MSI BLUE RIBBON PANEL REPORT

Charting the Future of Marketing Mix Modeling Best Practices

MSI at the ARF

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TABLE OF CONTENTS

CHARTING THE FUTURE OF MARKETING MIX MODELING BEST PRACTICES

MMM IMPLEMENTATION GUIDELINES: STATISTICAL ISSUES FOLLOWING FROM MMM DESIGN CHOICES

OVERVIEW

The objectives of this Marketing Science Institute (MSI) white paper are to outline how best practices in Marketing Mix Models (MMMs) have evolved in response to a rapidly changing marketing landscape, to outline opportunities for innovations, and to offer means to assess those innovations. The report intends to identify challenges for sophisticated MMM users, and to introduce MMMs to executives with a more passing familiarity in modeling who might introduce MMMs in their firms. This report is the first of several resources MSI plans to offer to support both groups.

In response to media digitization, firms have increasingly employed models requiring individual level data, such as Multi-Touch Attribution (MTA) models, to apportion credit for a sale among various touchpoints along a customer journey.[1] However, new privacy regulations (GDPR, CCPA) and Apple and Google platform privacy policies eliminating 3rd party cookies disrupt the ability of marketers to use individual-level customer data to understand the business consequences of their marketing actions.

In response to these new privacy policies, many firms are pursuing or expanding the use of MMMs that rely on more aggregate data to assess and predict the effects of changes in spending on different marketing activities and to optimize those activities. These models explain changes in sales over time and across geographic locations, or stores, due to variation in spending on marketing mix elements.

MMMs were developed decades ago by marketing scholars affiliated with MSI and by industry solutions innovators.[2 3 4 5 6 7 8 9 10] MMMs are resurgent because of the need to rely on aggregate data due to restrictions on collecting and using individual-level data.

MMMs face new challenges and opportunities with increasing fragmentation in how marketing dollars are spent across new and older communication channels and with the proliferation of "omnichannel" routes to distribution. How can managers know if channels are synergistic rather than substitutes for each other in driving demand? How can firms leverage new indicators of brand preference from user-generated text and images to better measure marketing effectiveness or integrate large-scale, online surveys into the MMM? What data systems integration will be required, and is it worth the investment?

Many consultants and suppliers are competing to offer updated MMM solutions to MSI member companies (e.g., AI-based and SaaS variants), all claiming certain advantages.[11 12] MSI members sometimes have difficulty sorting through competing vendor claims and innovations. Model details by the solutions' providers are sometimes a "black box", and the marketing and C-suite executives trying to assess the claims are not statisticians. Internally, the marketing executives making recommendations based on MMMs need tools to help others in their organizations align to make best use of MMMs.

To address the changing MMM landscape, the Marketing Science Institute has initiated an MMM Industry Challenge, partnering with leading academic and industry authorities on these models and with experts inside MSI member firms. Contributors are users whose current or former employers include marketers in automotive, business technology, consumer packaged goods (CPG), consumer services, healthcare, financial services, retailing, and sporting goods, and solutions providers in advertising, marketing analytics, publishing, and social media. Please see the Acknowledgements section at the end of this white paper.

The report begins by defining MMMs. It then identifies three prototypical ways MMMs are being used in industry, as uncovered by a series of industry interviews. In increasing levels of sophistication, these use cases are scorecards reflecting recent past performance, predictive models, and resource allocation in the context of marketing spending optimization.

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Building on these use cases, the report discusses design elements necessary for successful MMM implementation, and identifies promising innovation opportunities. It then discusses the challenges that corporate experts involved with the MSI MMM initiative find most pressing.

It concludes with details on next steps for MSI member firms wishing to join the initiative to chart the future of MMM models.

The report is supplemented with an MMM Implementation Guideline covering technical details about MMMs. This Implementation Guideline explains why different design choices affect the quality of usable insights from an MMM. The point of the Implementation Guideline is to allow analysts in member firms better ways to communicate with marketing users and C-suite investors in marketing.

DEFINITION: WHAT IS MMM?

A marketing mix model (MMM) is a model that predicts customer demand based on a broad set of marketing and other business drivers. MMMs quantify the impact of changes to those drivers to reveal actions a business can take, in order to increase favorable business outcomes by changes in the firm's marketing mix (product, price, distribution, promotion). A *media* mix model (mMM) is a specific type of MMM where firm actions are restricted to marketing *media* actions. actions. The parameters of MMMs and mMMs are estimated from real-world data and/or experiments.

"Customer" here refers to the ultimate buyer of the product or service, which can be an organization, a household, or an individual. "Demand" can refer to sales, consumption, new customers acquired, profit, long term value of customers, or any relevant KPI.

To make demand predictions, MMMs use data from the past several years to explain why demand was high or low at a given point in time or for a given geography. The highs and lows are statistically tied to changes in marketing actions by the firm as well as changes in uncontrollable marketplace factors. MMMs and mMMs quantify the effects of marketing action on demand. They do so by using established statistical modeling techniques or experiments that randomize which customers received business-as-usual marketing versus some potential improvement (e.g., new advertising or pricing).

Unlike MTAs and other individual level modeling approaches, MMMs and mMMs often operate on aggregate and less granular data (e.g., weekly advertising and sales) not subject to privacy concerns.

Within MSI firms using MMMs, the *designers or developers* of MMM include modelers, statisticians, or analysts. The users are marketing managers. The investors are C-suite executives. Their needs are different, which we will acknowledge in this summary.

USE CASES: WHAT IS MMM USED FOR?

Companies use MMM for a variety of purposes, which can be conveniently organized in three areas, going from least to most advanced: scorecards, forecasting, and optimization. Scorecards are descriptive and backward facing, forecasting is predictive, and optimization is prescriptive. Within each of the three, we describe use cases that are either *tactical* (e.g., allocating an advertising budget) or *strategic* (e.g., setting investment levels across marketing levers or across brand portfolios).

Each use case is affected by recent changes in the marketing landscape. For example, machine learning affords new means of specifying and calibrating predictive models. New KPIs suggest alternative benchmarks for business management such as social media measures of consumer sentiment.

SCORECARDS

AUDITING PAST MARKETING ACTIONS TO ESTIMATE HOW THEY IMPACTED BUSINESS PERFORMANCE

Many firms use MMMs to demonstrate that marketing contributes to top-line and bottom-line performance. MMM and mMM scorecards are primarily descriptive, reporting the return of past investments in terms of sales or revenue. They aim to provide a high-level account of what moved the sales (or other demand KPI) period over period. How much was it marketing, the economy, seasonality, etc.? Scorecards are also used to identify how each of a set of marketing channels (e.g., different advertising media) affect that KPI. The aim is to quantify the contribution to overall or channel-specific sales. This process allows managers to justify future investments to C-suite executives.

