Exploring Granular Data in MMM: UPDATED MODELS, BETTER INSIGHTS

accenture digital

Strong businesses have always prioritized advertising and marketing.

These cornerstones of business success are vital for enhancing a brand, pushing promotions and differentiating a business from its competition. Some of the channels for marketing and advertising have remained constant: direct mail, billboards, radio and television advertising are still important means for building a successful business. Yet the digital revolution has provided exciting new possibilities. Email, digital banners and social media are enabling businesses to access, expand and refine their audiences like never before. With competition so intense and so many available marketing channels, businesses need to be aware of how best to allocate their resources across different channels.

Without knowing it, many organizations hold the key to their own success. Many businesses maintain databases containing huge amounts of data. Yet many have failed to convert this data into actionable insights. Using this data intelligently could help companies to make more informed marketing decisions.

One way to make this happen is through **Market Mix Optimization (MMO).** MMO offers a two-tiered approach to marketing. The first stage involves the building of a statistical model called **Marketing Mix Modeling (MMM).** The second stage involves the analysis of MMM results through an optimization engine, which ensures the best possible allocation of resources.

> **Through MMO, organizations get a comprehensive view of their marketing activities and their impact on profits.**

This empowers marketers to identify potential new areas of investment or isolate areas of spending that can be cut without adverse effect. For example, MMO could help a company make an informed decision to reduce circular advertisements to once a month, rather than once a week, and reallocate that budget to a digital channel. In this scenario, the company would maintain the same marketing budget, but increase revenues.

As the digital world has grown, the market has changed. Today, information is generated and shared faster and businesses can't afford to delay their reaction to market changes. Organizations across the globe have been using MMO for many years. In this paper, we will introduce the historical approach to MMM that feeds into the mathematical optimization tools. We will then show how techniques have evolved over time to keep up with industry trends and how these newer methods, in conjunction with improved data, enable marketers to respond swiftly to consumer behavioral trends.

KEY LEARNINGS:

Granular data you already have could be used to make more **strategic investment decisions** across advertising channels

The evolution of MMM accounts for newer, faster-moving digital channels

Regression Approaches to MMM

Let's consider a toy manufacturer client that we will call ToyCo with a $100M budget. The client wants to know what proportion of their sales can be attributed to marketing. Within their marketing, they'd also like to analyze how each tactic impacts their performance, so that they can optimize their marketing mix. In the example, the KPI under analysis is sales, but ToyCo could also have considered modeling other KPIs like store traffic and brand awareness. To accomplish ToyCo's objective, MMM models are created to model sales against marketing activity.

In the 1980s and 1990s marketers trialed MMM by using linear regression models. Regression models assume a linear relationship between the dependent variable (i.e. KPI) and independent variables (i.e. Marketing activities and other external factors). External factors such as demographic, macro-economic factors, and competitive presence are beyond the control of marketers, but have a significant impact on the success of marketing campaigns. These factors can be introduced into the models and incorporated into our base sales estimate, so we can still separate marketing driven behavior. Thus, MMM establishes a relationship that describes the responsiveness of sales to specific controllable variables (marketing) while accounting for external influences (e.g. Macroeconomic, Demographic etc.)

Here is quick look at a functional form of regression model in marketing framework:

$$Y = \beta_0 + \sum_{j=1}^{m} \beta_j X_j + \epsilon$$

Y dependent variable (e.g. Sales)

X_j advertising spend/activity for j[th] marketing variable

m number of marketing variables

β_0 intercept or baseline in MMM

β_j coefficient for j[th] marketing variable

ϵ modeling error, the difference between predicted and actual values

The above equation splits sales into two parts:

Baseline Revenue – The revenue a company can expect to receive in the absence of any marketing tactics. It includes base sales, macro-economic trends, seasonality, other external factors etc.

Marketing Contribution – Incremental Revenue generated from each marketing tactic, where each coefficient measures the impact of every extra dollar invested in each marketing tactic, onto sales.

Mathematically, the marketing contribution to sales is defined by the summation of [Spend Coefficient] for all marketing tactics. Common examples of marketing tactics are Television, Radio, Magazine, Facebook, Paid Search etc.*

Linear models of this form are easily interpreted. Each coefficient represents the rate of change in the dependent variable—sales—for every unit change in marketing activity.

For ToyCo, we may find that

for every $1 spent on Direct Mail we see $2 incremental in revenue, while for TV the incremental in revenue is $1.75.

Analyzing these results through optimization can further enhance what we learn by suggesting a marketing mix that includes more DM investment than TV.

Regression models are very useful when sales can be explained via a linear relationship to marketing activities. However, in the absence of such a relationship, regression models are a poor fit. To compensate, we often transform variables to account for our business knowledge of these tactics. As an example, over time, advertising often has a diminishing effect on sales. There isn't, therefore, a straightforwardly linear relationship between sales and marketing channels.

