize our resources, how to maximize our return on investment? If we review the questions mentioned in the previous section (or any other marketing question for that matter) we will note that they are ultimately aimed at maximizing our return on investment.

This would indicate that what marketers are interest in is predicting the effects of different marketing mix and marketing variables. It would appear that what interests marketers are *predictive models*.

There are also occasions when it is useful to organize our customers into homogenous groups. This is achieved using *structural modelling*. Structural modelling has two uses. First, this procedure, when used in conjunction with predictive models can improve predictive efficiency. Second, classification of customers enable us to conserve marketing resources through refined targeting. In one sense, even classification models aim at predicting the impact of such classification on marketing efforts. In this sense, the fundamental objective of all marketing models is some form of prediction.

Paradoxically, while the aim of all structural models is eventually some kind of prediction, all predictive models, in reality, are only structural models. Predictability is an assumption of the modeller and is not directly derived from the data. This can be illustrated simply using a standard predictive type model, Multiple Regression Analysis. Such a model takes the form:

Sales of Outlet A =
.8* No. of items available
-.6* Average price index
+.6* Trade area population
+.5* # of office buildings in he trade area
+.3* Floor space in sq.ft.

The above equation would indicate that an outlet could increase its sales by increasing the number of items available, by lowering the average price etc. But suppose an outlet attempts to increase its sales by simply increasing its floor space. Will the strategy really work? Probably not.

Despite the predictive structure of the Multiple Regression equation (eg., lower price will result in higher sales), the basic relationship is structural. The relationship between price and sales, and between the number of items and sales may appear predictive, but they are in fact structural.

Mathematics does not guarantee predictability

In reality, all predictive models are in fact structural. The distinction between structural and predictive models is based on the assumptions made by the modeller and the mathematical nature of the relationships.

It is critical to understand that structural models become predictive *only* as a result of the assumptions made by the modeller. No mathematical model can, in and of itself, predict the future. Any claim of predictability attributed to a predictive model should first pass through logic or at least a face validity check. If this is not possible - as when we are not sure of the relationship - we need to observe the results closely if we take any marketing action based on the model.

As we already noted, one of the greatest errors in applying ‘predictive’ models is the mistaken belief that predictability is guaranteed by the underlying mathematics. Hence the frequent unquestioning acceptance of the claims made by modellers. It is not a wise policy for a marketer to accept any model that he or she does not properly understand, just because the model appears ‘scientific’ and is based on sound mathematics.

For the same reason, anyone buying a ‘canned’ or prepackaged model whose elements are ‘proprietary’ should be very skeptical of the product for the simple reason that the marketer cannot evaluate the mathematics (hence the underlying assumptions) of the model to examine the reasonableness of those assumptions.

In subsequent articles in this series we will look more closely at some major quantitative models and their applications.

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