Modelling Short & Long Term Marketing Effects in the Consumer Purchase Journey

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Marketscience
Validation through published research

- Modelling and forecasting brand share: a dynamic demand system approach (IJRM)
- Marketing mix modelling and return on investment (Palgrave)
- Brand management and the marketing mix model (JMA)
- Limitations of Conventional Marketing Mix Modelling (Admap)
- Dynamic MMM and Digital Attribution (Admap)
- Traditional ROMI is Dead. Long Live Marketing Effectiveness (Admap)
- Modelling short and long-term marketing effects in the consumer purchase journey (IJRM)

Today’s Focus

2005

2008

2010

2014

2021

Confidential - Marketscience 2021
Executive summary

• Modern MMM fails to resolve two key issues
  ➢ Selection bias of online media
    o Current approaches only deal with re-attribution of last-touch media and not simultaneity bias of self-selection
    o Last-touch coefficients such as paid search predominantly reflect the prior decision to purchase
  ➢ The true mechanics of brand-building
    o Successful brand-building programs generate persistent increases in consumer loyalty manifest in long-term sales evolution
    o Conventional long-term approaches treat long-term effects as simple extensions of the short-term structure – ignoring persistence and the precise mechanics of how brand loyalty is created

• Both issues result in significant mis-estimation of ROI and incorrect marketing resource allocation
• A preferable approach separates demand generation into short and long-term networks estimated with appropriate econometric techniques
Shortcomings of the standard marketing mix model
The standard marketing mix model

- Consumer journey from online search to off and online purchase

- However, this approach is subject to two main weaknesses

- Nested sequence of equations designed to deal with last-touch attribution problem
- Additive or multiplicative functional forms
- Media dynamics captured through Adstocks
- Regression techniques used to estimate response parameters
Ignores inherent selection bias of online media

- Nested equations only reattribute a part of last-touch media back to sources earlier in the chain

- Does not deal with the inherent selection-bias of last-touch media such as paid search
  
  - A (part of) the sales impact is caused by a factor that predicts the likelihood of paid search rather than due to search itself.
  
  - Consumers with the highest propensity to buy are more likely to take part in the paid search ‘treatment’
  
  - Paid search reflects prior purchase decision regardless of the ‘indirect’ influence of upper funnel media

- The result is over-estimation of the incremental lift from those last touch channels since we are essentially correlating a part of sales on itself.

- Models need to remove selection bias either by control for simultaneity of competing causal chains (DAGs) or conventional Instrumental Variable analysis
Short-term focused by construction

- Models need to reflect both short and long-term marketing effects
  - Short-term effects explain mean-reverting or transitory sales variation
  - Long-term effects explain persistent or permanent changes in underlying base sales
- Standard models focus solely on short-term sales effects with Adstock transforms
  - Long-term effects based on simple extensions of the short-term structure
    - Adstocks with long retention rates or arbitrary multiples of short-term effects
    - Brand metrics added to the sales equation with indirect marketing impacts defined as long-term effects
- Does not address the drivers of long-term sales evolution or mechanics of brand-building
  - Longer adstocks and scaling factors are still mean-reverting
  - Brand metrics need to link directly to base sales and explain persistent sales evolution (cointegrate)
  - Simple one-way causal chain through brand metrics to sales can overestimate brand effects
A more credible approach to marketing mix modelling
Short and long-term paths to purchase

- Economic model separates the demand generation process into two linked networks
Requires different econometric techniques

- More appropriate econometric estimation combines two advanced time series techniques

<table>
<thead>
<tr>
<th>Short-term demand network</th>
<th>Long-term demand network</th>
</tr>
</thead>
<tbody>
<tr>
<td>✓ Quantifies interactions between sales, online search interest, web traffic clicks and paid media</td>
<td>✓ Quantifies interactions between base sales, brand metrics, paid and earned (social) media</td>
</tr>
<tr>
<td>✓ <em>Unobserved component</em> time-series models, separating observed sales into short-term marketing effects and long-term base evolution</td>
<td>✓ A <em>VAR/VECM</em> model, incorporating long-term cointegrating relationships between base sales, brand metrics and other journey steps</td>
</tr>
<tr>
<td>✓ <em>Instrumental Variable</em> and/or <em>DAG</em> analysis to control for endogeneity</td>
<td>✓ Credible structural foundation for the brand-building effects of advertising</td>
</tr>
</tbody>
</table>
Worked example
Short-term UCM network: dynamic base (trend) extraction

\[ y_t = x_t \beta + \mu_t + \delta_t + \epsilon_t \] → Model with drivers \( x_t \) and dynamic baseline \( \mu_t \)

\[ \mu_t = \mu_{t-1} + \delta_t + \eta_t \] → Model for dynamic baseline

\[ \delta_t = \lambda_{t-1} + \zeta_t \] → Model for trend in dynamic baseline

\[ \epsilon_t = - \sum_{i=1}^{6} \delta_i + \kappa_t \] → Model for season

- Direct daily sales model
  - Dynamic base
  - Season/Daily dummies
  - Off and online marketing (with lags)
  - Promotions
  - Covid dummy and outliers
- Sub-equations for all endogenous variables
- DAG analysis for endogeneity control
- Decompositions and short-term ROI