According to one MSI member associated with this project, “Once a year we need MMM to demonstrate to our top management that marketing is an investment, not an expense.”

Examples of typical “scorecard” questions raised and answered by MMM:

- *How did our media spending work within specific markets? Which media drove the most sales in which markets or for which types of targeted consumers?*
- *How much revenue was lost last year when a regional market accidentally received no marketing support for two weeks?*
- *Does our advertising work better when a product goes on sale?*
- *Did advertising support make our sales force generate more sales?*

Two common types of scorecards are “due-to” reports and “marketing contribution reports.” Due-to reports estimate how change to some marketing driver affected sales, and “marketing contribution reports” aim to estimate the incremental sales arising from some marketing tool or channel. What would sales have been if there had been no marketing spend in that channel?

Scorecard models are primarily descriptive, reporting the return, in terms of sales or revenue, of past investment as opposed to assessing how much to invest. Nonetheless, they are sometimes (over)used to assess the performance of a firm’s ad agencies, media channels, or other marketing partners—or even of CMOs!

FORECASTING

PREDICTING THE IMPACT OF DIFFERENT MARKETING BUDGETS AND ALLOCATIONS ON FUTURE BUSINESS PERFORMANCE

Forecasting produces quantitative outputs such as monthly forecasts (e.g., revenue simulations) to evaluate different marketing scenarios or for use in developing financial forecasts in the context of marketing plans. Forecasts account for different market conditions, including accounting for changes in competitor actions. The forecasts can range from short term (e.g., weekly) to long term (e.g., quarterly for the next year).

Examples of typical "forecasting" questions raised and answered by an MMM are:

- *MMM shows that media channel X outperforms media channel Y in predicted effects of incremental spending from current levels. How much more revenue and gross margin will be generated if we double our spending in X, and cut Y in half or if we shifted $10 million from linear TV to cable TV?*
- *The economic outlook for the next six months is not as positive as in the recent past. How will that impact our revenue? If we increased our marketing spend by 15%, would this soften the impact?*
- *Based on recent mMM results, we launched a digital campaign this morning. How are the results tracking to what was expected and should we continue with the campaign?*

OPTIMIZATION

CHOOSING THE BEST BUDGET AND ITS ALLOCATION ACROSS THE MIX

Optimization adds a "best decision" perspective to the forecasts and simulations above. From an MMM designer perspective, parameter estimation (a statistical task) is now supplemented with optimization (a mathematical task) to recommend budget allocations. This optimization should model diminishing returns to spending in a given channel and positive or negative synergies between different marketing tools.

The distinction between forecasting and optimization is somewhat fluid. Naturally, when marketers use MMM for forecasting, they try to find specific allocation scenarios that are "good." This often leads to the development of an algorithm that can systemically search for good allocations across decisions within the marketer's control but beyond the specific forecasting scenarios.

The most critical decision is what to optimize or maximize. The following are examples of decision criteria that can be used when determining the optimal advertising budget and its allocation across media:

- *To maximize short-term profit (i.e., gross margin minus advertising spend)*
- *To maximize short-term profit, subject to a minimum sales revenue level*
- *To maximize top-line growth, subject to a minimum profit condition*
- *To maximize the lifetime value of customers*

Marketing managers must also decide which marketing actions to consider taking in the optimization, often accounting for limited past spending ranges that make it difficult to say how a marketing tool would contribute if changed. Many marketers use optimization to allocate their budget to specific media channels (constraining the optimization to plans that do not exceed the total budget.) Other firms may use a combination of forecasting and optimization to inform the strategic planning process that determines the overall marketing budget for a quarter or a year.

Optimization can be made *dynamic* when data streams arrive continuously, so that MMM model predictions and resource allocation recommendations are frequently updated to reflect possible changes in the market environment. This enables *course correction* in marketing allocations when outliers or new trends are detected.

Overall, the intended use cases can affect how the MMM is specified or implemented. For example, optimization often requires a non-linear MMM to implement while scorecards might not attempt to account for diminishing returns. Scorecards might be predicated on highly aggregated data, while forecasts might require more granular data. MMMs are critically important for resource allocation (optimization) adjustments within budget cycles. They also play a key role in getting internal buy-in for marketing actions (score cards), and operational aspects of the business (forecasting). Industry contributors to the MSI MMM initiative have expressed that their firms are most interested in the optimization of MMMs and mMMs resource allocation use cases.

DESIGN CONSIDERATIONS AND OPPORTUNITIES FOR INNOVATION

Marketing Mix Models differ in scope and objective, depending on the breadth, the frequency and the granularity of the data, and the intended use cases of the MMM.

MMM DESIGN CONSIDERATIONS: INPUTS, OUTPUTS, AND MODELS

All MMMs share a common architecture, in that, they process inputs using a model to generate outputs for the use cases. Below, we discuss design considerations along these dimensions.

INPUTS: WHAT MARKETING VARIABLES AND CONTROL VARIABLES ARE USED IN MMM MODELS?

The modeler should work with the marketing manager to elicit their mental models of what drives the business.

- What **marketing actions** are relevant to the marketing manager—e.g., spending on different advertising media (paid and owned impressions), brand, price, distribution, product characteristics, outbound sales contacts, and so on? The MMM designer must decide how each of these marketing actions will be measured (e.g., media spend versus reach, price per unit versus price per quantity, and so forth). These are key predictors and marketing decision variables in the models.
- What **environmental variables** affect demand, but that are outside the control of the marketing manager: other marketing mix variables, earned media impressions, geography, weather, competitive activity, seasonality, holidays, economic conditions? This will vary by industry and serve as control variables.
- Is **data quality** sufficient? Are there **sufficient data** to reliably estimate the number of parameters of the model (k) ? One simple starting point is: observations > 30 + 5*k, where k is the number of predictors in the model. Even more observations may be needed when predictors are correlated. Is there **sufficient variability** in the dataset on each predictor, over time and/or across products or markets to estimate the parameters? One cannot estimate the effects of marketing actions that don't change.

OUTPUTS: KPI MARKETING OUTCOMES MARKETING WANTS TO INFLUENCE

- What **KPIs** will the model predict—e.g., sales, orders, market share, clicks, brand awareness, new customer acquisitions, or what? These are the outcome variables for MMMs and focus on the business objectives at hand. The models generate elasticities measuring how the KPIs change with alterations in key marketing actions.