Accenture captures this volatility in advertising by applying the following, non-linear transformations to the marketing activities:

ADSTOCK
Marketing activity can have an impact on future time periods, with less impact carried over each ensuing period. For example, if a business advertises 100 units in week 1, it is expected that the impact of that advertisement recedes in the consumer's memory.

SATURATION
Marketing activity will carry diminishing rates of return as total spend increases. In other words, we can't spend an infinite amount of money and expect continued gains: every additional dollar generates fewer returns than the previous dollar.

LAG
Adjusting the modeling data set to consider the fact that the impact of marketing on a business is often not immediate. Consumers who view the advertisement today may wait a few weeks to buy the product.

Applying these transformations to the data solves some of the problems presented by a linear model. However, it does not address other important business concerns. For example, ToyCo may have many stores scattered across the country. They would want to optimize their marketing strategy for each individual store or direct marketing area (DMA) as is commonly used in the US. Unfortunately, the above regression approaches view each store or DMA as identical. This limits ToyCo's ability to target media buys geographically. To do this, we need a different modeling approach that can analyze each DMA.

Mixed Models

ToyCo liked the easy interpretability that the regression models offer but wanted to start setting their marketing strategy at a DMA level. By treating the DMA's as "panels", we create a so-called "mixed model", which maintains the same linear relationship we had before, but enhances it with the introduction of a random coefficient. The effect of each panel is then captured by a random coefficient, which in conjunction with the fixed coefficients from the linear regression model, helps construct models at more targeted levels. For ToyCo we are focusing on DMAs, but we could have narrowed the focus to a single store or zip code, so long as we have sufficiently specific sales and marketing data.

Thus, mixed models take on the following functional form:

$$Y^i = \beta_0^i + \sum_{j=1}^{m} \beta_{jF}^i X_j^i + \sum_{j=1}^{m} \beta_{jR}^i X_j^i + \epsilon$$

Y^i dependent variable for panel *i*

β_{jF}^i fixed effects for j^th marketing variable and panel *i*

i 1...n number of panels / DMAs

β_0^i intercept or baseline in MMM for panel *i*

β_{jR}^i random effects for j^th marketing variable and panel *i*

ϵ modeling error, the difference between predicted and actual values

X_j^i transformed advertising spend/activity for j^th marketing variable and panel *i*

m number of marketing variables

The equation splits sales into two parts:

Baseline Revenue – The revenue a company can expect to receive in the absence of any marketing tactics. It includes base sales, macro-economic trends, seasonality, other external factors etc.

Marketing Contribution – Incremental revenue generated in response to each marketing tactic, where coefficient measures the impact of every extra dollar invested in marketing tactic onto sales for each panel.

> **Fixed Coefficient:** the average impact of a marketing activity across all panels. This can be referred to as a global estimate which does not differentiate between each individual panel defined in the analysis
>
> **Random Coefficient:** the individual response of a marketing tactic for each panel.

Mathematically, the marketing contribution is defined as the summation of [Spend Fixed Coefficient] + [Spend *Random Coefficient] for all marketing tactics for each panel i. Typical marketing tactics can be defined as Television, Radio, Magazine, Facebook, Paid Search, etc.*

For each panel, the combination of fixed and random effects provides a more detailed estimate of how each panel responded to marketing activity.

Let's revisit ToyCo's regression model, which showed

Direct Mail drove $2 in revenue for every $1 investment.

In the mixed model, we can see that

New York gets **$2.50** for every $1 investment, while Chicago gets $1.50.

Once we run these results through the optimization engine, ToyCo can expect to see a significant increase in direct mail budgets in New York, while Chicago may see a smaller increase in budget depending on the ROI of other marketing channels.

While mixed models provide good, targeted results for ToyCo, **a significant amount of data is required to properly estimate the random effects.** Additionally, ToyCo would like their modeling coefficients to place a greater focus on more recent events. Yet the random coefficients generated through mixed models are computed as an average over the entire data set, which might contain several years' worth of sales and marketing behavior.

In the late 2000s, the global economy crashed. Marketers' budgets declined accordingly. At the same time, the potential of digital advertising and marketing platforms was expanding rapidly. Digital media meant campaigns could be run with a lower budget, but with greater personalization. Furthermore, more campaigns were being run, with shorter intervals between them.

> The shift in practice and focus meant marketers needed to be able to **react faster** to the latest market trends, while also being able to **evaluate the efficiency of different marketing tactics** at various points in time.

The result was a shift away from classic regression approaches, to a refined technique that is much more reactive to the latest developments and market activities.

State Space Modeling

Continuing with ToyCo, let's consider a hypothetical scenario where they face a sharp decline in sales due to macro-economic factors and, as a result, decide to reduce their marketing budget from $100M to $75M, a 25% reduction. Yet they don't want to cut their budget indiscriminately: ToyCo wants to reduce its marketing during the time frame that will least affect overall sales. To help them do this, we need a strategy that can accommodate **seasonal as well as geographic factors.** This will allow ToyCo to yield results for a specific point in time rather than adopt a generic strategy for the whole year.

