OBJECTIVE PARTNERS
NEXT LEVEL ANALYTICS

The Impact of Facebook Advertising:

Measuring Facebook with Media Mix Modelling

Recommended Best Practices and Industry Learnings

Index

About Objective Partners

Objective Partners is a fast-growing marketing analytics company and the leading producer of media optimization software. We create marketing measurement and prediction software designed to track and optimize advertisers' multi-channel media investments. Our clients receive detailed insights into their on- and offline customer journeys, allowing them to make data-driven decisions, optimize their media budget and increase the return on media spend.

In this paper commissioned by Facebook we independently investigate the effectiveness of Facebook advertising using our media mix model. We first recommend best practices and provide industry standards on MMM, and subsequently measure the impact of Facebook advertising in terms of sales and search volume.

Introduction: Advertisers Re-evaluate Media Budget Spends

Recently, many industry-leading advertisers have been actively re-evaluating their media budgets. Adidas stepped away from TV advertising to focus more on digital engagement and established giants P&G and Unilever considered stopping with certain online media[1]. These examples reflect the significant changes in the global media landscape.

One of the most important changes is the rise of large online platforms such as Facebook, Instagram and YouTube. In the past, you were able to reach your complete target audience by advertising on TV. Nowadays advertisers find their audience more scattered across an ever growing amount of on- and offline channels. The 'new' online platforms such as Facebook are superior to traditional media in their ability to combine their enormous reach with the possibility to place targeted ads.

Another driving factor behind the changing media landscape is the increasing importance of data-driven measurement. Now that it's possible to calculate the incremental value of media channels, advertisers demand data-driven and objective measures for media effectiveness. Attribution models, including **Media mix modelling (MMM)**, have become an important tool for calculating this effectiveness and the incrementality of both on- and offline media.

Among the online media channels, Facebook has become essential for many advertisers due to its enormous reach and potential to deliver targeted ads. We as Objective Partners will investigate the effectiveness of Facebook advertising using our media mix model. We will first recommend best practices and provide industry standards on MMM, and subsequently measure the impact of Facebook advertising in terms of sales and search volume according to the following question:

How impactful is Facebook in driving key outcomes: sales and search volume?

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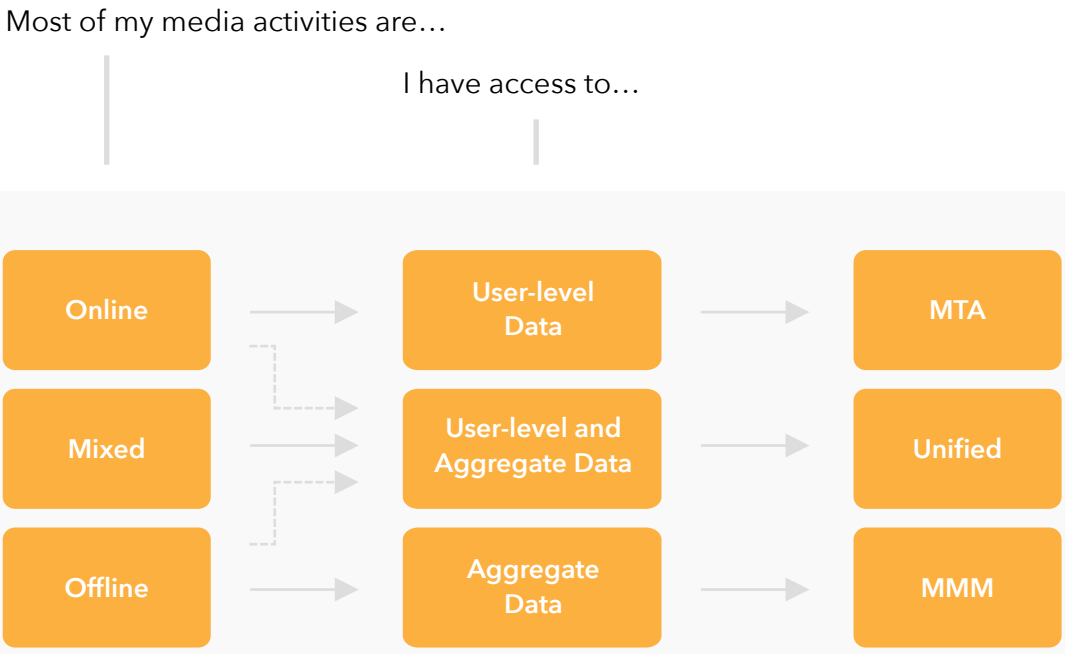
[1] www.businessinsider.nl/adidas-says-its-ditching-tv-advertising-because-young-people-engage-with-the-brand-on-mobile-2017-3

Attribution Modelling

Marketing managers want to know how to invest their budget. Ideally, they want to invest in channels with the highest incrementality; the channel that causes the most uplift in conversions and revenue.