MODEL: ASSESSING THE MMM'S DESIGN

- Do the **mathematical relationships** between the marketing actions and KPIs follow established scientific principles? For example, some marketing mix models in use assume a linear relationship between spending in that mix element and sales. A well-designed MMM model will allow for *diminishing returns* to marketing spending and will estimate the extent to which those returns are diminishing (or nonlinear decay of lagged marketing spending). Similarly, a well-designed model may allow the spending on one media channel to affect the impact of other channels. These criteria are well explained in the statistical and econometric literature and are implemented in MMM software packages.
- How well does the **model fit the data?** Are the estimates of effects of marketing actions valid and made with low uncertainty (confidence intervals)? Does the model also predict well outside of the range of the estimation data or forecast accurately on a hold-out/validation sample? See the discussion on "the shape of the advertising response function" in Hanssens (2022).[13]

In designing an MMM, the analyst will have to consider inputs, outputs, and model specification in conjunction with one another. For example, the marketing manager may want to understand the effect of a control variable like "influencer marketing", but the firm may not have sufficient data on the spending or reach. Maintaining data sources, doing ongoing validation of the model and improving the model's mathematical formulation are key components to building and maintaining a strong MMM capability and modeling pipeline.

USER REPORTED CHALLENGES AND INNOVATION OPPORTUNITIES

Our interviewees identified the use cases summarized in Section 3, but also specific challenges with MMM that come up in the context of these use cases. The committee organized the challenges along different MMM design elements, shown in Table 1. Solving these challenges provides *opportunities for successful innovation*, which are also listed in the table.

TABLE 1

DESIGN CHALLENGES AND OPPORTUNITIES IN MMM MODELS

DESIGN ELEMENT	CHALLENGE	INNOVATION OPPORTUNITY
Data refresh frequency and latency	MMM on "old data" is not trusted by management; need timely assessment of rapidly evolving ad technologies	Technology driven supply of lower-latency data, e.g., from monthly to weekly to daily data updates
Data granularity	Markets are defined too broadly to be useful in execution	Technology driven supply of higher-granularity data, e.g., from national to DMA level or finer granularity
Data breadth	Explanatory insights are missing in MMM, such as when why and how advertising drives sales	Advances in natural language processing allow measuring "consumer sentiment" for use as a KPI or a mediator to explore the efficacy of marketing campaigns
Data completeness	Data unavailable for some marketing actions (e.g., vendors with mismatched APIs, or limited 1st and 3rd party data)	Create privacy-compliant tech infrastructure and customer data platforms to support MMMs, develop data fusion approaches and/or identity graphs, encourage vendor partnerships
Variation in marketing actions over time	Managers stick to what works (e.g., Spend on SEM can be flat over time), or never vary mix elements independently, making it difficult to disentangle effects for allocations that covary highly	Create intentional variation in marketing spend for each channel over time, combine MMM with experiments
Return on Marketing Investment (ROMI) as a KPI	While ROMI is an accepted managerial metric, maximizing marketing ROMI can lead to poor decisions	Develop KPIs that use ***marginal*** ROMI instead. That is, instead of looking at average returns for all spend, look at the return of an additional dollar of spend
Efficiency vs. effectiveness	Chasing efficiency metrics like cost per incremental outcome is good for cost control, but may lead to suboptimal marketing allocations	Develop KPIs that focus on marketing effectiveness
Future technology environment	Because of lag in MMM outputs, forecasting and optimization is often done for advertising technology that has changed since the MMM was estimated	Develop methods that allow forecasting for new technologies out of data created using old technologies—e.g., take estimates generated using an old technology (such as Instagram or YouTube ad) and calibrate predictions for a new technology (such as TikTok)

MSI's MMM Blue Ribbon Panel met with MSI member company users and industry MMM experts to identify which of these challenges were most pressing.

1. **Use cases.** MSI members are likely to be more advanced in these uses than many non-members. Many of our members have moved beyond using MMMs for historical *scorecards* of effects of past actions. Our members were most concerned about improving their practices for *optimization* use cases—how to allocate scarce financial resources across different marketing tools.

2. **Design elements, challenges, and opportunities.** The design elements that are most challenging are data frequency and latency, data granularity, data breadth, and a lack of variation on spending in some channels to estimate the effects and optimize Return on Marketing Investment (ROMI).

It may not be obvious to CMOs investing based on MMM models or managers using these models *why* such design elements are so critical. Marketing Mix Modelers recommend resource allocations based on a set of coefficients in statistical models. The design challenges in Table 1 can lead to random errors in forecasts or to model misspecification—so that the models are not correctly capturing the effects of incremental investment in some marketing action. As a result, misallocations of marketing spend can occur with an adverse effect on ROI.

The **MMM Implementation Guideline** explains some of the statistical challenges that result from having data with little variation on some marketing mix element with either no data or with coarse data that shows no variation over time, to allow confident parameter estimates of the effect of spending in that channel. The firm's internal "Investors" in the C-suite must make resource allocations based on MMM models and orchestrate investments, and managers and analysts must set up the information systems to tie the model variables together. In some cases, one can "solve" a problem—e.g., of too coarse data granularity—by paying a data supplier more money for more granular data. The small expense often more than offsets the cost of a suboptimal marketing spend allocation.

NEXT STEPS FOR THE MSI AND MEMBER FIRMS

The Marketing Science Institute will continue to work with the Blue-Ribbon task force of academics to develop tools to help our industry and our members improve their Marketing Mix Models. Our overall initiative has three phases:

Phase I: *What is current MMM practice?*

Phase II: *What makes for a successful MMM?*

Phase III: *A processes for validating MMMs*

We are now working on the Phase II task of coming to a consensus on desired or required elements in an MMM model mapped to given use cases. We aim to set industry standards for best practices. We will then develop an **MMM Checklist** for MSI member firms to evaluate their own internal MMM operations by benchmarking their use cases against best practices and (confidentially) sharing areas that are challenging. Member firms can contract with MSI to facilitate their internal discussions on using checklist results to improve their MMM model pipelines. MSI will ask members to (anonymously) share checklists to allow an aggregated summary report on the state of the industry. We will also be developing resources to help firms develop an MMM model pipeline if they have not developed that competence to date.

We plan to work with MSI members on a third **validation** phase. MSI members will contribute to the initiative through direct academic-member interactions. This will allow MSI to provide feedback to participants of how well their (or their vendor's) MMM pipeline and strategy address member use cases and what, if any, changes may be desirable.

CONCLUSION

Successful Marketing Mix Model (MMM) implementation puts demands on data, models, users, and the C-suite. Innovation opportunities exist where there are gaps between the desired and actual levels.

- Data and methods need to be matched to the needs of the use case.
- Data needs to be updated to keep the model "fresh" and the results actionable. This is often an organizational challenge.
- Models need to be validated according to scientific standards, consistency with marketing principles and econometric standards for evaluating predictive accuracy.
- Managers need to appreciate the strengths and limitations of MMM models, especially in the face of modeling innovations and new media channels.
- Investors need to understand MMM and offer strategic guidance on the choice of KPIs.