R-sq = 0.95 DW = 1.92 Std. error = 0.098 Het (611) = 1.04 Normality = 10.92
Long-term VAR network: model of the long-term dynamic system

\[ \ln y_t = \Psi(L)\ln y_{t-1} + \Omega_k(L)\ln x_{kt} + \gamma_k D_{kt} + \varepsilon_t \]

- Consumer-journey steps \((y_t)\):
  - Base
  - Price
  - Unaided awareness
  - New business starts
- Exogenous regressors \((x_t)\):
  - Social media (earned)
  - TV
  - Dummy events \((D_t)\)

Residual diagnostics

<table>
<thead>
<tr>
<th></th>
<th>R-2</th>
<th>AR(1-7)</th>
<th>Normality</th>
<th>Het</th>
</tr>
</thead>
<tbody>
<tr>
<td>BASE</td>
<td>0.85</td>
<td>1.86</td>
<td>6.4*</td>
<td>0.84</td>
</tr>
<tr>
<td>PRICE</td>
<td>0.95</td>
<td>0.43</td>
<td>7.4*</td>
<td>1.12</td>
</tr>
<tr>
<td>AWARENESS</td>
<td>0.86</td>
<td>2.42</td>
<td>15.6*</td>
<td>0.38</td>
</tr>
<tr>
<td>NEW BUSINESS</td>
<td>0.91</td>
<td>1.03</td>
<td>13.2*</td>
<td>2.1</td>
</tr>
</tbody>
</table>
Test the economic structure and identify true long-term impact

**Economic structure**

<table>
<thead>
<tr>
<th>Regressor</th>
<th>$\text{CV}_1$</th>
<th>$\text{Alpha}_1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base sales</td>
<td>1</td>
<td>-0.171 (-4.10)</td>
</tr>
<tr>
<td>Base price</td>
<td>-0.501 (4.75)</td>
<td>0</td>
</tr>
<tr>
<td>Unaided awareness</td>
<td>0.350 (2.1)</td>
<td>0.085 (1.82)</td>
</tr>
<tr>
<td>New business</td>
<td>1.14 (5.10)</td>
<td>0.043 (3.70)</td>
</tr>
</tbody>
</table>

**Full long-term impacts**

<table>
<thead>
<tr>
<th></th>
<th>$\sum \hat{\epsilon}_\text{Base}$</th>
<th>$\sum \hat{\epsilon}_\text{Price}$</th>
<th>$\sum \hat{\epsilon}_\text{Aware}$</th>
<th>$\sum \hat{\epsilon}_\text{New Business}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base Sales</td>
<td>0.315 (3.8)</td>
<td>-0.731 (4.0)</td>
<td>0.120 (2.8)</td>
<td>0.951 (4.4)</td>
</tr>
<tr>
<td>Base Price</td>
<td>0.022 (0.00)</td>
<td>1.40 (10.0)</td>
<td>0.0007 (0.00)</td>
<td>0.005 (0.00)</td>
</tr>
<tr>
<td>Unaided Awareness</td>
<td>0.167 (1.3)</td>
<td>0.10 (1.3)</td>
<td>0.912 (10.2)</td>
<td>-0.381 (1.1)</td>
</tr>
<tr>
<td>New Business</td>
<td>0.211 (3.8)</td>
<td>-0.10 (.03)</td>
<td>0.01 (1.1)</td>
<td>0.792 (4.5)</td>
</tr>
</tbody>
</table>

- Economic structure shows one long-term equilibrium (cointegrating) relationship between base sales, price, awareness and new business starts.
- Feedback between base sales and awareness shows how awareness both *drives* base and *adjusts* to word of mouth and product performance/experience.
- Impulse response reflects feedback and delivers true long-term impact of awareness on base.
- Provides more credible estimates of marketing effects that work through long-term brand metrics.
Estimate the time taken for long-term effects to accrue

- Dynamic response to a 1% change in unaided awareness

- Long-term effects work through unaided brand awareness onto base sales (wear-in)
  - Long-term elasticities equal to awareness elasticity weighted by base-awareness elasticity (0.12)

- Base sales decomposition deliver long-term sales volumes over model sample and beyond
  - Combined with NPV calculation of average weekly base volumes over a two-year forecast horizon
Conclusion

- Traditional MMM measurement approaches do not provide a robust understanding of the true impact of marketing activity
  - Ignore selection bias of last-touch online media
  - Short-term focused by construction
  - Standard long-term measurement techniques are flawed and ignore time-series properties of the data
- A preferable approach combines:
  - Dynamic time series models to capture short-term effectiveness and extract long-term base sales
  - A network model for brand-building, capturing interactions of paid media, base sales, brand metrics and earned (social) media
    - Long-term preferences embodied in attitudinal data causally linked to long-term preferences reflected in base sales
    - A credible structural framework for quantifying the emotional foundations of brand-building media campaigns