MSI Marketing Mix Model Initiative Progress Report

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What is a marketing mix model (MMM)?

First introduced in the 1950s along with the 4Ps of marketing by Prof. Jerome McCarthy.

The variation in brand performance measures should be explained by price, product, place (distribution), and promotion.

MMM determines how much impact is driven by each of the 4Ps and forecasts the future impact of altering or optimizing the marketing mix.

Begin with sales being the DV and extend to measure profits and ROI.

What is MMM?

Promotion
  - Channel 1
  - Channel 2
  - Channel 2
Price
Product
Place (Distribution)
External conditions
  - Economy
  - Weather
  - Holidays

MMM → Sales Forecast

An MMM predicts sales* as a function of the marketing 4P's, factoring in external conditions.

You can use it to understand how media and other factors affect sales.

*or other brand performance measures

Marketing vs Media Mix Models

Entries in the table are elasticities.

Elasticities are the responsiveness of sales to a change in each variable.

E.g., if the price elasticity of demand is -2.6, a 1% increase in price leads to a 2.6% decrease in demand.

Absolute value>1 ➜ elastic

Absolute value<1 ➜ inelastic

	Typical Elasticity	Range
Price	-2.6	-2.5 to -5.4
Personal selling	0.35	0.27 to 0.54
Advertising	0.1	0 to 0.3 New products higher
Distribution	0.6 to 1.7	S-shaped
Product innovation	>0	Higher for radical
Price promotion	-3.6	-2 to -12 (short run) 0 (long run)

See Table 3 in Hanssens, Dominique M., and Koen H. Pauwels. "Demonstrating the value of marketing." Journal of Marketing 80, no. 6 (2016): 173-190.

Why are MMMs becoming important - Privacy regulations and walled gardens

Forbes

FORBES > INNOVATION

A Comparison Of Marketing Measurement Approaches In A Cookieless World

Constantine Yurevich Forbes Councils Member
Forbes Technology Council COUNCIL POST | Membership (Fee-Based)

Jan 11, 2023, 06:00am EST

Founder and CEO of SegmentStream, a Conversion Modelling Platform that solves marketing analytics in a cookieless world.

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News & Analysis

What's Old Is New Again: Marketers Adopt Marketing Mix Modeling

October 25, 2022 by Joseph Zappa

Why are MMMs becoming important
- Innovation and digitization are accelerating

AdAge

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Data-Driven Marketing →

ADOBE USES AI TO SPEED UP MARKETING MIX MODELING

Process that takes months is reduced to weeks, becoming practical for more marketers and potentially helping prove their worth

By Jack Neff. Published on October 06, 2022.

Exploring Marketing Mix Modeling (MMM) and Conversion Lift Experiment (CLE) blending
The Alshaya Group/H&M Case developed by Deloitte

News & Analysis

Keen Brings SaaS to Marketing Mix Modeling

November 7, 2022 by Joseph Zappa

Goal of this initiative

Developing and disseminating best practices for the design, validation and use of MMM to increase trust and ensure marketing spend is as effective as possible.

Panel – Industry Leaders

airbnb – Sam Barrows, Zhiying Gu, Linsha Chen

AstraZeneca – Matt Gray

AT&T – George Wu, Rob Cederbaum, Linette Mookanamparambil, Michael Guber

Citi – Tony Michelini

Coca-Cola – Greg Pharo

Colgate-Palmolive – Agustin De Dios Iglesias, Sandipan Sinha, Helen Wolf

Dell – Saleel Gadgil

Domino's – Hanna Wilder, Samuel Sokolowski, Pierre Gardan

FiServ – Mike Anderson

Google – Tina Daniels, David Kaul, Stephen Mangan, Casey Cowgill

Kantar – Satya Menon, Patrick Moriarty

Marketing Attribution – Ross Link

Meta – Neha Bhargava, Jessica Nguyen

Netflix – Wayne Huang, Asaf Davidov

Neustar – Michael Schoen, Marc Vermut, Emiko Seale

Nike – Shaun Desmond, Matthew Hanlon, Matt Kane

Pernod Ricard – Karen Chisholm

Pinterest – Uri Weg

Sequent – Jim Spaeth, Alice Sylvester

UHG – Martyn Crook

Vanguard – Kristin Federico, Jing Wang, Russ Messner

Wayfair – Rob Corbin, Scott Collins, Carter Noordsij, Connor Richmond, Suki Lau

Panel – Academic Leaders

Ron Berman, U. of Pennsylvania

Elea Feit, Drexel

Dominique Hanssens, UCLA

Alice Li, The Ohio State

Mitch Lovett, U. of Rochester

Carl Mela, Duke

3 Phases

Phase I: What is current MMM practice?

We are here

Phase II: What makes for a good MMM?

Phase III: A processes for certifying MMM pipelines

Phase I: Scoping current MMM practice

Formed academic and industry panels with deep expertise

Introduced the initiative at the 2023 MSI Annual meeting

Dyadic industry/MSI interviews

Academic group produced a paper on the scope of the initiative

Joint meeting of both academic and industry panels

- Refined priorities

- Collected user cases

- Developed specific objectives to focus in the next two phases

- Follow up with a broader set of MSI partners

Stakeholders

Data providers provide data used in MMM

Designers design and build MMM models

Users use MMM evaluate and optimize marketing spend across channels

Investors make decisions about marketing investments (and often don't know much about MMMs)

What issues are important today?