If your firm wishes to take part in the MMM Industry Challenge, reach out to MSI Research Director Keith Smith: research@msi.org

MMM IMPLEMENTATION GUIDELINE: STATISTICAL ISSUES FOLLOWING FROM MMM DESIGN CHOICES

MARKETING MIX MODELS (MMM) VERSUS MEDIA MIX MODELS (mMM)

MMM models were originally developed as "Marketing Mix" models, estimating combined effects of all "4 Ps" of Product, Price, Place (channels of distribution), and Promotion. Some firms now use Media Mix Models rather than Marketing Mix Models, which only include data on different channels of advertising spending. This is likely a missed opportunity.

Extensive academic research shows that the effects of advertising on sales are small relative to the effects of increasing spending in other elements of the marketing mix. That is particularly true for advertising of established products. Users of media mix models are at risk of omitting marketing variables, other than advertising, that can have powerful effects on sales, both in the short and long run. They also risk missing important interactions, for example when advertising helps draw customers to a temporary price promotion. Section 2 below expands on the consequences of omitted variables in MMM models.

TABLE 2

TYPICAL MARKETING MIX VARIABLE ELASTICITIES[14]

MARKETING MIX VARIABLE	TYPICAL ELASTICITY	RANGE	DRIVERS (+)	ORGANIC GROWTH DRIVER?
Advertising	0.1	0 to 0.3	Product Newness, Durable	Minor
Sales Calls	0.35	0.27 to 0.54	Early life cycle, European Market	Major
Price	-2.6	-2.5 to -5.4	SKU Level v Brand Level, Early Life Cycle, Durables	Minor
Price Promotion	-3.6	-2 to -12	Storable vs Perishable	No
Distribution	>1	0.6 to 1.7	Brand concentration, high-revenue categories, bulky items	Major
Innovation	Positive	N.A.	Radical v. Incremental	Major

Table 2 above comes from a summary by Hanssens and Pauwels (2016), which includes hundreds of studies estimating the *elasticity* of sales to changes in each of the elements of the marketing mix. An "elasticity" asks the question of what % change in sales comes from a 1% increase in investment in that channel, given current levels of spending. The "organic growth driver" asks to what extent any observed, short-term effects of that variable can result in long-term impact.

Table 2 shows that the typical ad elasticity is quite small. For a 1% increase in ad spendings, sales increase by 0.1%. Many studies show ad effects are *larger* for new products vs. mature products and for durables vs. frequently purchased products. Advertising has only minor long-term effects on organic growth.

In contrast, the effects of increased spending on sales calls are much larger. A 1% increase in spending on sales calls increases sales by 0.35% and can have major effects on long term organic growth. For price, a 1% increase typically leads to a 2.6% decrease in sales. For short-term price promotion, a 1% price cut leads to a 3.6% increase in short-term sales, with no benefits for long-term growth. For increased spending on distribution, a 1% increase typically yields an increase of greater than 1% in sales, and major effects on long-run profitability. There are fewer studies of the effects of new product innovation, but they generally show a large positive effect, particularly for more "radical" innovations.

A key conclusion from Table 2 is that for firms that currently use only Media Mix Models, there are many advantages to modeling the effects of all marketing investments simultaneously. Modeling all aspects of the marketing mix is informative for allocating marketing spend across the various investments. In the next section, we also show that ignoring these other marketing mix variables in Media Mix Models makes it likely that effects of advertising are overestimated because increased advertising is confounded with increasing spending on some other marketing mix variable.

OMITTED VARIABLES BIAS

When firms use Media Mix Models, they do not account for the fact that advertising spending is correlated with investments in new products, channels of distribution, increased sales force effort, or changes in price. That opens the opportunity for "omitted variable bias". This is when, unbeknownst to the firm, the coefficient on a media mix element modeled is actually showing returns to both investment in that media channel and in omitted changes in other marketing mix elements.

The cause of this bias is that advertising spending in a particular media channel is often increased or decreased along with changes in some other element of the marketing mix. When this occurs, not including those other elements of the marketing mix, the model produces "omitted variable bias" in model estimates of returns to spending in those channels.

To understand the point, imagine that a firm has two channels for communication, A and B. Suppose that the firm increases in advertising on channel A are accompanied by temporary price promotions, and that is not true for communication on channel B. If the MMM does not include price in a media mix model, the coefficients for channel A will confound the effects of advertising on channel A with the effect of price cuts, making it appear that the advertising itself was the sole cause of any increase in sales. For the same reason, the coefficients might imply that a 1% increase in spending in Channel A is having a bigger impact than a 1% increase in spending on channel B, because only the coefficient for Channel A is confounded with the omitted effect of price discounting on sales.

To gauge this concern, one can compare MMM estimates of advertising effects to implications of quasi-experimental or experimental analyses of ad spend. If they converge, this supports belief in the MMM estimates and builds management trust. If they do not, this may help identify omitted variables and to assess whether including them would increase or decrease estimates of the effects of marketing actions included in the MMM.

The same point holds for estimating elasticity of advertising effects in models that do not model the full marketing mix. For example, advertising increases when firms have new products to introduce, and they are supporting those new product introductions with increases in sales force or trade promotions or expanding channels of distribution. If so, and if those other mix variables are omitted from the model, returns on advertising will be overestimated.

Relatedly, omitted variables that affect both sales and the marketing mix can lead to biased estimates via selection bias. In selection bias, individuals receiving different marketing mixes are different from each other. It is not like marketing mixes are randomly assigned to the same customer pools.[15] For example, if ads are served to individuals more likely to convert, the typical ad effects are larger as well. This problem is more pronounced in modern digital ad systems where ads are highly targeted. It is necessary to either control for the targeting variables or run randomized experiments to ensure causal variables are not correlated with outcomes. In the example above, one could vary ad exposure for all groups, not just those who are predicted to be likely to convert.

The key point is that the dangers of omitting other marketing mix variables in an mMM depends on whether those omitted variables are unchanging over time and geographic location. If models are estimated for periods where the firm and its competitors are in a steady state, with no major strategic moves, it is likely not a problem to omit mix variables with little variation over time or geographies. The important criterion here is that the excluded variables should be uncorrelated with the ones included in the model. However, many of our member firms are using mMMs that omit the effects of marketing mix variables of new product development, sales force spending, and expanding channels of distribution that have elasticities far larger than elasticities for changes in advertising. That is problematic.

FACTORS AFFECTING THE UNCERTAINTY OF EFFECT ESTIMATES OF A MARKETING MIX TOOL

When MMMs rely on time series econometric techniques that are in the family of multiple regression models, their β_i coefficients tell us the best estimate of the effect of a 1-unit change in some marketing mix predictor i, on changes in the dependent variable (e.g., log sales). Analogous quantities characterizing marketing response exist for other modeling approaches such as Meta's Robyn and Google's Causal Impact.

