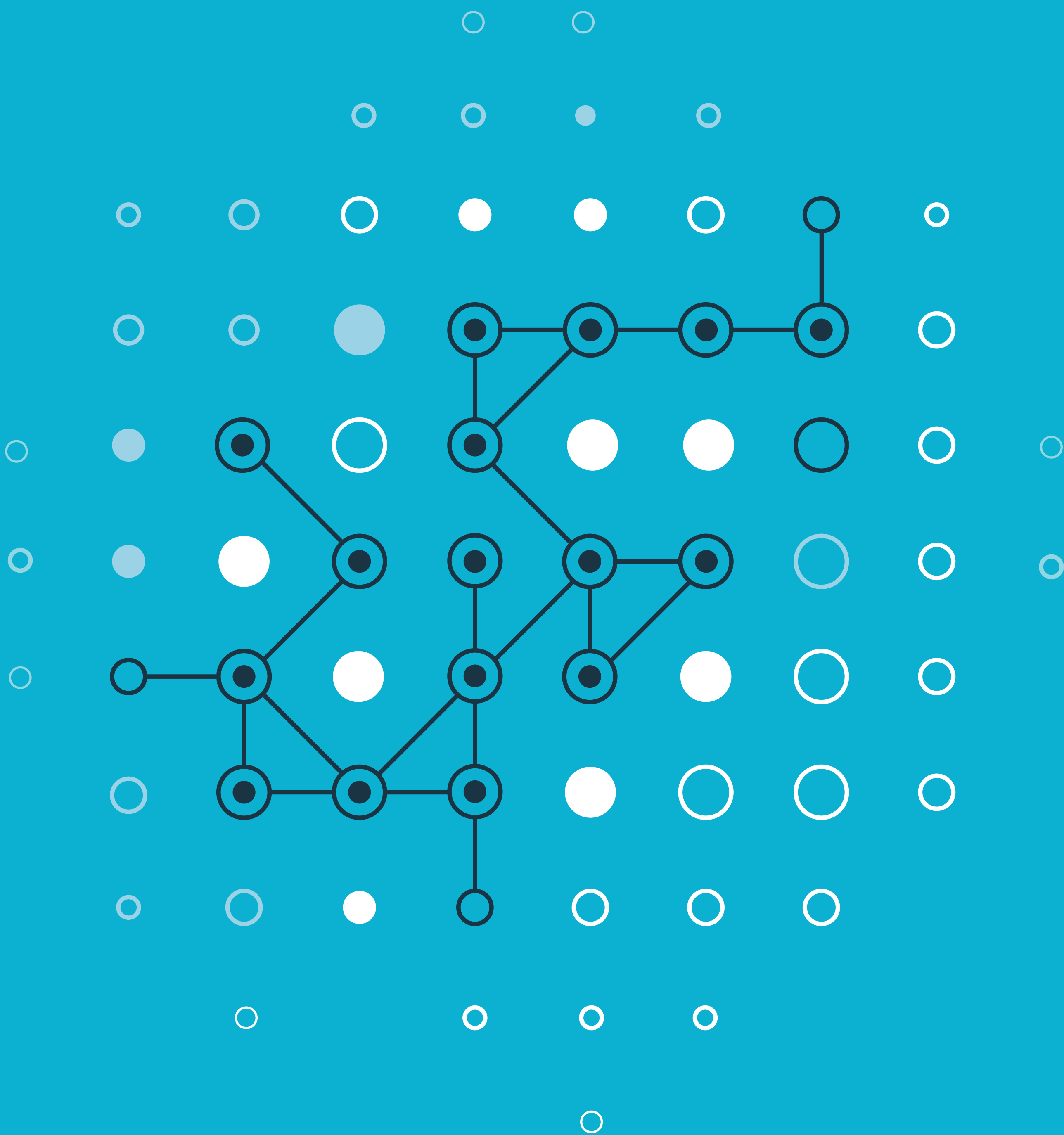
Ekimetrics.

EVOLVING MEASUREMENT TO ACCURATELY CAPTURE FACEBOOK PLATFORM ACTIVITY

2019



WHITE PAPER • **FACEBOOK**

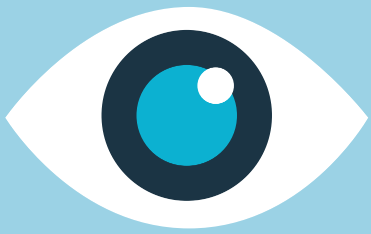
SUMMARY & KEY FINDINGS

While many global brands are placing more and more responsibility on CMOs, all indications are that there is an increasing squeeze on marketing budgets – these same CMOs must make the most with limited resources and be able to actively track the efficiency and effectiveness of that spend.

This has partially led to a rapid increase in the share of media spend taken by digital channels. Facebook, as one of the quickest growing channels in this space with rapid innovation in their ad offering, is one of the more critical channels to understand. Accurately measuring the impact of Facebook activity on brand sales and other KPIs, within the context of all spend, can be the difference between driving quick growth vs. deploying a wasteful plan. **The core question is – how should any brand, agency, analytics company, or research company incorporate Facebook into a holistic measurement capability, such as Marketing Mix Modeling (MMM)?**

Ekimetrics has designed an expansive test to identify best practices and actionable recommendations that can be incorporated into a typical MMM approach. This meta-analysis was conducted based on benchmark studies across multiple regions, industries, and brands – allowing us to identify the patterns and best practices that we feel can be applied industry-wide to the measurement of Facebook. We looked at the timeframe of modeling, the length and shape of Facebook impact to KPIs after ad delivery, and variations across campaign type.

The core question is – how should any brand, agency, analytics company, or research company incorporate Facebook into a holistic measurement capability, such as Marketing Mix Modeling (MMM)?



KEY FINDINGS

Custom modeling approaches are necessary to achieve the most precise measurement, and a custom test-and-learn process (as opposed to a one-size-fits all solution) may be ideal to most accurately understand Facebook activity impact on results for industries or brands.

Splitting Facebook variables by recency helped maximize accuracy, robustness, and comprehensiveness in our testing. No clear improvements to models were found by splitting Always-On and Burst campaigns.

Models with a conservative recency split of the Facebook variable (last 12 months) **significantly outperformed models where no recency split was applied.**

Weibull-based adstock formulations for Facebook variables consistently performed best among models where any adstock transformation is utilized.