The question that arises is: how do you determine how much uplift was caused by which channel? For example, if a customer gets an e-mail, then a Facebook impression and finally looks up the article via paid search and converts, how much value from this conversion can be attributed to each of these channels?

This is the area of attribution modelling. There are two established attribution models: multi- touch attribution (MTA) and media mix modelling (MMM). The model you should use depends on the type of data you have, as depicted in the flowchart below.



For online channels, most touchpoints can be measured at the user level and you can track which touchpoints were shown to your customers, in which order. You can accurately model the value of each touchpoint using MTA[2]. Depending on your tracking, you might only have aggregate data for some online channels like Facebook or display. If you only have access to aggregate data, you should use MMM. If you have both user-level and aggregate data, a unified model leverages the strengths of both models.

How does it work?

Imagine a customer with the following converting path:

In general, MMM can be used to measure the impact of all your channels, but not at a granular user level. MTA is much more granular, but is limited in its capacity to measure traditional media and online impression channels. The unified model is both granular (where it can be) and holistic.

Consider the following example: a customer sees an ad on Facebook and then decides to take a look via paid search. Since Facebook impressions are available on an aggregate level, you are not sure which user saw which Facebook ad on an individual level.

In other words: you can't place these impressions in individual customer journeys. In this case, you have a mix of user- level and aggregate data. If you would use MTA, the lack of user level data would make it seem as if the customer went straight to paid search, giving paid search all the credit for the conversion. Paid search is overvalued and the impact of Facebook is ignored. Measuring the impact of Facebook on this conversion thus requires MMM. Only by combining MTA and MMM in the unified model will you eventually get a complete view of the value of all channels.

