Advanced Methods in Marketing Econometrics

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Econometrics is broadly defined as the application of statistical and mathematical models to test and quantify economic theory. Marketing econometrics specifically aims to quantify the role of marketing in driving consumer purchase behaviour and is often called Marketing Mix Modelling (MMM).

All marketing mix models are essentially price demand curves augmented to include a wide range of media and economic variables and routinely offered by consultancies and media agencies to assist clients in three main areas:

1. Price elasticity, marketing performance and Return on Investment (ROI)
2. Optimal allocation of marketing resources for business growth
3. Forecasting consumer demand to aid supply chain planning

The economic foundations of marketing mix models are typically approximated with simple single equation regression models of product demand. However, these approaches are ill-equipped to solve many client business issues. In this article, I look at how marketing analytics has evolved to provide more accurate representations of consumer demand.

Competitive structure

MMM analysis is based on microeconomic theories of demand behaviour, where consumers choose between competing products based on price, marketing and an income constraint. This structure is more accurately represented using information across the full product consideration set. Consequently, more advanced MMM approaches use interactive systems of brand choice that treat the entire category as a single unit. This leads to improved estimation of competitive steal, cannibalisation and halo effects across client product portfolios, together with category expansion effects of brand specific marketing. The result is more accurate price elasticities, marketing ROI and budget allocation facilitating the manufacturer-retailer relationship (Cain, 2014).

Short and long-term behaviour

Consumer demand comprises two core components: short-term call-to action behaviour and longer-term brand evolution. In MMM terms, these are referred to as incremental and base volume respectively. Many marketing strategies are designed to build long-term brand loyalty, driving evolution in base sales over time. However, the baselines of all conventional MMM analyses are fixed or deterministic by construction and consequently incapable of accommodating long-term marketing effects.

To address this, modern MMM approaches require more flexible time series estimation techniques such as Unobserved Component Modelling (UCM). This directly separates the short and long-run features of the data, generating a dynamic evolving baseline which can be meaningfully analysed to quantify long-term ROI (Cain, 2008, 2010).

Digital and social media

MMM has historically focused on traditional offline marketing evaluation. However, the advent of multi-channel off and online marketing, has forced modellers to re-think the basic economic structure in order to incorporate the online world (Cain, 2014).

Incorporating digital media such as paid search and online display involves an explicit recognition of the off and online consumer journey. At its most basic, the focus is predominantly on paid and owned media, with traditional marketing investments stimulating a purchase cycle that starts with natural online search, continuing through to website research and finally onto online and offline purchase. This approach is intended to capture how holistic paid media strategies drive owned media and the brand content experience.

Social or earned media is the next step in this process, dealing with how consumers talk about and share the content experience within their networks. This is typically handled via incorporating additional steps into the purchase cycle such as Twitter feeds, Facebook likes or consumer sentiment metrics. Dynamic UCM estimation is particularly critical in this setting, where the viral nature of online sharing implies that social media plays a key role in long-term brand building.

The consumer journey approach to MMM constitutes a structural equation model, where dependent (explained) variables also serve as independent (explanatory) drivers. This poses a problem for standard regression methods, where valid causal inference requires that each explanatory variable is exogenous or fixed outside the model. Dependent variables are determined inside the system and defined as endogenous. If used as contemporaneous explanatory variables, this leads to what is known as an *identification* problem, confounding correlation and causation. The result is biased estimation of the system parameters. Various econometric techniques are deployed to handle this, where the causal relationships are modelled subject to a chosen identification scheme.