To adjust to ToyCo's new circumstances, we will shift to State Space Modeling (SSM), which breaks sales into a function of a baseline trend and marketing activity but adds two new enhancements. The first enhancement is that the baseline is adjusted to incorporate a **seasonality effect,** *meaning our baseline sales will fluctuate, rather than remain static throughout the year.* The second enhancement is the coefficients for each marketing tactic are created at **different points in time,** *instead of one coefficient computed as an average across all time points.* As a result, ToyCo can now increase baseline sales in the lead up to Christmas, rather than attributing the large sales volume to the marketing tactics that are being used at that time. In a regression or mixed model approach, the baseline sales would not have adjusted to account for the holiday season. This would mean that an increase in sales during the holiday season could be wrongly attributed to the marketing approach used during that period. Equally, the sales decline after Christmas might also be attributed to the marketing mix at that time.

While the prior modeling tactics could calculate a single coefficient for each marketing tactic, this technique works recursively to produce **coefficients for each marketing tactic at each point in time** often referred to as time varying coefficients. This process analyzes sales as a time series and uses each observation to predict the next. Since ToyCo likes to view their sales on a weekly level, this technique can help predict this week's sales based on last week's sales, as well as incorporating new insights from this week's sales. This procedure is repeated at every time step to work recursively and produce coefficients for that specific week, without requiring anymore observations other than the previous week.

> **This means our coefficients represent behavior in that specific week and reflect the activity seen in the prior week.**

The new model adjusts to:

$$Y^i = \beta_0^i + \sum_{t=1}^{T}\sum_{j=1}^{m} \beta_{jtF}^i X_{jt}^i + \sum_{t=1}^{T}\sum_{j=1}^{m} \beta_{jtR}^i X_{jt}^i + \epsilon$$

Y^i	dependent variable for panel *i*	β_{jtF}^i	fixed effects for j[th] marketing variable and panel *i* at time *t*	T	total time period
β_0^i	intercept or baseline in MMM for panel *i*	β_{jtR}^i	random effects for j[th] marketing variable and panel *i* at time *t*	ϵ	modeling error, the difference between predicted and actual values
X_{jt}^i	transformed advertising spend/activity for j[th] marketing variable and panel *i* at time *t*	m	number of marketing variables		

The above equation splits sales into three parts:

Baseline Revenue – The revenue a company can expect to receive in the absence of any marketing tactics. It includes base sales, macro-economic trends, other external factors etc.

Marketing Contribution – Incremental Revenue generated in response to each marketing tactic at a single point in time. Here the time varying coefficient measures the impact of every extra dollar invested in a marketing tactic onto sales specific to that time.

Mathematically, the marketing contribution is defined as the summation of [Spend Fixed Coefficient] for all marketing tactics. Typical marketing tactics can be defined as Television, Radio, Magazine, Facebook, Paid Search, etc.*

Seasonal Effect – The revenue generated owing to seasonal occurrences like holidays or any specific seasonal pattern.

The new model now becomes a linear combination of a baseline performance, an adjustment to that baseline for seasonality and the incremental impact from marketing tactics at each point in time.

Tracing back the journey of ToyCo,
we observed that through **linear regression**

DM drove $2 in sales for every $1 invested,

while **mixed models** showed

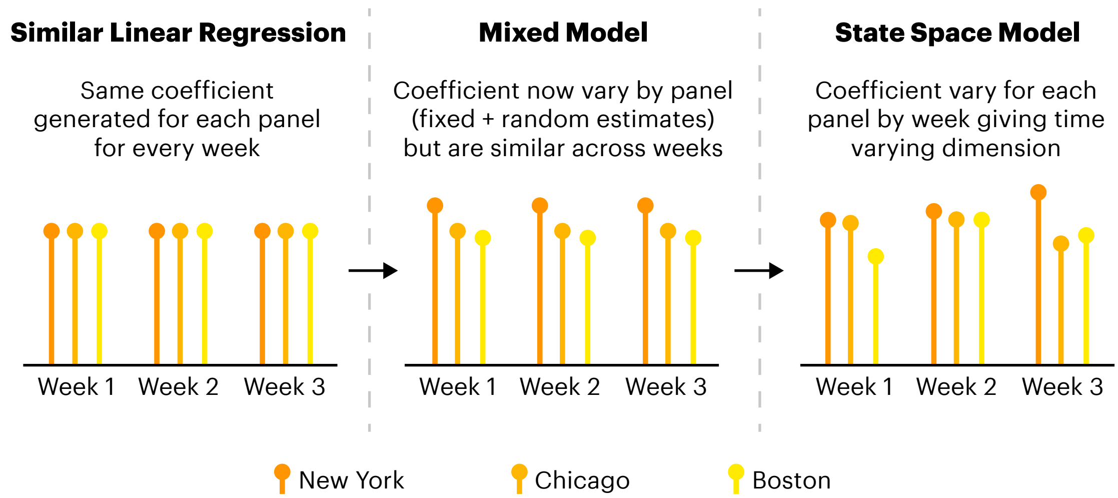
DM drove $2.50 in NY and $1.50 in Chicago.