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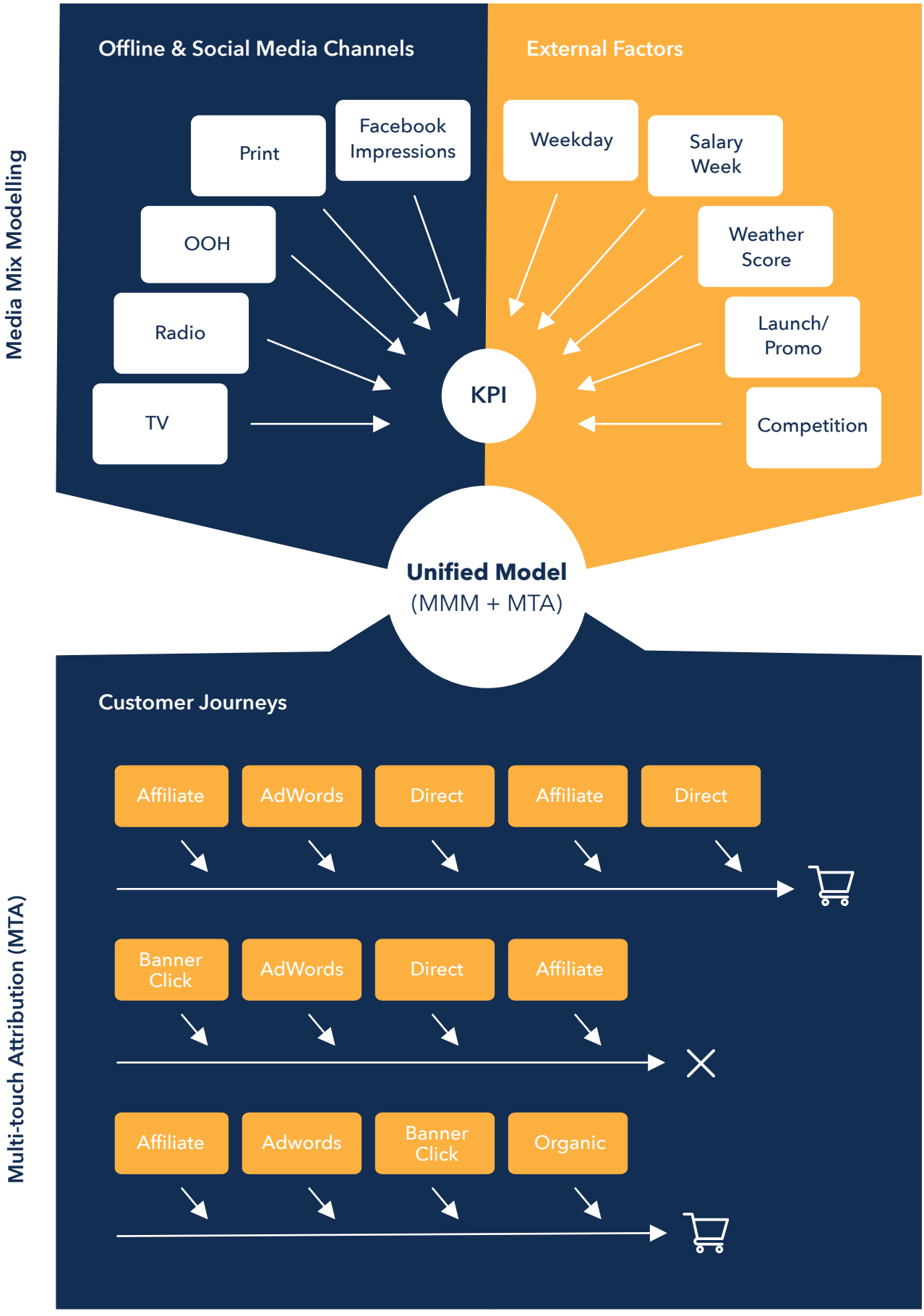
[2] Since this paper focuses on MMM, a detailed description of MTA is beyond the scope of this paper. The interested reader can refer to: https://www.objectivepartners.com/multi-touch-attribution-blog/ or https://www.objectivepartners.com/introduction-multi-touch- attribution/

First, MTA divides the credit over all channels in the path that can be measured at the user level. MMM then decides how much credit the Facebook impression deserves, but also indicates which channel is overvalued by MTA, SEA in this example. This is then corrected by re-attributing part of the credit to Facebook, as shown by the arrows in the table below.

	SEA	Organic	SEA	Facebook	Direct	Total
MTA	€15	€10	€25		€30	€80
MTA + MMM	€15	€10	€15	€10	€30	€80

How does MMM do this? A media mix model is a regression model that finds the relationship between total impressions for a channel and total conversions. The next section gives a detailed explanation of how to set up a media mix model taking six considerations into account.

The attribution model you choose thus depends on whether your data is available on a user or on an aggregate level. Subsequently combining the MMM results with MTA gives you a holistic overview of all your media investments. This allows for the comparison of the effectiveness of media spend across all media channels.


Media Mix Modelling
Offline & Social Media Channels
External Factors
Print
Facebook Impressions
OOH
Radio
TV
Weekday
Salary Week
Weather Score
Launch/ Promo
Competition
KPI
Unified Model
(MMM + MTA)
Multi-touch Attribution (MTA)
Customer Journeys
Affiliate
AdWords
Direct
Affiliate
Direct
Banner Click
AdWords
Direct
Affiliate
Affiliate
Adwords
Banner Click
Organic

Media Mix Modelling

How, then, do we carry out media mix modelling (MMM)? The main goal is to gain a holistic view of all on- and offline media investments. There is a wide range of ways in which to estimate media mix models, some more extensive than others. MMM can be estimated individually, but can also be used in combination with MTA in the unified model.

DEEP DIVE – Media Mix Model

We define our media mix model as a regression model where the dependent variable is a certain KPI and the independent variables are the different marketing or media channels used. Variables can be added to model seasonality, special events and other factors of influence.

In our paper, the media mix regression model is defined as follows:

$$y = \beta_0 + \sum_{i=1}^{m} \beta_i X_i + \varepsilon$$

Where

y = KPI

$\beta 0$ = intercept (base)

Xi = spend for channel i

βi = coefficient for channel i

m = number of channels/variables

ε = modelling error

In the remainder of the paper we will elaborate on extensions of the model to incorporate diminishing returns, external events and lagged purchasing effects.