EVOLVING MEASUREMENT TO ACCURATELY CAPTURE FACEBOOK PLATFORM ACTIVITY

The necessity and importance of Facebook's role in the marketing ecosystem continues to grow, with ad revenue and active user count generally increasing YOY.

Given this growth, CMOs and marketers cannot afford to ignore these trends or not accurately measure their investment on the platform. Additionally, Facebook's products are continuously evolving and are now available through a wide offering of platforms (Facebook, Instagram, Facebook Audience Network, Messenger, WhatsApp), devices (desktop, mobile), placements (Feed, Stories, In-stream), formats (photos, posts, videos), and campaign objectives (from awareness to conversion drivers). These platforms and product are at the forefront of cultural change, and Facebook advertising is served and consumed in a different context than traditional media channels. In this dynamic environment, measurement techniques need to be adapted to ensure accurate understanding of impact and drive the best and brightest decisions moving forward.

The question is simple – how should any brand, agency, analytics company, or research company incorporate Facebook into a holistic measurement capability, such as Marketing Mix Modeling (MMM). Should Facebook be modeled differently than other channels? Should Facebook be measured in the same way as TV or other media channels? Are there any signals in the data that need to be explored to produce more robust results? How do we know that we are capturing these changing dynamics accurately? Given that we now have enough history of brands devoting significant investment in the Facebook platform, we are able to explore these questions.

Ekimetrics, a global data science leader and a Facebook MMM partner, has set out to answer some of these questions and provide guidance and best practices for incorporating Facebook into MMM. A form of regression analysis, MMM is a highly regarded marketing measurement tool due to its holistic consideration of all marketing levers. Access to more granular data and agile use of methodologies mean the approach is relevant and powerful in the digital age. Given our extensive experience with MMM, Ekimetrics undertook a meta-analysis utilizing a set of benchmark models from our experience to answer these important questions. A wide range of models (40+) has been analyzed across multiple regions, industries, and brands. This robust sample provides a good mix of Facebook investment levels and strategies, and covers industries such as FMCG, Appliances, Banking, Insurance, Retail, Beauty and Fragrance.

Through this analysis, we are exploring how Facebook compares to other media in terms of both measured return and modeling approach.

We will consider improvements to modeling approaches of Facebook in MMM: covering timeframe of modeling, the length and shape of impact after ad delivery, and variations across campaign type. Ultimately, we will shine a light on some best practice ways to incorporate Facebook into long-standing MMM frameworks to produce more accurate and actionable results for brands.

WHY DO WE NEED DEEPER APPROACH FOR FACEBOOK IN MMM?

Facebook advertising has two key attributes that we believe mandate more focused investigation in modeling projects: various campaign playout options such as device, format and objective that can drastically impact performance, and generally strong Return-on-Investment.

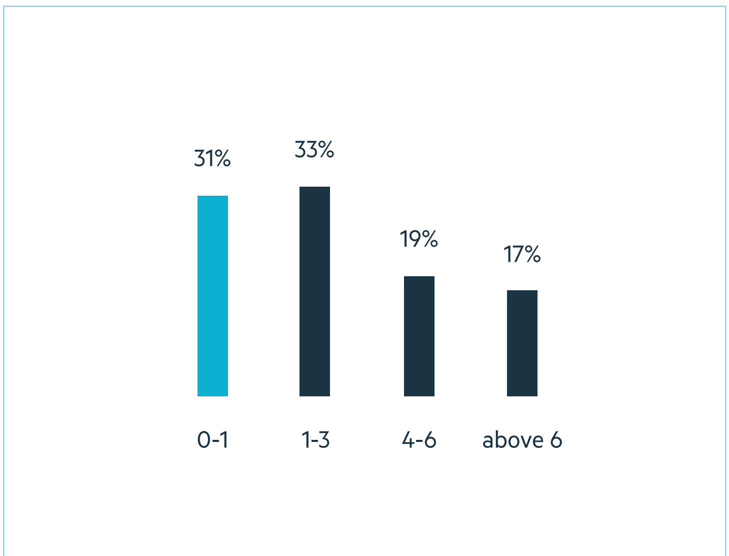
Facebook displays strong performance on average

Using the wide set of benchmarks that we have tested, we compared the average level of impact and efficiency of Facebook campaigns against another common media channel, TV, which is one of the most established channels that still plays a significant role in most brands' media mix. To create an anonymous study-pool, we have looked at ROI and incrementality of Facebook via a ratio of Facebook impact to TV impact.

Return-on-Investment

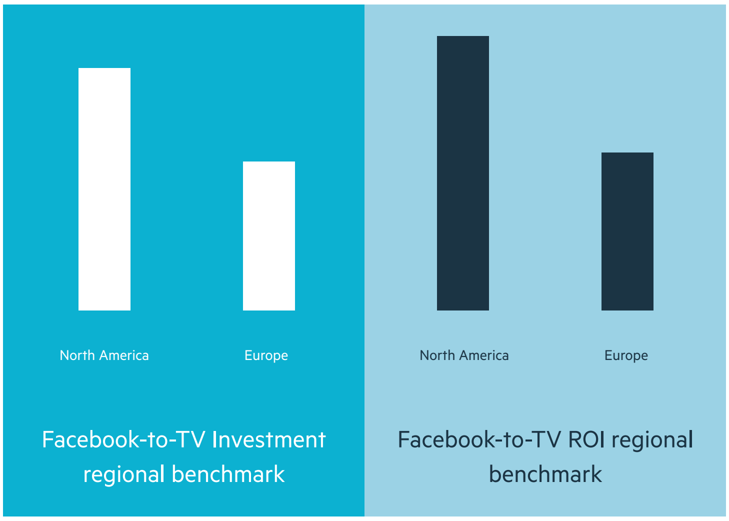
$$\text{ROI} = \frac{\text{Incremental Revenue from lever}}{\text{Investment in lever}}$$

> For example, if a given brand has an absolute Facebook ROI of 4.0 and a TV ROI of 3.0, we display these results as a Facebook-to-TV ROI ratio of 1.33 (4.0/3.0).