When State Space Model is employed, we see that in the final week of November we get

$1.50 for every $1 invested in DM, but in the 1st week of December we get **$3.50** for every $1 invested in DM.

While SSM enables ToyCo to target their marketing based on seasonal behavior and latest trends, the ability to deploy marketing strategies at a DMA level remains important. We can adjust for DMA level variation by building SSM for each DMA. ToyCo can create 210 models, 1 for each DMA. While building 210 models requires more work than building one, it will allow us to reap all the benefits SSM provided over regression and mixed models approaches, while maintaining the ability to understand our business in each DMA.

The chart below displays the movement of coefficients for a single marketing channel by each methodology discussed.



Clearer Insights Through our Facebook Partnership

Each of the modeling approaches outlined above has its advantages and disadvantages. Yet a model can only be as good as the data used to train the algorithm and identify trends. In recent years, IT departments have been under pressure from businesses' need for granular data at an expedited time frame. In the digital age, campaigns are short-lived and targeted. Marketers need to react as the market changes and businesses need to constantly capture and analyze digital activity.

Accenture and Facebook have formed a partnership that enables us to access aggregated data for MMM in a streamlined and efficient manner.

Facebook captures the results of paid marketing campaigns on their platform and once client approval is in place, Facebook provides Accenture with aggregated campaign data for use in MMM. The quick fed results of Facebook data enables building and refreshing MMMs in a shorter time that helps measurement of shorter campaigns in a more timely manner. In addition, the data includes geographic information, meaning the models can respond both quickly and according to geographically-specific activity.

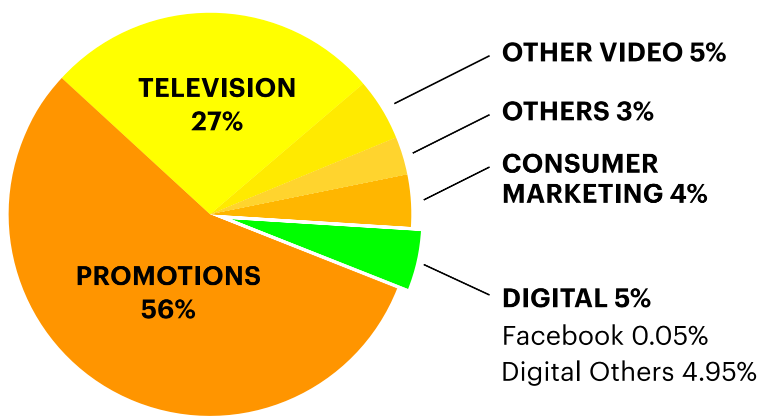
CASE STUDY

Let's consider a further case study of ToyCo. This client has worked with Accenture through multiple iterations of MMO, beginning with mixed models and progressing to SSM. This client analyzes their business at a national level and executes a national media buying strategy, so all marketing activity is captured nationally. Seeing that this approach limits their ability to make targeted media purchases, we decided to re-evaluate this model by leveraging granular campaign data provided from Facebook, to produce a DMA specific model. This model focuses on sales and marketing data from May 2014 through April 2017 for one subset of this client's business, pre-selected by the client. **We will be recreating 210 DMA specific models, leveraging the exact same variables that went into the national model to enable comparisons.** These models will tell us the impact of DMA specific Facebook plus national media buys for other tactics have on DMA specific sales. These 210 models can then be aggregated up to a national level and compared with the national model.

Our client has been investing across a diverse portfolio of advertising platforms from traditional media like television and print, to emerging channels such as digital media, promotions and online video. The current national model contains over 20 marketing variables, which are rolled up into seven main marketing categories. Television and Promotions account for 83% of the marketing budget, so there is likely to be an opportunity to grow their investment in other channels. The breakdown of the client's spend across these buckets is shown in the pie chart on the next page.

Our client treats Facebook as a part of their digital category, but for the purposes of this case study, we have separated this sector into Facebook and Digital Without Facebook. As the chart below shows, Facebook only accounted for 1.1% of total digital spending and 0.05% of all marketing spend. As the investment in Facebook marketing was so small, Facebook was attributed with one of the fewest incremental sales among all the marketing channels in the national model. However, the return on investment generated through Facebook was relatively strong compared with other channels. Given the client's current, extremely small investment in Facebook marketing, there is considerable room for growth in this area.