But that β_i estimate has uncertainty that is captured in the "standard error" for that coefficient. In an OLS multiple regression, the standard error (SE) for X1, for example, has the form:

SE(β_1) = [Standard Deviation (Y)/Standard Deviation(X(i))]

*** Square root of [(1 – $R^2_{Y|X1,X2,...XN}$) / (df model)]**

*** Square root of [1 / (1 – $R^2_{X1,X2,...XN}$)]**

The first line of this equation says that, holding constant the variation in the outcome Y, the estimate of the effect of X_1 becomes more uncertain if there is relatively little variation across time, locations, and retailers in spending on X_1. Many of our member firms say that they tend to hold spending for certain marketing mix tools (e.g., search engine marketing) relatively constant over time. There must be variation in X_1 in the data set to precisely estimate the effect of a 1-unit change in X_1.

The second line of this equation says that uncertainty in the estimate of β_1 increases when the MMM model does not explain large portions of the variance in the outcome measure Y when using the full battery of predictors X1, X2, ..., XN. As the outcome measure of sales is affected by all elements in the marketing mix, an MMM that ignores X variables apart from advertising will have larger error in estimating the effects of advertising, even if there is only modest collinearity.

The third line of the equation measures collinearity. It shows the VIF (Variance Inflation Factor) arising from correlations among the predictor variable X1 with the other predictors X2, X3, ... XN. If X1 is the value of a marketing mix variable (say, advertising) in a given period or location and the amount spent on advertising can be predicted by other observed marketing mix variables, this will inflate the standard error on the effect of advertising. Note that this last line = 1 when the predictor variables are completely uncorrelated. Another way of thinking about this effect is that, if all other regressors predict X1 perfectly, then it is hard to know if it is the change in the other variables or the change in X1 that drives the outcome.

Our members tell us that certain tools in the marketing mix are synergistic – the effect of X1 increases when X2 is high compared to when it is low. When firms learn that kind of insight, they will then use the tools in tandem: in any time period or location when X1 is high, X2 will also be high, and in any time period or location when X1 is low, X2 will also be low. This creates correlation between X1 and X2 over time, making it very difficult to precisely estimate the effect of either tool. If a product is always advertised and discounted at the same time, it becomes hard to know whether it is the advertising or the discount that drove outcomes. An experiment to independently vary these variables would be helpful to enhance confidence in which drives outcomes. Note that such experiments do not necessarily have to lower variables to zero. For example, for a constant value of X1, an experiment could randomly choose X2 to be higher, lower or equal to its normal level.

Adding more predictor variables will tend to help model prediction in line 2 in the equation above, at least slightly. For example, instead of having one variable for advertising on Facebook, the firm might have separate variables for spending for video ads, for spending on Messenger, Instagram Stories, and Instagram Posts. The problem with this model choice is that it tends to inflate standard errors by increasing line 3 of the equation. With more predictors, there is greater potential for any given predictor to be explained by some linear combination of spending in other channels and marketing mix elements. Related challenges include that each channel within the multitude of channels may not have a sufficient level of ad spend, ad spend may be highly correlated across channels, or a channel may not have enough variation in ad spend. Even though managers wish to have very granular insights on how to optimize sub-channels within a particular channel, this can lead to a lack of precision in one's ability to estimate anything.

We have described uncertainty in the estimates in terms of traditional time series econometrics because they provide a well-established framework for thinking about uncertainty in MMM forecasts. Using machine learning (ML) instead of traditional econometrics does not resolve these uncertainty issues, which are fundamentally an issue with the data. In fact, the greater flexibility of ML models can magnify these issues.

In sum, firms using MMMs must think about how their design choices affect:

a. whether there is enough variation in a marketing mix predictor to accurately estimate the relationship between the predictor and the outcome;

b. whether the model itself is accurate in predicting the outcome for a given time period, geography, or retail channel;

c. whether the individual mix elements whose effects are being estimated are highly correlated with other marketing mix elements, making it impossible to separate their effects; and

d. whether the available mix elements correlate with unobserved predictors of sales response, and how unobserved variable biases might affect MMM parameters.

DATA STRUCTURE AND GRANULARITY: EFFECTS ON THE VALIDITY, RELIABILITY AND STABILITY OF COEFFICIENTS IN MMM MODELS

Problems of the granularity of data in a Marketing Mix Model or media Mix Model on different marketing channels, different geographies, and different time periods is a top priority, meetings with MSI MMM Industry Challenge participants show. This report considers three cases that can exacerbate granularity concerns: cross-sectional granularity (channel and geography), time granularity, and data duration.

CROSS SECTIONAL GRANULARITY: GEOGRAPHY AND CHANNEL

Geographically, firms may have sales data at the store level, chain level, or market level. Similarly, data can be disaggregated across channels; for example, social media channels can be combined into a single channel. Several considerations emerge when considering these dimensions of aggregation.

- ***Signal vs. noise.*** When observations are too agglomerated, it becomes difficult to assess whether marketing mix effects are primarily driven by certain geographies or channels. Variation in independent measures is necessary to get a reliable read on their effects. When aggregating across markets or geographies, variation in these measures is often reduced. On the other hand, too much disaggregation leads to a greater chance to include largely redundant observations in the analysis. For example, if the observational level of the model is across hundreds of channels, some will exhibit little variation in outcomes or no usage. In these instances, it becomes challenging to obtain a reliable read on how marketing affects outcomes because more noise (in the forms of no variation or zeros) is added to the data than signal. Modeling solutions to address these tradeoffs include approaches that control for large numbers of zeros or potential redundancy between observations.
- ***Common or region-specific marketing mix parameters.*** Another consideration is whether to specify common marketing mix parameters across regions, for example whether to allow price sensitivity to vary by region or be constant across regions. Various tests exist to determine whether parameters can be pooled cross-sectionally or over time. These tests consider the signal vs. noise problem, as each geography has fewer observations from which to infer a geography

specific parameter. With advances in computational power, hierarchical Bayes models can be used to strike a balance between high and low granularity. These approaches presume a common response parameter across regions or channels but allow regions to deviate from that common parameter to the extent there are sufficient observations. Another approach to modeling data with many zeros are models that include mixtures of distributions (e.g., "zero-inflated" models) and/or oversampling. That said, choosing the right level of granularity is a balance between too little information per region/channel to estimate differential effects and having too much aggregation to infer different marketing effects across regions and channels, in order to better allocate spend across them.

LONGITUDINAL GRANULARITY: TIME

Similar considerations (e.g., noise vs. signal) arise in choosing more or less granular time periods for measurement, but there are other unique concerns when considering the dimension of time.