Facebook outperforms TV in 69% of the cases

Across most of the benchmark studies, Facebook activity displayed stronger ROI performance than TV. **The overall average ratio of Facebook-to-TV ROI was 2.9, meaning that, on average, Facebook's ROI was 2.9x greater than that of TV.** The distribution of these ratios indicates that 69% of cases had stronger performance for Facebook than TV, with 17% showing Facebook performance to be >6x stronger. While TV has the benefit of a large and attentive audience and arguably a larger impact in the long term, the consistent out-performance of Facebook ROI stands out. A proportion of this performance may also be attributed to lower spend levels, but most brands do not fully know the saturation effects of Facebook. Given this high return for brands, the importance of measuring Facebook accurately becomes even stronger.



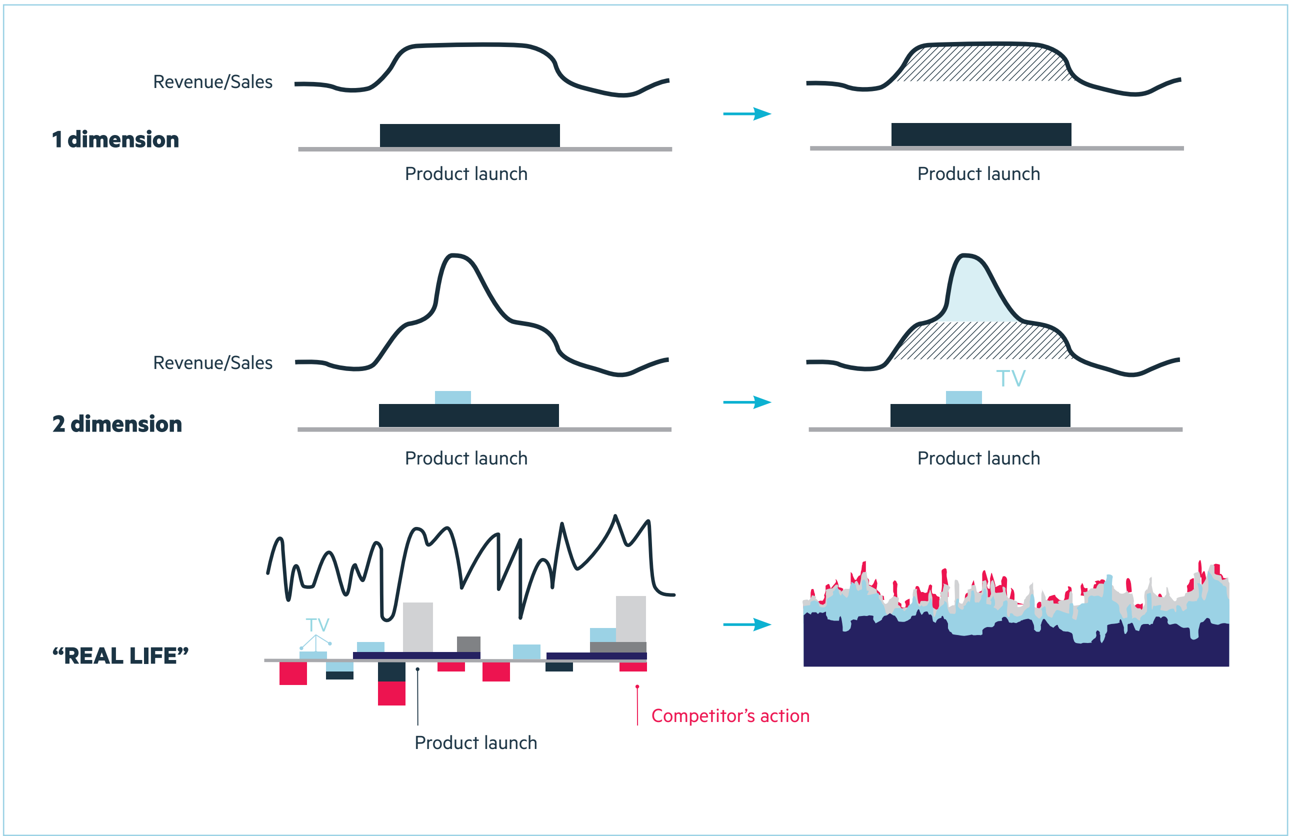
Was this the case globally? On a regional level, we have benchmarks for North America and Europe. Here, **the average Facebook-to-TV ROI ratio was 4.1 for North America vs. 2.4 for Europe**. Facebook activity in North America is more mature, with higher budgets than Europe, and a clear pattern of stronger ROI performance compared to TV. In both regions, performance is strong and, in our view, would deserve closer focus in modeling exercises where there has been significant spend.

Beyond its strong performance, **Facebook's objective, targeting, and playout options had a fundamental impact on ad-serving and the response that can be expected from campaigns with different configurations**. Much as TV can be measured differently for spot length, dayparts, in-break positioning, etc., Facebook can be examined in greater detail than we believe is happening in the industry currently. Campaign objectives in three broad buckets – 'Awareness', 'Consideration' and 'Conversion' – change the optimization approach of the Facebook algorithm, while the granular audience targeting options allow mass reach or more focused targeting based on the advertiser's requirements. While our paper focuses on the fundamental methodology for capturing Facebook accurately at an aggregate level, there is certainly a need for further study into how to best capture the detail of the different playout options.

Given the strong return in the benchmark studies explored and the variety of buying options, Facebook clearly represents a highly interesting prospect for any marketer. As budget spent on the platforms continues to grow, accurate measurement is critical – especially as the risk of saturation rises. Many brands are still spending at low levels across all digital channels when compared to offline, and gaining the most accurate measurement of return is critical in identifying how to scale. In our opinion, analytics need to be designed in a way that very clearly and accurately measure the impact of Facebook advertising for each brand against all other factors.

Facebook's objective, targeting, and playout options had a fundamental impact on ad-serving.

A Refresher on Marketing Mix Modeling



MMM Methodology visualization

A HOLISTIC APPROACH TO MEASURE MARKETING PERFORMANCE

Marketing budgets have been under significant pressure over the last years, and so more and more companies, led by the top tier brands, conduct analyses to estimate the incrementality of marketing on performance. One of the most relied upon and established approaches is Marketing Mix Modeling (MMM).

MMM involves running statistical analyses such as multi-variate linear regressions, hierarchical Bayesian networks, or other methods in between, to isolate and measure the impact of various marketing levers on sales or other key metrics. MMM fills the need for a holistic statistical approach, as elements acting alone (1 Dimension) are easy to identify, but the real world has multiple overlapping channels and levers, which need to be separated. Agencies, analytics pure-players, internal teams and others around the world have been deploying a multitude of different approaches to run this type of analysis for the last 25 years.