Current spend % across media channels

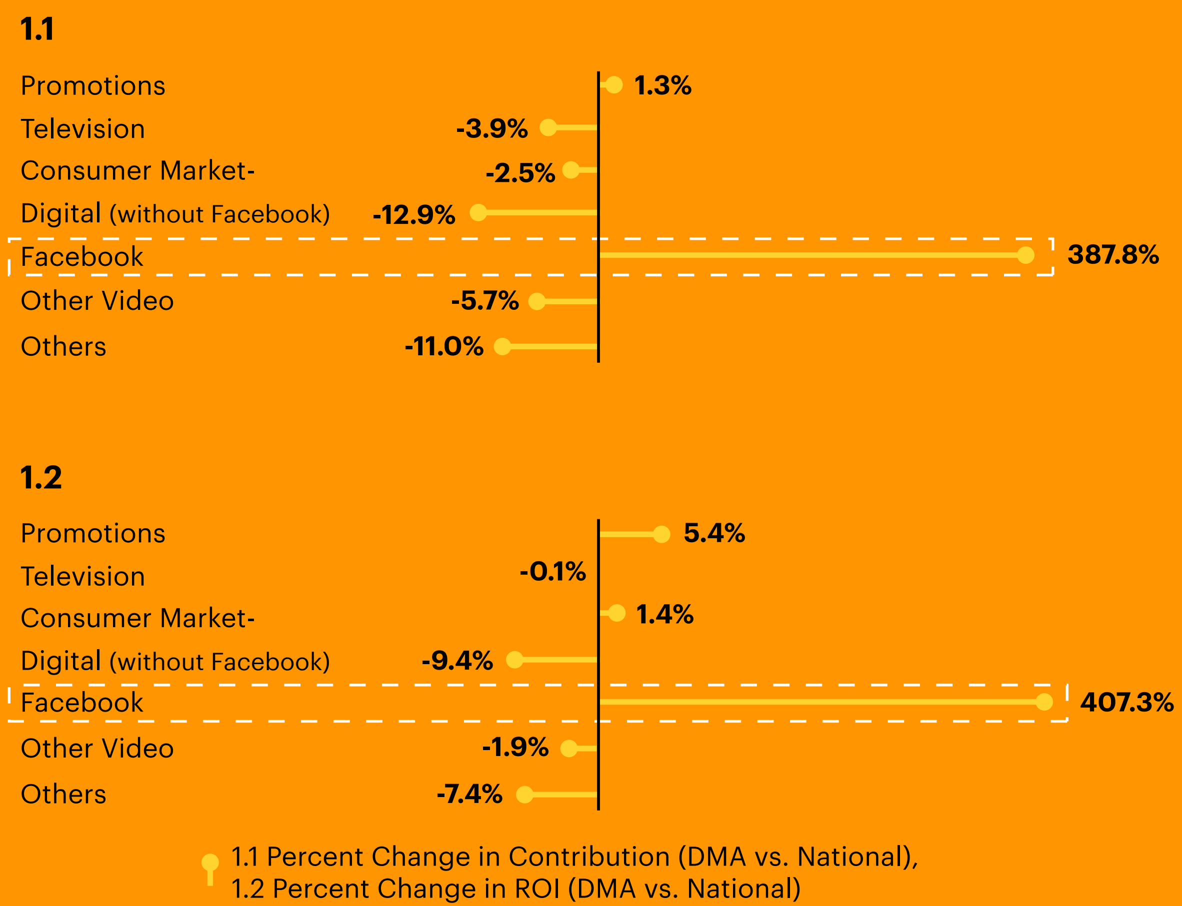


Indeed, this is true of their entire digital category, which currently accounts for only 5% of total marketing spend.

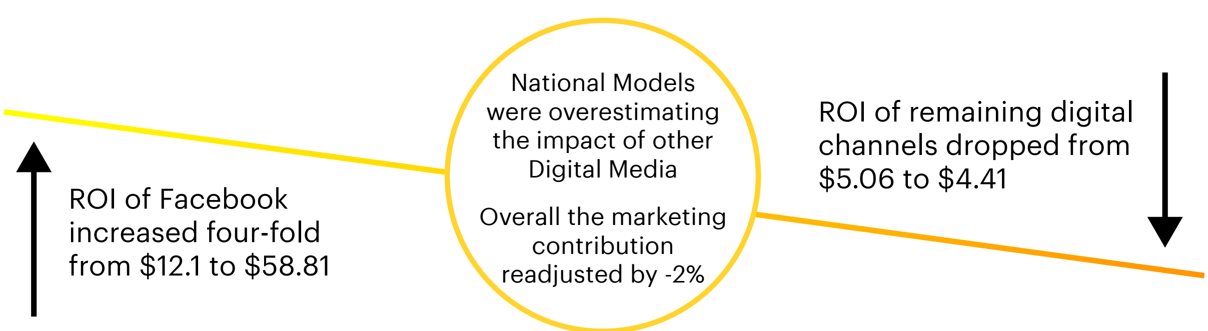
By aggregating the 210 DMA specific models, and comparing it with the national model, we saw a ~2% decrease in sales attributed to marketing. However, this % varied across DMAs, with some markets showing a higher marketing ROI than the national model, while some DMAs were considerably below the national standard. Looking at the total incremental sales from each marketing tactic, the aggregated story remains broadly the same. What changes is that we can now tailor the client's marketing mix to each DMA.