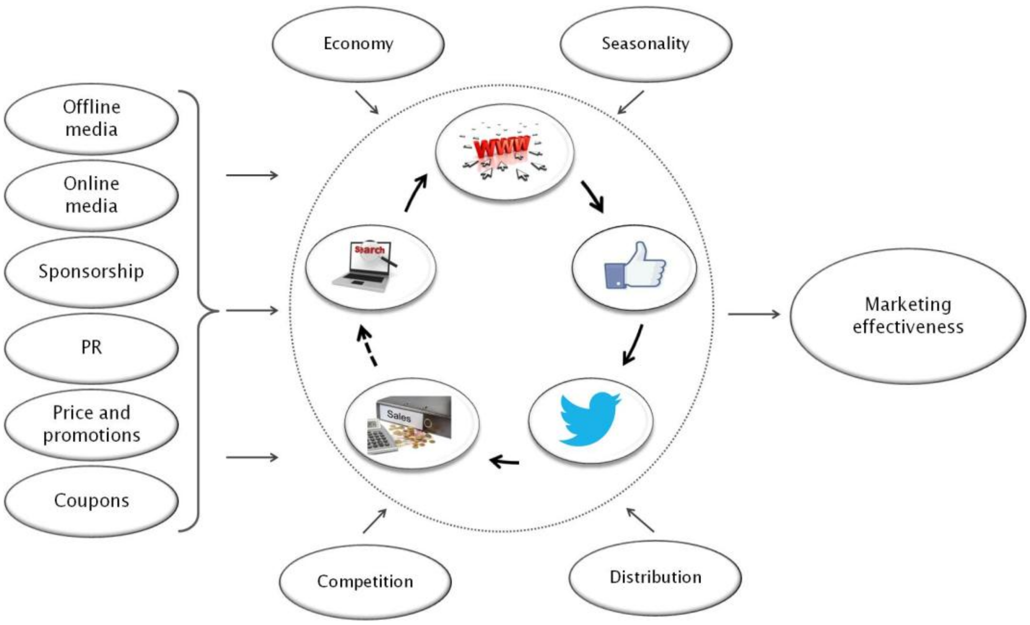
Path models

Path models are sets of regression equations with an assumed causal ordering across outcomes. For example, consider a simple consumer journey represented by the following sequence of conditional probability statements, where Z denotes a set of exogenous marketing and macroeconomic explanatory variables.

$$P(Natural\ search|Z)$$
$$P(Webtraffic|Natural\ search, Z)$$
$$P(Facebook|Webtraffic, Natural\ search, Z)$$
$$P(Twitter|Facebook, Webtraffic, Natural\ search, Z)$$
$$P(Sales|Twitter, Facebook, Webtraffic, Natural\ search, Z)$$

This sequence forms a system of equations with a recursive 'triangular' structure, equivalent to a set of identifying restrictions. Starting with natural search, the journey follows a sequential path where each step is pre-determined and handed down as a driver into the next level. This is illustrated by the causal flow in Figure 1.[1,2]

Figure 1: Offline-online consumer journey



Bayesian Networks

Bayesian networks represent sets of conditional dependencies between groups of random (outcome) variables. This essentially generalises the path approach by looking at the combination of all possible chains that can explain the final outcome. For example, the chain illustrated in Figure 1 is just one possible route to off and online sales with a given overall likelihood. However, there are many others such as Twitter driving Facebook, Facebook directly driving Web Traffic, or social media indirectly impacting sales via Web Traffic.

A set of key causal structures can be found using machine learning techniques or score based approaches. Plausible candidates are chosen based on economic and relative likelihood criteria, with network parameters estimated by either frequentist or Bayesian methods.[3] The final model for sales can be viewed as a weighted combination of each estimated network.

[1]Typically, Z differs across equations and endogenous regressors can be removed from some steps due to collinearity or insignificance. Note too that causal effects can be direct or indirect where the effect is mediated by another outcome variable.

[2] Note that where it is certainly possible that final sales can subsequently drive natural search, this is typically excluded since the system is then circular, where no clear causal path can be defined. Consequently, Bayesian Networks are known as Directed Acyclical Graphs (DAGs).

[3] Bayesian Networks are so called owing to the use of Bayes' rule when conducting probabilistic inference, rather than the statistical approach to parameter estimation.

Structural Vector Autoregressions (SVARs)

Vector Autoregression (VAR) models are systems of simultaneous regression equations, where each endogenous variable is specified in terms of its own past behaviour together with lags of all other outcome variables and current and lagged exogenous variables. As such, they are *reduced form* equations, where the contemporaneous (causal) relationships between the outcomes are not modelled in any way.[4] All such relationships are absorbed into the error covariance structure, leading to an identification problem manifest in significant off-diagonal error matrix correlations.

Structural Vector Autoregressions (SVARs) resolve the problem by removing cross-correlation in the error matrix. Various approaches are available. The simplest option imposes zero restrictions on all off-diagonal matrix elements. As for the path model, this gives a recursive structure and an assumed causal ordering between the variables, although order-agnostic solutions can be provided through generalised impulse response analysis. Alternatively, model restrictions can be imposed based on economic theory or the causal relationships can be explicitly modelled using instrumental variable estimation.

Concluding remarks

This article has outlined three broad innovations in MMM techniques ranging from competitive structure and the measurement of long-term effects through to incorporation of digital and social media. All such innovations lead to increased flexibility and realism with more accurate client deliverables, helping to maintain the relevance of MMM in the modern digital economy.

[4] VAR models are often used to test for Granger causality between variables. However, this is a specific form of predictive causality based solely on past values of the variables concerned. It does nothing to address the identification problem at the heart of causal analysis in structural systems.