In comparison to Multi-Touch Attribution, an individual journey level analytics approach, MMM assesses the impact of all internal and external levers on sales; attribution only covers those channels that can be tracked to an individual/ cookie level. When trying to look at a growing channel like Facebook, it is crucial to make sure you take a holistic approach to understand the tactic's place in the ecosystem against more established channels, and MMM is a solid method to achieve this.

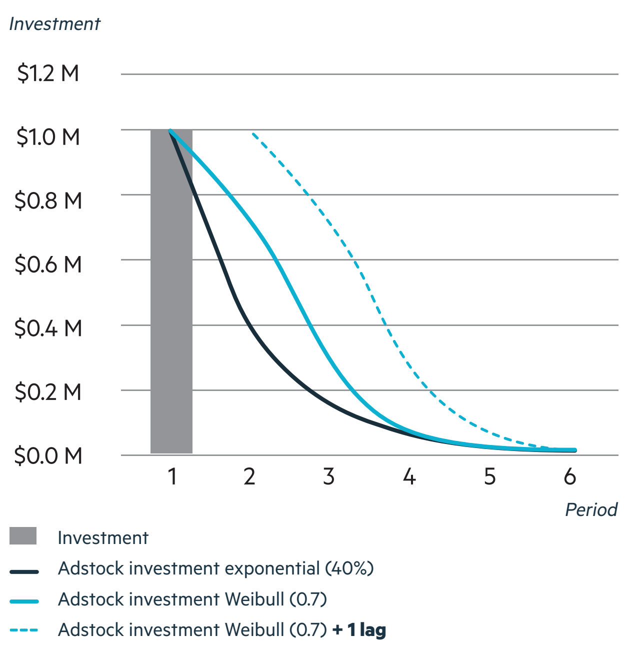
EKIMETRICS APPROACH TO MMM – REFLECT THE BUSINESS, NOT JUST THE DATA

At Ekimetrics, we use a tailored approach for the specificities of each client that combines multivariate regression with smart feature engineering to align with the real-world impact of a given variable. By starting from the business – the challenges, questions, and drivers of performance – not the media, we are able to build holistic models that incorporate all drivers of sales (often led by market and non-media factors first), to ensure that the measurement of marketing activity is truly incremental.

For us, the following concerns are fundamental to ensuring you have models that reflect the business, and not just the data you have available:

1. Identifying key variables

Deciding which variables to use in a model isn't just about the data you have available; without a deep focus on the dynamics of the particular business being modeled, key elements that have structural significance in a model could be missed. Many brands want to focus on the impact of media, but to understand the true incrementality the model must also account for baseline drivers of the business (distribution, relative pricing, product launches, market dynamics etc.).



Adstock and Lag visualization

2. Reflecting how the variable impacts the consumer

Marketing impact, and the impact of other drivers, is not only isolated to the week it is activated – your big Superbowl ad doesn't only affect customers during that one single week. Transformations can be applied to variables to account for how marketing affects sales in the real world. Two of the most common transformations are adstock and lag:

- **Adstock:** Impact can last longer than the week of activation. This decaying effect is called an adstock, and represents the carry-over effect of the advertisement, often explained by customers remembering the ad at later times, different purchase cycles, and word of mouth. Different adstock shapes can be tested to see which most closely supports the real effect in market.
- **Lags:** Media impact on sales may not always be immediate, and the time between an ad appearing and a conversion being driven by it may be one or more weeks. This can be accounted for when modeling by lagging the variable or shifting every point forward by a set number of periods.

3. Validating the model you've built

Once you have started to construct your model, you need to ensure that what you are building is valid. There are textbook-length details around model validation, but we maintain three core principles for our models to ensure we are closely representing the business outcomes: Accuracy, Robustness and Comprehensiveness.

Our Core Convictions for Marketing Mix Models

Building an accurate model

If your model doesn't closely follow the historical performance of the business, it cannot be trusted to drive future strategy

Metrics such as R-squared and MAPE give insight into where a model is stronger or weaker

Predicting the future

A model that only explains what has happened but is weak in predicting the result of activity yet to be activated is a poor model

Robust models do not overly rely on any specific data points, outliers or assumptions, and so perform well when faced with updates over time

Being comprehensive

Focusing on getting the math right is only a small part - models need to make business sense and be comprehensive in variables included

For example, a huge media campaign that plays out when the product is out of stock will not have impact, so capturing stocking is important

GENERAL TESTING PROCEDURE

With these considerations in mind, we designed an expansive testing procedure to be able to draw actionable conclusions that we can incorporate as modelers when including Facebook activity in a holistic model. For the purpose of this meta-analysis, we deployed this process on our set of 40+ models, in order to ensure the best practices and guidelines are not dependent on an industry/region. **We focused on specific questions linked to the principles of our modeling approach:**

All models were audited against the three key considerations of accuracy, robustness, and comprehensiveness. The ideal model was taken to be one that adhered closely to those considerations and demonstrated clear improvements in the validation metrics over the baseline.

The process of testing the different techniques explored in this analysis consisted of the following steps:

1. Taking an existing set of verified, complete models that included Facebook as a variable as the baseline for performance

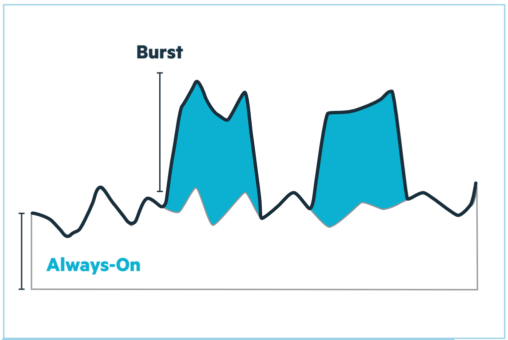
2. For testing timing: Splitting the existing baseline Facebook variable into two variables based on the splitting criteria, applying the same set of transformations as were applied to the base Facebook variable

3. For testing adstocks: Applying the chosen combination of adstock function and parameter, keeping all non-Facebook variables unmodified and maintaining the lag of the original Facebook variable

4. Running the new updated model, recording data on both the variable significance (p-value) of Facebook in the model and overall model validation metrics like R-squared, MAPE (mean absolute percentage error), and MSE (mean squared error)

5. Repeating Step 2 & Step 3 for all split combinations or transformations. (Combinations/transformations tested are detailed in their appropriate sections)

Splitting the Facebook variables: Does Facebook impact vary over time or across different strategies?