For example, consider the effect of temporary price reductions, which may lead to a large increase in sales due to stockpiling, followed by a decrease in sales as consumers work through their inventory. Weekly sales will reflect this phenomenon with a spike in sales followed by a post-promotion dip. When aggregating across weeks, the effects tend to cancel out, making it appear as if promotions have no effect at all (a form of temporal aggregation bias).

As another example of temporal aggregation bias, consumer response and firm feedback patterns are often intertwined and may lead to exaggerated marketing mix effects. For example, while consumers can react to advertising instantly, managers can only adjust their ad spending, say, with a weekly latency. When only monthly data are available for modeling, the following pattern may occur:

Advertising (Week 1) → Consumer Response (Week 1) → Advertising (Week 2) → etc.

Monthly data contain four weekly consumer response cycles, but also three weekly advertising feedback cycles. The true response effect is hidden in these monthly data, which combines the effect of ads with the reverse causal effect of consumers on ads. Hence, the analyst must take care when choosing the granularity and duration of MMM time-series data.

- ***Choosing a periodicity.*** Should MMM data be hourly rather than daily, weekly, etc? As with cross-sectional granularity, time series data can also be too disaggregate. In addition to the signal and noise problem in cross-sectional data, more observations generate more lags and often exhibit greater redundancy. For example, last hour's sales may be more predictive of this hour's sales than last month's sales are of this month's sales. As such, highly disaggregated data (e.g., at the hourly level) may require a distributed lag model to capture these dependencies, and this approach consumes more degrees of freedom. Moreover, as in cross-sectional data, higher frequency data will be dominated by 0s, further adding more noise than information.

  Overall, the right level of agglomeration is affected by the cadence of firm decision making and how long it takes markets to respond to those decisions. If the required decision frequency is daily and there are no hour-by-hour feedback effects, then daily data are likely sufficient for response modeling. In terms of modeling approaches to address the problem, the analog of hierarchical models in cross-sectional applications is smoothing the time series (e.g., moving averages or windows), where more smoothing is required when observations are redundant or non-informative.

- ***Mismatched data granularity.*** Another common consideration is mis-matched data granularity. For example, a manufacturer and retailer might record sales as transacted or booked and a publisher might capture ads as they air. But a manufacturer might not be able to attain retailer sales records or ad exposures at more than a daily or weekly cadence. This raises questions about how to merge data from different frequencies.

  Firms have two options: either sum the high-frequency data into lower periodicities (for example, summing daily sales across days to obtain weekly sales), or split the low-frequency data into higher frequencies, usually by dividing by the number of periods in the higher frequency data (such as dividing weekly ad exposures by seven to approximate daily ad exposures, or assuming based on prior information that 80% of ad spend is during the weekend) or by creating a moving average of the divided data.

  Splitting low frequency data is, in essence, a forecast of what the data would be at the higher frequency. This leads to measurement error, and we know that in a regression model, measurement error in the spilt predictors biases coefficient estimates toward zero. However, the alternative of combining the high-frequency data into lower frequencies reduces variation and leads to weaker power. Which effect is worse relates to the previous discussion about signal versus noise. The dilemma can be eased if the firm is able to persuade the data provider to provide data at higher granularity.

DATA DURATION

Finally, we consider the question of how far back in time data should go in MMM. Much depends on how stable the market response is over time, and whether one seeks to estimate long-term effects such as brand-building investments (for instance TV ads), or short-term effects (for instance a temporary price reduction on sales).

Longer data streams provide more information to reliably estimate market response, such as price sensitivity, but there is a presumption that market response is constant over time. This can be a strong assumption, if, for example, the sample used in estimation changes over time. Moreover, data might not exist for longer periods of time (e.g., advertising on TikTok did not exist until recently). On the other hand, longer streams of data are needed to ascertain whether there is a long-term effect of marketing on baseline sales or brand equity.

One way to ascertain whether consumer response has changed over time is to work with moving-window regressions, i.e., estimate models with different start dates and trace the evolution of key parameters over time (or, similarly, interact mix variables with dummy variables for the windows). If parameters are stable, the longer time windows are preferred. If not, either shorter windows should be used, or interventions should be coded that capture changes in parameter values. See, for example, Pauwels and Hanssens (2007)[16] for an extensive marketing application. Note that there is a tradeoff: shorter windows have fewer observations to estimates and are noisier, while longer windows have aggregation bias to wash out the variation in parameters over time.

In sum, data aggregation involves tradeoffs between signal and noise. The MMM requires a sufficient amount of data, and how much one needs depends on the data and the model. In general, more complex models, e.g., machine learning, typically require more data.

MODEL SELECTION FOR MMM

Most traditional marketing mix models were specified as linear or nonlinear regression models and estimated using well-understood frequentist or Bayesian techniques. Newer machine learning methods offer great promise and power, but also the risk of misapplication, especially if developed without a working knowledge of marketing phenomena. Machine learning models are well suited for data that are tall (lots of observations) and wide (lots of independent variables).

NON-LINEARITY IN MARKETING MIX MODELS: MACHINE LEARNING APPLICATIONS

Non-linear models allow the outcome variable Y (say sales) to have a curvilinear relationship to individual predictors, as with the case of diminishing returns. Nonlinear models also capture interactions, where the effects of changes in sales, due to changes in marketing mix variable 1, depend on the level of spending on marketing mix variable 2. For example, advertising may have bigger effects on sales for a new product than for an established product, or ad effects may change with the firm's sales force spending.

With many predictors, modeling interactions explicitly increases model complexity and can raise multicollinearity concerns (see "Factors Affecting the Uncertainty of Effect Estimates of a Marketing Mix Tool" above). Machine learning methods, such as Lasso and Elastic Net, can help balance competing concerns about model completeness and overparameterization by explicitly managing the "bias-variance" tradeoff. More complex models always fit training data better than simpler models, and often reduce omitted-variables concerns, but those advantages can come at the cost of cross-validation performance due to overfitting concerns. A variety of machine learning algorithms and estimators can help to balance the competing concerns.

Although machine learning is often focused on improving prediction, it is important to not confuse a model's predictive ability with causal effect estimation. A causal model may overfit the data and hence predict poorly, and a model that predicts well may still estimate associations rather than causal effects, due to unobserved variables. A related concern is that machine learning models that automatically prune predictors to maximize predictive performance may omit truly causal variables in favor of correlated but non-causal variables.

Caution is especially warranted when using machine learning techniques for optimization use cases of MMMs. Marketing domain knowledge can complement analytics skills in developing and deploying such models. For example, business stakeholders may want to "sign off" on the various model training criteria, before estimation, to ensure the results address their needs. Different approaches may lead to radically different solutions, with respect to which variables matter and how much. When using machine learning for optimization, additional care should be taken because model nonlinearity can lead to multiple local optima with substantially different implications.

SUPERVISED, UNSUPERVISED, AND SEMI-SUPERVISED MACHINE LEARNING

Machine learning techniques can be categorized as supervised, unsupervised, or semi-supervised, depending on the availability of labeled training data.