As expected, Traditional TV and Promotions continue to be responsible for a majority of marketing-driven sales due to the size of their investment. This is partly because the client invests significantly more into these channels than others. At the same time, we find a higher ROI for Facebook, bringing its total incremental sales number much closer to other channels in the digital category.

The graph below represents the comparison between National and DMA level model results across the seven marketing categories.

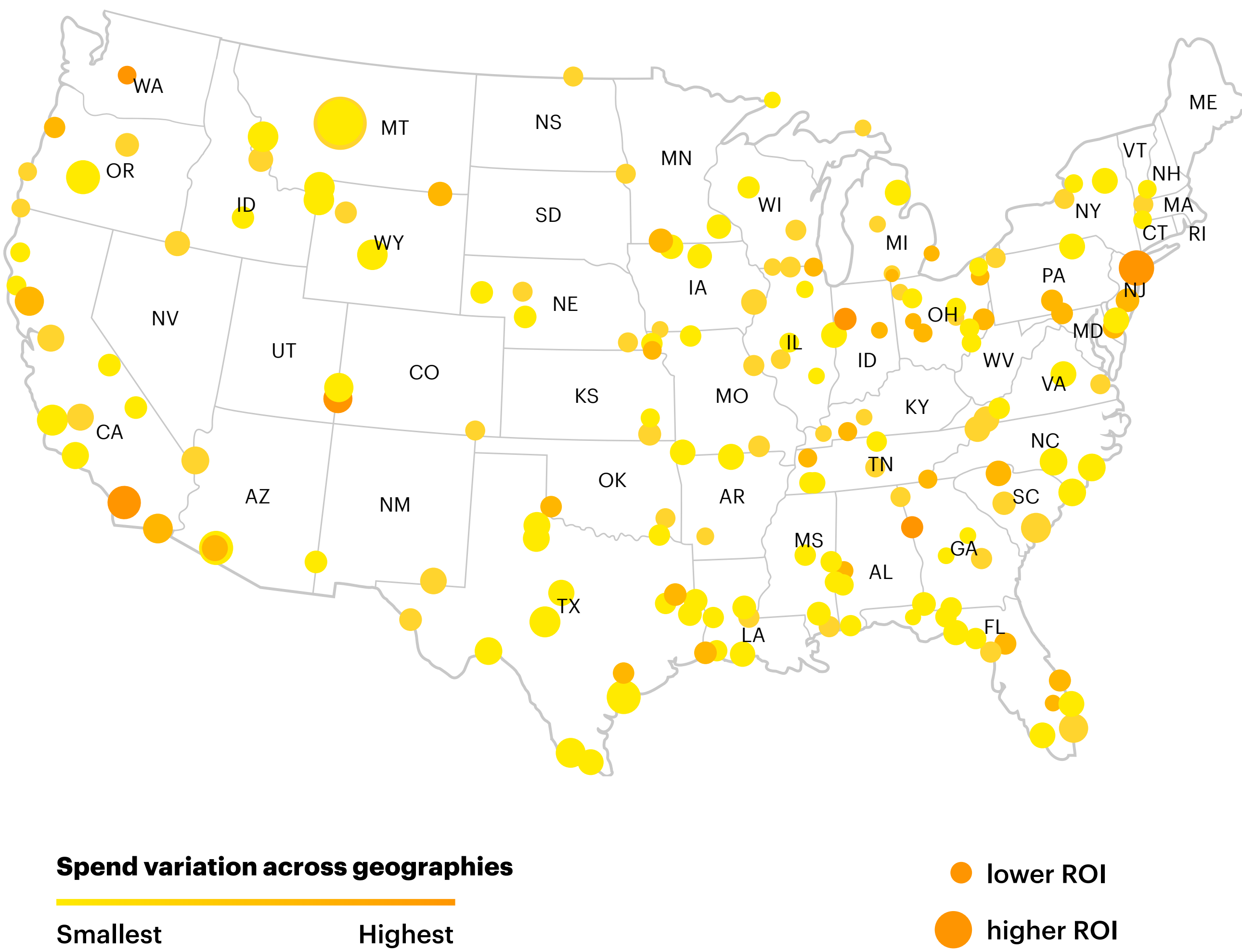


As seen in figures 1.1 and 1.2, **Facebook's contribution and ROI in the DMA model increased nearly four-fold,** while other digital channels saw a slight decrease in effectiveness. Facebook's improved performance figures can be attributed to two factors. The first is that Facebook accounted for a very small share of total investment, which led to a low sales contribution. Given this low baseline, there was considerable room for growing the client's Facebook



marketing presence. Second, we had DMA specific data for Facebook, but not for other digital channels. To correct this, we recommended that our client capture other digital channels spending activity at a DMA level which will enable them to evaluate those channels in the same way.