Always-On and Burst components of a Facebook variable

SPLITTING VARIABLES – ACCURACY VS. ROBUSTNESS VS. COMPREHENSIVENESS

Variable splits are one key technique for improving the quality of a model. Whether splitting a variable by time, campaign, or any other factor, the newly created component variables may increase the total information available to the model, strengthening it. While this can be beneficial for accuracy and comprehensiveness, a large number of variables in a model can jeopardize robustness and lead to possible over-fitting. Any potential splits must be chosen carefully and justified.

In this analysis, two methods of Facebook variable splitting were tested to determine which of them most improved the models and whether there is a strong case for testing them in any MMM process involving Facebook variables.

EXPLORING DIFFERENT TYPES OF VOLUME CAMPAIGNS: BURST VS. ALWAYS ON

From a timing perspective, advertisers employ two major categories of Facebook campaigns: Burst and Always-On.

Burst campaigns consist of a shorter period of high investment, typically coinciding with a product launch, rollout of new creative, or a period of high seasonal sales – often to drive short-terms sales lift or introduce new messaging.
Always-on campaigns consist of a much longer, sometimes continuous period of much lower investment to ensure continued brand awareness, engagement, and presence.

As these strategies have different goals and reach the consumer differently, a variable split between Always-On and Burst campaigns was tested.

Inconsistent spend levels and campaign mix limit usefulness of Always On / Burst splits

Across the models used in this study, splitting between Always-On and Burst campaigns drove some improvements in overall model accuracy, but there were complicating factors. Specifically, splitting variables in this manner made the measurement more susceptible to biasing effects of seasonality and timing of competing levers. More importantly, gains in accuracy from such a split did not appear to be consistent enough to justify the high potential of loss in robustness and comprehensiveness. Over 40% of models tested showed signs of low robustness or produced coefficients that were not supported by business intuition.

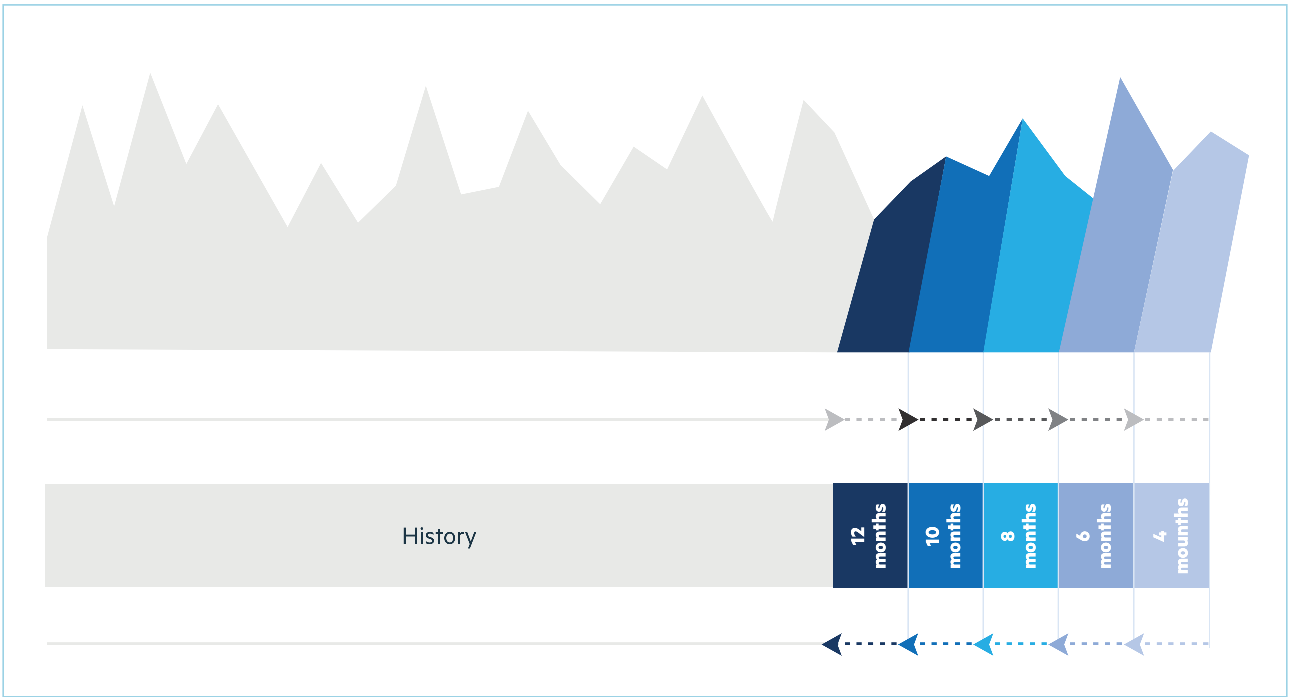
Unless a brand has a very clear set of strategies employed in distinctly different periods, we do not see a substantial benefit for modeling Always-On vs. Burst campaigns differently. Rather, it is recommended to look at these time periods with a close eye to account for potential saturation effects and synergies with other tactics.

Ultimately, due to the sparseness of the Burst campaigns, as well as a lack of consistency in strategies for advertisers in utilizing these types of campaigns, splitting variables by Burst vs. Always-On did not appear to drive model improvement.

ACCOUNTING FOR FACEBOOK'S CHANGING ROLE OVER TIME: RECENCY SPLITS

While the purchase method and consumption of legacy channels like TV or Radio have remained mostly consistent over the years, Facebook ad products have been constantly evolving. As the platform develops over time, one single variable over a 3+ year period may not properly capture the true impact of the next dollar historically and looking forward.

Our hypothesis was that there is significant value in splitting Facebook variables with respect to recency. Being wary of overfitting, a single split between the most recent 2-12 months and all months prior may be an ideal strategy to ensure that a model accounts for recent changes in the product offer without putting the strength of the model at risk. Specifically, we tested splitting existing Facebook variables into two variables, with varying lengths:



Varying recency splits of a Facebook variable

Recency Split Combinations Tested				
Last 12 months & all previous	Last 10 months & all previous	Last 8 months & all previous	Last 6 months & all previous	Last 4 months & all previous

Clear indication of model improvement with long recency splits applied

When testing this hypothesis, we see that models incorporating a split for recency clearly outperformed the baseline model (where Facebook is only one variable) in 77% of cases, without a clear loss of robustness or comprehensiveness. With longer window splits, (splitting out the last 10-12 months of Facebook campaigns) we saw low deviation from the baseline measure and a low risk of lost robustness or business coherence. Among models where a 12-month split was possible (i.e. where Facebook campaigns appear throughout the last 12 months of data and in the months or years prior), the average MAPE of those models was up to 10% lower than the average MAPE of models where no split was performed.