- ***Supervised machine learning.*** In supervised machine learning methods, both input and output data can be observed—both X's and Y's. The objective of supervised machine learning is to establish a function that maps input to output variables. Linear regression and logistic regression are both simple examples of supervised machine learning. There are also newer methods, like deep learning, that can better handle high dimensional data and nonlinearity.

  Supervised machine learning uses input variables, such as the 4Ps of marketing, economic conditions, and so on, to predict output variables such as revenues and sales. Supervised ML lends itself to automation, which enables the generation of updated results and projections in a timely manner. It allows firms to enhance MMM with machine-generated "flags" to provide insights on the changing dynamics. For example, flags can indicate the power of channel X1 is diminishing and channel X2 is increasing. These automated flags can serve as indicators for managers to revise their decisions.

  Managers like models that are interpretable. Some AI and machine learning models that are highly predictive can be black boxes. If the MMM goal is to estimate the true causal coefficients of marketing mix variables for purposes of resource allocation, the black box aspects present a hurdle. "Interpretable AI" is an attempt to make models less of a black box. As models improve over time in their interpretability, these approaches to MMM—based on supervised machine learning, should become increasingly useful for MMM prediction use cases.

- ***Unsupervised machine learning.*** Unsupervised machine learning is often used to uncover hidden patterns and structures within the data. In the context of MMM, unsupervised machine learning can help prepare the input variables for MMM by reducing data dimensions and transforming non-numeric data (such as text or images) to numeric inputs. The latter enables firms to ascertain how advertising design affects social media mentions and sales.

  Consider advertising on five media as an example. These five media create five own-media effects and 26 cross-media interactions between two, three, four and all media, all of which are input variables for the MMM. Moreover, when considering lagged media effect, goodwill stock, and nonlinear relationships, the number of right-hand side variables can quickly increase the MMM complexity and computational burden. Unsupervised machine learning tools can be used to reduce computation requirements in MMM, handling the high dimensionality by identifying the most relevant variables, or to represent complex relationships in a lower-dimensional space.

- ***Semi-supervised machine learning.*** Semi-supervised machine learning models can be used to add new predictor values to MMM data by labeling qualitative or unknown input variables. This subset of machine learning tools can be used in preparing MMM input data for subsequent analysis. For example, in preparing touchpoints data as part of the promotion variable for the MMM, managers can manually label certain types of touchpoints as early-funnel or late-funnel based on their domain knowledge, while leaving the rest to be determined by the machine learning algorithm. Similarly, when using a semi-supervised natural language processing (NLP) method to understand consumers' online reviews, managers can label certain words or phrases as product-related or price-related, and let other latent topics emerge freely from the data. These extracted themes can subsequently be used as input variables for MMM. By incorporating semi-supervised machine learning in MMM, managers can have greater control and influence over the process, ensuring their domain knowledge and expertise are effectively integrated into the MMM.

MARGINAL RETURN ON ADVERTISING AND OPTIMAL SPENDING

Return on investment—the fraction of the initial investment that is returned in profit—is a common financial evaluation metric for various firm investments. We see three main commonly occurring errors in how marketing executives use ROMI (Return on Marketing Investment) to evaluate and allocate budgets across a set of marketing tools.

- First, marketers often think in terms of sales "lift" from a marketing tool rather than lift in profit contribution, net of cost of goods sold and the cost of the marketing campaign.
- Second, marketing managers often ignore diminishing returns in spending on a given demand-generation tool and calculate ROI of all use of a particular tool rather than the marginal effect of change from current spending.
- Third, marketing managers use measures of short-run rather than long-run effects of marketing investments.

THINK LIKE A CFO ABOUT RETURN ON MARKETING INVESTMENT

Analysts, marketing managers, and C-suite investors often unintentionally speak different languages when they talk about Return on Marketing Investment.[17] Suppose a firm has base sales of $10 million on its product or service and runs a $2 million campaign that raises sales to $14 million. Assume gross margins of 50%. What is the ROMI?

Some might say ROMI = $4 MM / $2MM = 2. The firm gained $4MM in sales and spent $2MM. Others might say ROMI = $4MM * .5 / $2MM = 1. The firm made $2MM in profit from the incremental $4MM in sales and spent $2MM to get that incremental profit.

The CFO, however, would say: ROMI = [($4MM * .5) – $2MM] / $2MM = 0.

After all, the firm made no incremental profit net of variable costs of the sales and the cost of the marketing campaign.

DIMINISHING RETURNS: EVALUATE *MARGINAL* ROMI, NOT ROMI

In marketing, some measure of ROI is typically used to assess the return on marketing spending. The challenge here is that consumer response to spending, in a tool like advertising, is subject to diminishing returns: the incremental sales lift you get from the first $1,000 you spend on advertising is nearly always higher than the tenth $1,000. However, the ROI for a campaign is the *average* return for the entire campaign spend. This means we cannot compare the ROI for two different campaigns, unless the campaigns were equally costly, which seldom happens.

What are the consequences of using ROI metrics in advertising impact valuation? Generally, it will result in *underspending*, because the smaller campaigns will have higher ROI than the larger ones (assuming equal consumer response).

The more relevant metric is the **marginal** ROI of a campaign: what is the incremental sales lift of the last dollar (or $1,000 if one dollar is too granular to be practical) of spending? Ideally, if spending is optimized, that last-dollar return should be zero, or close to it. The point where marginal ROI = 0 is exactly the point at which profits are maximized. A positive marginal return implies that money was left on the table (due to underspending). A negative marginal return implies that money was lost (because the cost of the ads exceeded the incremental sales lift). These issues are explored in more detail in Hanssens (2023).[18]

The difference between marginal and overall ROI is critical when trying to optimize spend. The term "optimal" implies a value judgment, i.e., what criterion does management attempt to maximize? We know that ROI should **not** be maximized. "Profit" is a better criterion, though in most cases it can be approximated by "contribution to overhead" (assuming that fixed costs have no impact on consumer response and can be ignored in optimization).

In our context:

Profit = Sales * Gross Margin – Advertising Spend – Fixed Costs

or, simplified,

Contribution to Overhead = Sales * Gross Margin – Advertising Spend

To see this, consider the ad-sales relationship in Figure 1 showing ad spending (in $000s) and revenue (in $000s). In the example shown, revenue is $2 million without advertising. At any level of advertising greater than 0, a 1.0% increase in ad spending yields a 0.1% increase in sales. (This is commonly called a *constant elasticity* model as the ad elasticity is constant at 0.1 for all spending levels). This example reflects *diminishing marginal returns* in the relationship of ad spending to revenue.