The greatest benefit of a DMA level model is that it enables businesses to assess the impact of Facebook in each local market. Below, you can see a bubble chart of the US, where the size of each bubble represents the relative performance of Facebook in that market. The color shading represents the relative levels of investment level in Facebook marketing in that area. This information allows marketers to identify geographic trends and use them to refine their marketing strategy. Using the map below, it is easy to see that for our client, a smaller market in the west like Bend, Oregon, performed equally well as a major east coast market like New York, but with the caveat that investment was much higher in New York than in Bend.

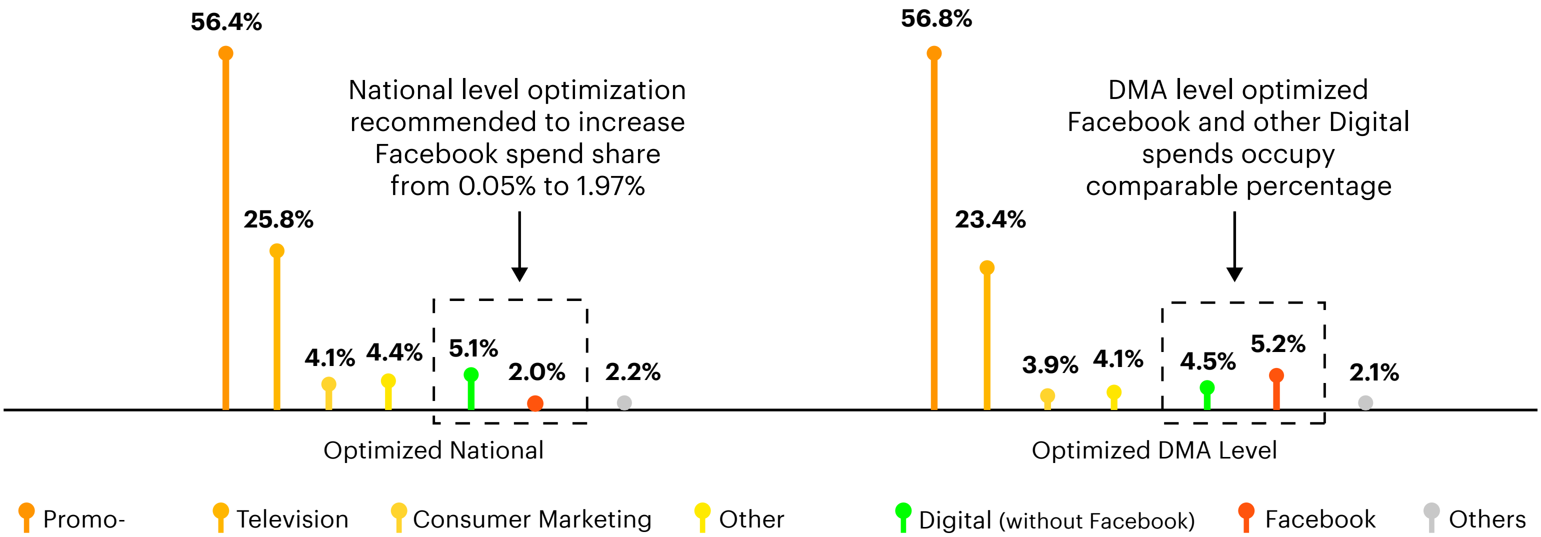


The aggregated DMA level model displayed a similar story to the national model. On one level, this reinforces the credibility of both modeling techniques. **However, while it is true that at the aggregate level the story is similar, the accuracy and the confidence in the model increases significantly as we add more regional detail: the more data points we add, the easier to identify the relationship.** The other advantage of using greater detail and regionally sourced data, is that it allows the model to be more responsive to recent developments. This makes it a better gauge of new and evolving digital strategies and platforms. Indeed, the DMA level model did perform better than the national model. There are many ways to assess the strength of a model: for this case-study, we used the Mean Absolute Percentage Error or **MAPE.** We typically want our **MAPE** to be less than 5%. Our national model had a **MAPE** value of *4.8%*, while our new DMA specific model, once aggregated, produced a *4.2%* MAPE, a 12.5% improvement on our national model.