MAPE (Mean Absolute Percentage Error)

$$\text{MAPE} = \frac{(100\%)}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right|$$

Where A_t is the actual value and F_t is the forecasted value.

62%

of models did perform best with the longuest possible split applied

23%

of models did not perform better with a recency split applied

15%

of models performed best with a **6-month recency** split applied

in cases where the 6-month split was not the longest possible

Percentage of best-performing models by recency split

Models with the longest split window possible (up to 12 months) performed best in 62% of cases, while 15% of models were most improved by a 6-month recency window, judging by the three core principles (accuracy, robustness, comprehensiveness). Shorter windows (splitting out the last 2-4 months of Facebook campaigns) were more susceptible to large coefficient shifts (200% difference) versus the baseline. Ultimately, a number of model stress-tests may be necessary when using these shorter splits, given the higher risk of competing effects or seasonality to bias the measurement.

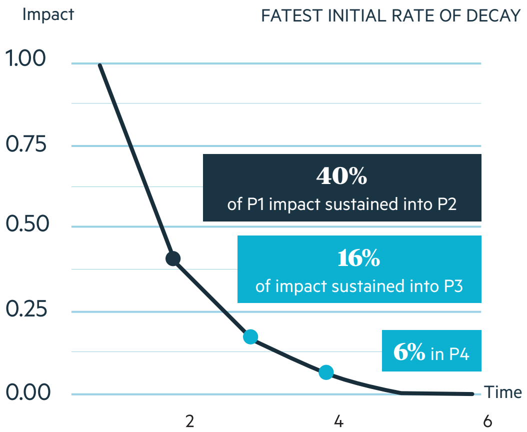
This indicates that when possible, **a large window split of isolating the prior 10 to 12 months could likely improve a model and help account for the evolution of Facebook impact, and could be a strong tool for maintaining a consistent story but getting more accurate results**. Similarly, a 6-month recency window may also be tested to incorporate more short-term evolutions in Facebook strategy and implementation without the risks of robustness and comprehensiveness seen with shorter splits.

Using Adstocks: Does Facebook advertising impact consumers differently over time?

WHY APPLY AN ADSTOCK TRANSFORMATION?

With most kinds of media, sales impact is not entirely localized during the week of investment (the airing period, P1). A campaign appearing in one week may continue to have a lasting effect on sales in the weeks as the consumer remembers the ad, has time to shop, is exposed to other factors, etc. The standard and well-tested conclusion is that sales impact from advertising decays over time as the weeks progress, and we use Adstock transformations to account for this decaying effect. Adstocks generally work by reshaping the variable to more closely match the expected pattern of impact from a given campaign over time.

Given the interaction of Facebook advertising and the consumer, there are three types of adstock transformations that seem to make the most sense for an MMM model. In order to provide the best guidance, we experimented with all three types of adstock across a wide set of benchmark models.

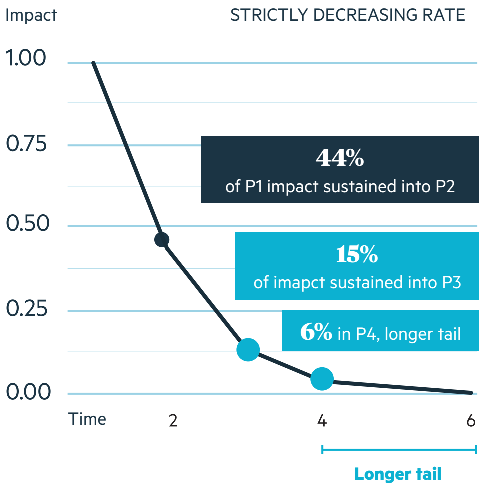


Exponential adstock impact curve
(P1 is the week of investment)

Traditional Adstock (Exponential)

A traditional exponential decay model assumes that the impact from media decays by a set percentage each week following its initial appearance. For example, with an assumed adstock rate of 40%, a campaign would produce 100% of its impact in the week where the ads appear, 40% in the week following, 16% in the next week, and so on. This rate of decay is strictly decreasing in absolute terms, meaning that the decrease from one week to the next is always higher than the following decrease.

This is the standard transformation used for modeling levers like TV, but it may not reflect the true pattern of impact for Facebook advertising. Broadcast levers like TV and Radio touch potential customers in a variety of locations, but are not as highly targeted, while Facebook advertising incorporates a large amount of targeting data in each ad delivery regardless of objective.



Log-Logistic adstock impact curve (P1 is the week of investment)

Logistic Adstock (Longer-tail)

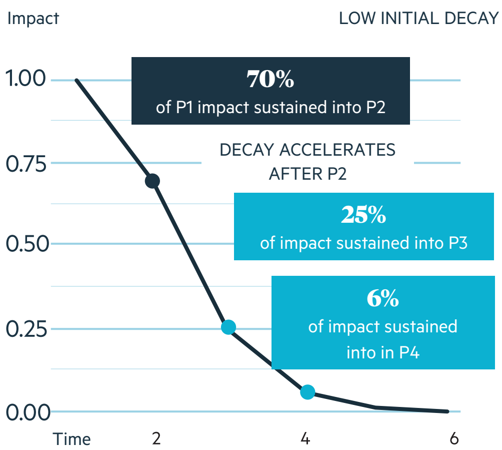
The key differences between the Log-Logistic adstock and the standard exponential are a slightly higher sustaining impact from P1 to P2, and a longer tail of low sustaining impact (P4 onward).

The business interpretation of this decay function is similar to that of the standard exponential decay, but with a slightly higher concentration of impact within the first two periods (week of investment and the week following), assuming a lower drop-off in impact in the second period. Additionally, the longer tail indicates a sort of "long-term" impact from the marketing in question, contributing a small number of sales even a month or more after the week of investment.

$$Impact_t = \frac{(\beta/a)\,(t/a)^{\beta-1}}{(1+(t/a)^{\beta})^{2}}$$

$x = (t\ 0.5)/2 \qquad \beta = 2$

Where $Impact_t$ is the media impact t weeks after the week of delivery (t=0) β is the shape parameter and a is the scale parameter (analogous to adstock rate)



Weibull adstock impact curve (P1 is the week of investment)

Weibull Adstock (Variable Decay)

With a Weibull-based decay function, the hypothesis is that the majority of impact from media occurs during the week of investment (P1) and the week following (P2). After those first two weeks, the impact decays more rapidly before leveling out to near 0.