Figure 1: Ad Spend Effects on Revenue

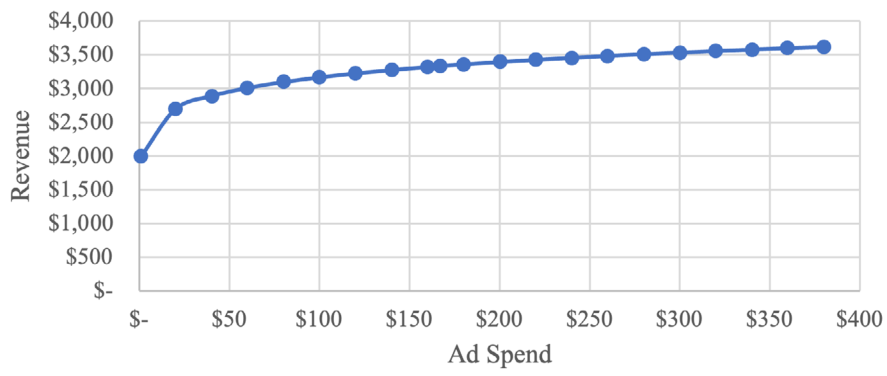
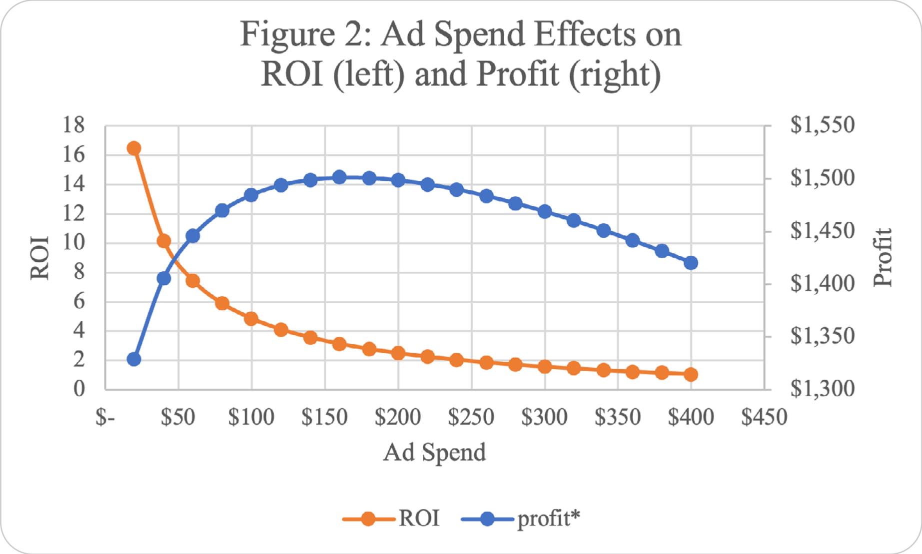


Figure 2 shows the contrast of ad spending effects on profit vs ROI. Figure 2 makes clear that ad spending to maximize ROI (near zero) also represents the lowest level of profits. In this example, profit is maximized at an ad spending level of $167 million—far higher than what would be recommended if maximizing ROI.



The general patterns in Figures 1 and 2 hold for any constant elasticity demand model when ad elasticity < 1, which is almost always true for real-world ad elasticity. In all such cases, the level of ad spending that maximizes ROI will be much lower than the value that maximizes profit, or, equivalently, the level that makes the marginal ROI of the last dollar of ad spending = 0.

OPTIMAL ALLOCATION ACROSS CHANNELS

The principles above apply equally well to budget allocation decisions, i.e., how much should each channel or medium optimally receive? This was answered in the economics literature by Dorfman and Steiner in 1954. The answer is remarkably simple: the optimal media allocation is given by the ratio of the media elasticities.

If channel A has an elasticity of 0.05 and channel B's elasticity is 0.03, then A should receive .05/(.05+.03) = 62.5 percent of the budget and B should receive the remaining 37.5%. Note that, if a channel's elasticity is zero (i.e., consumers are unresponsive), its optimal allocation is logically zero percent of the budget.

The Dorfman-Steiner rule holds for any continuous and differentiable (i.e., no kinks or discontinuities) response function that recognizes diminishing returns, so long as each channel uses the same spend metric (e.g., dollars).[19] When using a log-log formulation (akin to the well-known Cobb-Douglas production function in economics), the resulting elasticities are constant, so the allocation math is very simple. For MMM models in general, it is best to find the optimal allocation by mathematical optimization of the profit function. That also allows for the inclusion of practical considerations such as a total budget constraint, various minima and maxima spend levels by medium, etc.

Some managers believe that the correct advertising response function is S-shaped, i.e., increasing returns at low spend, followed by decreasing returns at higher spend. There is very little empirical support for this pattern, however. In case of doubt, one can conduct a Johansson (1979) test on the data, which compares the performance of S-shaped vs. concave functions.[20]

SHORT-TERM VERSUS LONG-TERM METRICS

How about long-term considerations? In many cases, short-term profit is a myopic view of performance which, in fact, can underestimate advertising's total impact.[21] If the brand can estimate the typical loyalty (in the form of repeat buying) that can be expected from a newly acquired customer, the profit definition can be extended as:

Long-term customer profit = customer profit / (1 – loyalty rate)

As an example, if firms A and B each achieve, on average, $100 of gross margin per year from their customers, and firm A has an 80 % annual loyalty rate (or 20% churn), while firm B enjoys 90% loyalty (10% churn), then each newly acquired customer provides—in nominal dollars—$500 in incremental gross margin for firm A, but $1,000 for firm B. Thus, even with equal consumer response to their advertising, firm B can afford to invest significantly more on acquisition advertising than firm A.

Insofar as *intermediate* performance (funnel) metrics are used—such as awareness, leads, clicks and likes—it is important to estimate a separate equation that measures the *conversion rate* of the intermediate metric to actual revenue generation. For example, we may find that the elasticity of advertising on lead generation is 0.2, and the elasticity of leads on revenue generation (i.e., conversion rate) is 0.4. The resulting advertising to revenue elasticity is then 0.2*0.4=0.08.

In the above we only consider the case of customer acquisition through advertising. Similarly, marketing dollars can be allocated to customer retention, upselling and cross-selling, though advertising's role in these has been shown to be more limited. See, for example, Blattberg and Deighton (1997)[22] for a marketing optimization framework that combines customer acquisition and retention spending.

In conclusion, best practice in marketing mix optimization will require an objective function to be maximized that reflects the priorities of the firm. When profitability is concerned, a realistic profit function should be used, including gross margins and advertising costs. The estimated marketing mix model should reflect diminishing returns to advertising spending, lest it results in unrealistic optimal spend recommendations. Various practical restrictions on spending (e.g., minimum and maximum allowed spend levels by medium) are incorporated by adding constraints to the optimization.

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