This begs the question: how should the client's marketing mix change to take advantage of the greater accuracy of the new DMA specific model? With a completed model, we can input the new coefficients into the optimization tool to analyze the results. When we run optimization scenarios, we use constraints that are pre-defined by the client. A possible constraint might be that, due to internal business dynamics, a client is unwilling to reduce their Promotions budget by more than 50% in order to reallocate spending to other channels. To work within this constraint, we would define thresholds for each channel, usually +/-20%, beyond which a marketing budget cannot be altered. In our current comparative study, we decided that a good way to understand pure model recommendations would be to take our client's preferred scenario from the national model and amend it to allow all tactics to grow without restriction except for promotions and television. This allows smaller channels like Facebook to show bigger shifts, if the optimization engine deems that to be more appropriate.

> **However, please note that unconstrained growth for any tactic is neither ideal nor practical. This scenario is only discussed here for ease of understanding and to show how changes in marketing strategy might be prompted by a more accurate and detailed model.**

The graph below displays a comparison of our marketing mix recommendations post optimization from the national model and the DMA model.



*In the optimization scenario displayed above only Television and Promotions have been restricted within +/- 30% bucket. All other media tactics were left unrestricted to gauge their recommended growth.

As the graph shows, the DMA level model registered the higher ROI in Facebook and reallocated more of the budget to Facebook than the national model. Facebook's share of total investment, which was originally 0.05% of the budget, increased to 2.0% in the national model and to 5.2% with our DMA model. Facebook now accounts for a significant part of the marketing mix with our new recommendation showing a reduction in other Digital channels from 5.1% of the budget to 4.5%. If we place Facebook back into the digital bucket, we see our original investment of 5.0% increase to 7.1% in the national model and to 9.7% in the DMA model. It is also noteworthy that for Promotions, the category with the largest spend at 56%, the DMA model recommended an increase to 56.8%, while the national model suggested upping spending to 56.4%. Using the scenarios generated by both models, it was further observed that the DMA level recommended mix recorded a 2.9% sales uplift, as compared to a 0.9% uplift from the national models.

The total optimized marketing budgets do not deviate significantly from the original amount of investment in either model. This is because this client already leverages MMO to allocate their marketing budget. Though the total budget remained as is, reallocation within the digital bucket provided a deeper understanding of Facebook behavior. The main advantage of the DMA approach is that we can now strategically purchase Facebook advertising and marketing. This new, targeted strategy should ideally drive higher ROI for Facebook than we currently see.

Conclusion

With the rapidly evolving digital media spectrum, the traditional methods used to analyze the impact of marketing are no longer the best. MMM has become a key tool for making strategic budgetary decisions; its accuracy and adaptability have made MMM an essential advertising and marketing tool. The absence of detail and a failure to account for the latest developments and trends, mean that conservative approaches to MMM produce lopsided results that fail to give businesses a true picture of the impact of media. This is especially true of digital media. This paper has attempted to provide an overview of the evolving MMM methodologies, while showing—with a focus on digital channels—how the use of granular data can improve the accuracy of models.

Our case-study sheds light on the importance of using granular data. It clearly shows that a highly-detailed and targeted DMA level model enables a more comprehensive assessment of the benefits of individual marketing channels and especially digital channels such as Facebook. The recommendation to increase the proportion of the marketing budget allocated to Facebook from 2.0% to 5.2%, further highlights how with more accurate and detailed data, organizations can make better use of this ever-evolving and fast growing social media platform. Indeed, we believe that similar lessons would apply for any digital platform or channel.

> **Furthermore, models that are constructed at a granular level, such as a DMA or similar, should be considered the new standard for analyzing and improving marketing strategies.**

This is even the case for businesses that wish to maintain a national, rather than more localized marketing plan: as shown, building a DMA level model and aggregating up to a National level, still provides a more accurate picture than a National level model.

We are on the cusp of a media revolution. Media will become increasingly more targeted and personalized. Marketers must adapt to this reality: to evolve their business, they must think about how they can take full advantage of the boom of targeted digital media.

We recognize that MMO is not the only way to do this: there are several machine learning algorithms that provide quick and streamlined assessments of marketing strategies and budgetary allocations. However, there is huge potential for MMO to be used in tandem with these algorithms. The algorithms would provide a first run of a model, finding the most predictive variables for the model and providing an up-to-date view of your customer-base. This may, in turn, lead to a new wave of marketing optimization, where your mix is being constantly updated as new data is collected. With Telstra in Australia, Accenture has developed this very approach.

In the end, the measure of any model is its ability to provide a deeper understanding of the business outcome in question. This quintessential understanding often lies in the several rows of data that comprises of information at the most basic level. In our case study DMA and, in this case, geo targeting might well hold the key to providing a marketing strategy that is both more personalized and more fruitful.

AUTHORS

David Johnson
david.b.johnson@accenture.com

Dr. Nilesh Kumar Gupta
nilesh.kumar.gupta@accenture.com

Purvika Bazari
purvika.bazari@accenture.com

Nikhita Mehndiratta
nikhita.mehndiratta@accenture.com

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