In a business sense, this decay function may indicate a lever closer to conversion in the purchase funnel or a lever that is more targeted. With these kinds of targeted levers, the majority of successful conversions would come from those best targeted and occur shortly after the time the ad is delivered. The remainder of impact would be more gradual and resemble a more traditional decay. Thus, this Weibull-based decay function may be an ideal fit for Facebook advertising with its powerful targeting capacity.

$$Impact_t = \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1} e^{-\left(\frac{x}{\lambda}\right)^{k}}$$

$x = (t+0.5)/2$

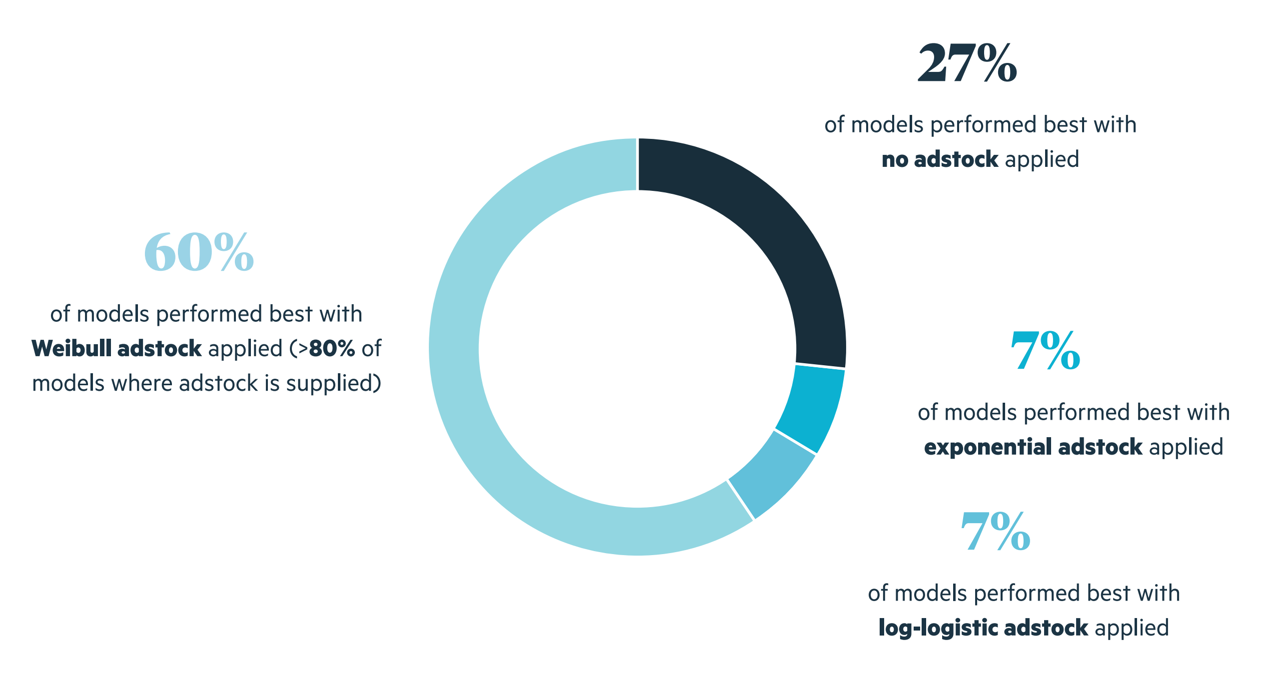
$k = 1,5$

Where $Impact_t$ is the media impact t weeks after the week of delivery (t=0), k is the shape parameter and λ is the scale parameter (analogous to adstock rate)

In order to understand the best transformation that produces the most stable and accurate model, we employed these different transformations across the benchmarks and looked for patterns that might indicate a best-practice method. Additionally, we compared results against using no adstock formation at all – as in some cases there is a more immediate, single time period effect due to the nature of the campaigns

Adstock Transformations Tested			
No Adstock	Standard Decay (20%, 30%, 40%)	Log Logistic Decay (Scale = 0.3, 0.4, 0.5)	Weibull-based Decay (Scale = 0.4, 0.55, 0.7)

Clear indication of improved precision with a Weibull-based formation



Percentage of best-performing models by adstock type

What emerged was a clear and consistent trend of the Weibull-based adstock formulation outperforming both the traditional exponential decay and the alternative log-logistic decay with Facebook variables. Among the 73% of models where the use of adstock improved overall performance, 80% performed best with a Weibull-based adstock function (based on model accuracy as measured by R-Squared and MAPE). Exponential and Log-Logistic adstock functions performed best for only 10% each of that group of models.

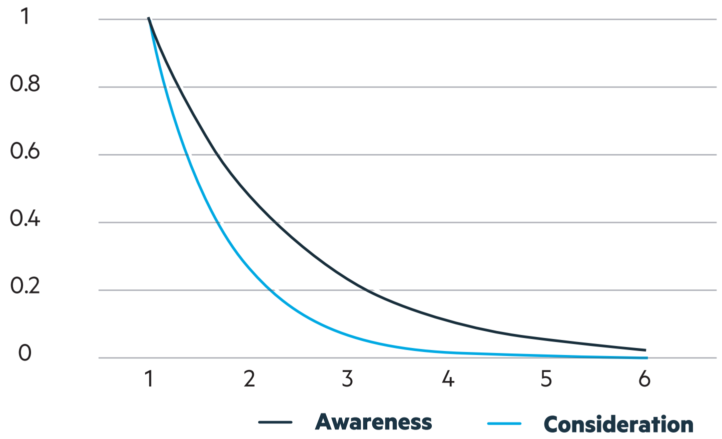
The average MAPE improvement of the Weibull-transformation was quite small in each model, however the overwhelming consistency of those models outperforming the alternatives is an indication that the consumer reaction to Facebook advertising follows a similar pattern. Further analysis would be required to determine whether this principle holds true for all media variables or if it is driven by specificities of Facebook advertising. But we believe that this helps confirm the key hypothesis that Facebook is a touchpoint lower on the funnel and a more direct step before conversion in many cases.