Data

    Accuracy

    Frequency, latency & agility

    Granularity, across geography, time and channel **◄ Panel Interest**

    Adjusting to changes in ad tech

    Lack of variation, e.g. a new channel with no history

    New data: sentiment, creative quality, media attention

Optimizing marketing spend using MMMs **◄ Panel Interest**

    Marginal versus total ROI

    Efficiency versus effectiveness

Training investors to use MMM

Why data granularity?

AGGREGATION BIAS IN PRICE ELASTICITY

Parameter	Model	$\varepsilon < -1$	$-1 < \varepsilon < 0$
Promoted Price Elasticity	Store	🟢	🟢
	Retailer Store-Group	⬇	⬆
	Retailer	⬇	⬆
	Market Multiplicative	⬇	⬆
	Market Additive	⬆⬆	⬆⬆
	Hybrid	NA	NA
Regular Price Elasticity	Store	🟢	🟢
	Retailer Store-Group	⬇	⬆
	Retailer	⬇	⬆
	Market Multiplicative	⬇	⬆
	Market Additive	⬆	⬆
	Hybrid	NA	NA

Source: Nielsen DMC1 synthetic data tests

from Aggregation Bias Test Summary, Ross Link, Marketing Attribution LLC, 2023

The level at which we can track varies by marketing channel

   User

   Market

   Nation

But we know that aggregating data can lead to bias in estimated elasticities

Developing a scorecard

Develop a MMM "scorecard" to be used for self-evaluation

We may collect self evaluations to study the industry

	Standard	Evaluation
Data	- Accuracy validation - Geo granularity - Channel granularity - Sufficient variation in inputs - ...	
Model Features	Model includes: - Diminishing returns to advertising - Time-decay - ... Model pipeline includes: - Regular re-estimation cadence - Validation by simulation - Out-of-sample validation - Comparison to industry benchmarks - ...	
Optimization	- Equalizes *marginal* ROI across channels - Guardrails against extreme extrapolation - ...	

Industry benchmark elasticities

Collect estimated elasticities across industries and media channels

This can be published (in an aggregated form) to facilitate industry benchmarking

Marketing Effort		Sales Elasticity
Media	TV	[----]
	Broadcast Radio	[-------]
	Print	[----]
	Streaming Video	[-------]
	Streaming Audio	[---]
	Social Media	[--------]
	Search	[-----]
Pricing	Promotional Price	[----]
	Regular Price	[----]
Distribution		[-----]

Industry comparison ranges
e.g. 25-75 %-tiles

Creating a certification service for MMMs

Provide ways for member companies to validate their MMM pipeline using MSI expertise

Build credibility within the organization

Identify opportunities for improvement

Develop the skills of internal teams

Set standards for data and analytics providers

Get involved!

Any MSI member company can join the MMM initiative, where you can

- Work with other companies to set guidelines and standards

- Meet academics who are interested in innovation

- Benchmark your advertising performance against others

Backup

Use cases

Promotion
 - Channel 1
 - Channel 2
 - Channel 2
Price
Product
Place
Economic conditions

MMM → Sales Forecast

Given the broader scope of MMM, should we use a straight arrow point back to the bracket instead of one item in the model.

Benchmark elasticities from academic work

TABLE 3
Response Elasticities Summaries

	Typical Elasticity	Range	Drivers (+)	Organic Growth Driver?
Advertising	.1	0 to .3	Product newness, durables	Minor
Sales calls	.35	.27 to .54	Early life cycle, European markets	Major
Distribution	>1	.6 to 1.7	Brand concentration, high-revenue categories, bulky items	Major
Price	−2.6	−2.5 to −5.4	Stockkeeping unit level versus brand level, sales versus market share, early life cycle, durables	Minor
Price promotion	−3.6	−2 to −12	Storables versus perishables	No
E-word of mouth	Positive	.24 (volume) .42 (valence)	Low trialability, private consumption, independent review sites, less competitive categories	Possibly
Innovation[a]	Positive	N.A.	Radical versus incremental innovations	Major
Brand and customer assets[a]	.33 (brand) .72 (customer)			Major

[a]On firm value.
Source: Hanssens (2015).
Notes: N.A. = not applicable.

Networking Break

Upcoming Events:

MSI at the **ARF**

- **5/9** – **Ensembling Experiments to Optimize Interventions Along the Customer Journey** | Yicheng Song, University of Minnesota

Workshop:

- **5/16** – **The Customer-Base Audit** | Peter Fader, University of Pennsylvania

Workshop:

- **5/23 – Digital Customer Engagement** | Wendy Moe, University of Maryland

Book Series Webinar:

- **5/30 – Power and Prediction: The Disruptive Economics of Artificial Intelligence** | Avi Goldfarb, University of Toronto

Webinar:

- **6/27 – Regulating Privacy Online: The Economic Impact of the GDPR** | Samuel Goldberg, Stanford University

In-Person Event:

- **Fall 2023** – **MSI Accelerator** | New York, NY

Register Now at msi.org/2023-calendar-of-events/