A good strategy for brands and modelers to use when working with Facebook variables could be to begin first with the null hypothesis of no observed adstock effect and then proceed to test Weibull-based transformations, adjusting the scale parameter to tune the magnitude of this decaying impact effect. The methodology used in these tests restricted the range of the scale parameter to more closely compare with traditional adstock rates of 20%, 30%, and 40%, but greater adstock effects may be ideal in some cases.

Make sure capitalization rules are consistent

For a subset of models where Campaign Objective data was gathered through the Facebook UI, the impact of different types of Facebook campaigns could be tested. There are upwards of ten (10) buying types or campaign objectives that can be chosen at the point of purchase, but these objectives more generally break down into the broader categories of Awareness, Consideration, and Conversion.

Given the more limited subset of models within the benchmark set where this campaign objective split was possible, a full study of the unique dynamics of each of these categories was not feasible, but key patterns did emerge around the characteristics of Awareness campaigns in particular.



Optimal Adstock Scale: Awareness vs. Consideration campaigns

Indications of lower statistical significance but longer impact of awareness campaigns

On average, the p-value of a Consideration or Conversion campaign in a model is 30% lower than a similarly tuned Awareness campaign. This makes sense, as a campaign that aims to reach potential customers earlier in the purchase funnel will not show as direct a correlation to sales.

However, Awareness campaigns continue to impact sales for a longer period of time than Consideration or Conversion campaigns. The optimal adstock rate by campaign was between 17% and 22% higher for Awareness campaigns, indicating a longer tail of impact.

When a modeler wants to focus on a split by objective, they can consider testing longer rates of adstock for Awareness campaigns, where we have observed less immediate impact than in the case of other campaign objectives.

Conclusions & Best Practices

Overall Takeaways

We aimed to explore and experiment with the Facebook variable in a wide set of MMM models, in order to derive a set of best practices that could be employed when a brand, agency, or modeler is building a holistic model. At Ekimetrics, we systematically use variable splits and try a varying set of adstock transformation to test for the specificities of each client's model and each media channel's role but given the wide set of testing there are some clear recommendations that can be used by all modelers. Specifically, we believe that:

Key benefits were found from splitting Facebook variables based on timing of campaigns

While consistent model improvements were not achieved by splitting Always-On and Burst campaigns, it was identified that splitting Facebook variables by recency helped maximize accuracy, robustness, and comprehensiveness.

Models with a conservative recency split of the Facebook variable (splitting out the last 12 months) significantly outperformed the models where no recency split was applied displaying around a 10% lower MAPE on average. Modelers could explore a standard practice of splitting by recency and testing the effect before finalizing a model.

For Facebook variables, Weibull-based adstock formulations consistently performed best among models where any adstock transformation is utilized

The consistent improvements in performance indicate that a Weibull-based adstock most closely captured the real-world impact to consumers for Facebook campaigns.

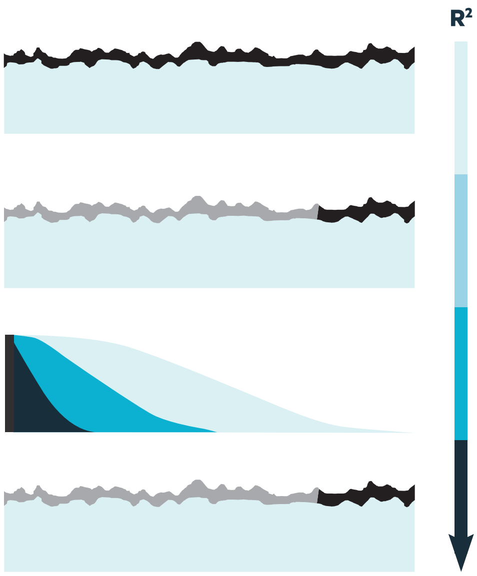
When including a Facebook variable in an MMM model, an ideal testing process may be as follows:

1 **Building the MMM model**
Build your MMM model by integrating Facebook data as a distinct variable

2 **Facebook timing split**
Look at spliting Facebook variables based on the timing of the specific campaigns. Consider spliting the variable Facebook with 12 months granularity

3 **Facebook variable transformation**
Transform the Facebook variable following the Weibull law by altering the parameters until the most accurate combination is found

4 **MMM model with optimal Facebook modeling**
Validate your completed model, judging it for accuracy, robustness, and comprehensiveness



Based on our exploration, there are some clear patterns that were found to be consistent across a wide set of models, but we strongly recommend that modelers use best judgement in employing these best practices. The intent of each campaign, the type of industry involved, and the region targeted must also be taken into account when making these types of choices.

Limitations and Moving Forward

The analysis was designed to evaluate how Facebook is treated as a channel in an MMM framework, challenge some traditional measurement conventions, and explore new hypotheses with the intention of creating a series of best practices for what we believe is an ideal way to measure Facebook, a constantly evolving media channel. While a wide sample base has been used, important details such as industry and spend level have been anonymized. Any measurement approach will need to consider the other factors that influence business as well as the approaches explored throughout this analysis, and as is best practice, be tailored to consider these factors.

Additionally, this testing framework has been applied to Facebook in isolation. However, measurement best practices could be transferred onto other channels to try and improve measurement overall, particularly other social channels and wider digital channels. In the case of extension to other channels, model and variable performance would have to be closely monitored. MMM can also be used alongside other forms of analysis such as Multi Touch Attribution to better understand the roles of channels and their effectiveness.
Performing these in-depth tests does necessitate using the most granular data available. Such data is obtainable through close relationships with clients, agencies or directly through the platform using services such as the FB MMM UI. Particularly in the case of campaign objectives (i.e. awareness, consideration, and conversion), future analyses with larger sample sets may be able to fully analyze the unique traits of each campaign type and unlock a greater potential for optimizing investments on Facebook.

As mentioned previously, the share of marketing budgets dedicated to Facebook and other digital channels is growing and this trend is likely to continue. As the marketing landscape evolves so must the tools used to measure it. Through our findings we hope to equip analysts and modelers with a wider range of methods and options to use when modeling Facebook and importantly explain why they can do so. Moving forward these methods and best practices can be used alongside traditional methods with the aim of driving insight and improving overall understanding and measurement of the channel.

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