A minimum requirement for any form of modelling is, of course, the availability of high-quality data. Under the assumption of sufficient high-quality data, we will now discuss **six general considerations** that should be taken into account when carrying out MMM.

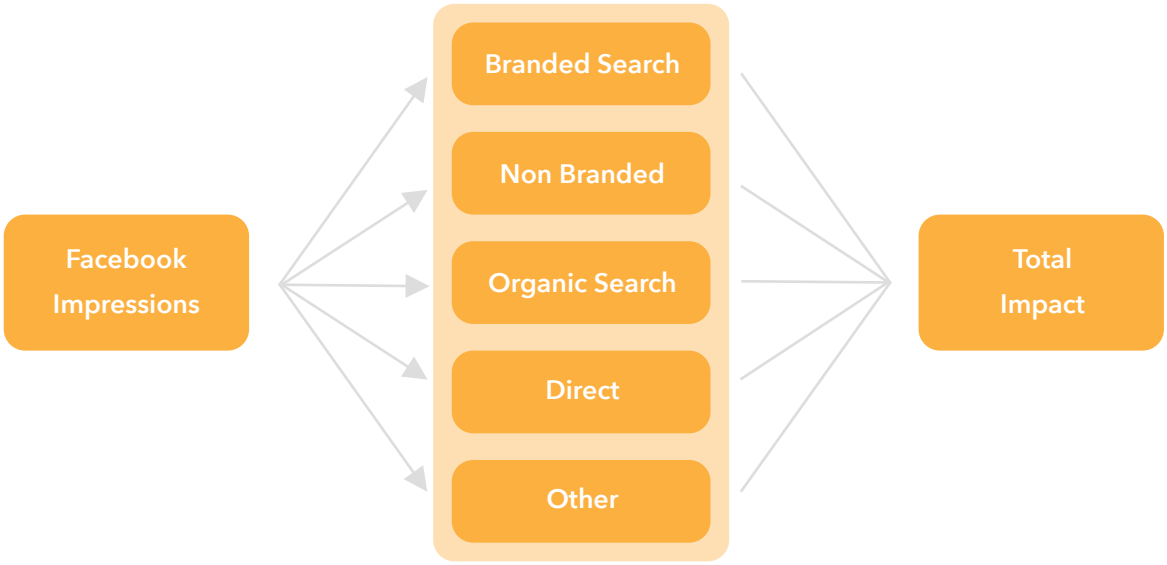
1. Do I Model Revenue, Conversions or Sessions?

The KPI you are measuring matters. Data on sessions, compared to data on conversions, contains relatively more randomness and non-media effects. For example: when a mobile network is down many customers might visit the website for the status of the disturbance. This will cause a huge peak in sessions but no related sales or conversions. The randomness in sessions makes media modelling more challenging. Measuring conversions, in turn, could encumber the fair comparison of model outcomes. Some media channels lead to high-end conversions (such as the newest iPhone), whereas other channels might be used to advertise for low-end conversions (such as a sim-only subscription). A telco, for example, might advertise the newest iPhone via TV and advertise sim-only contracts via Facebook. Facebook might therefore generate more conversions, but the value of the TV conversions might actually be higher in terms of revenue or net profit. It is therefore advisable to measure revenue as well.

Depending your available data, you can choose to model different KPIs. Where possible, we recommend to measure your media mix model for both conversions and revenue.

2. Media has a different effect on different online channels

It's unlikely that the effect of Facebook on display will be the same as on paid search. After seeing a Facebook ad, it's conceivable that someone looks up a product, but it's not equally likely that they will click on a display banner.



In the figure above, there is no 'general' Facebook effect; the effect of Facebook on every channel is different. The same reasoning can be applied to conversion dimensions. A telco, for example, might market both handset and prepaid contracts, or sell via both etail and retail channels, and these differentiations can be captured using conversion dimensions. Channels and conversion dimensions should be modelled separately.

This raises the question of how to define channels. When advertising via Facebook, Instagram and Snapchat, do you model them as separate channels or combine them into one social channel? There is not one single rule to determine this, and it depends on a combination of the percentage of spend, the subjective importance of the channel for the marketing manager and the actual impact of the channel.

A channel needs to have a significant percentage of spend to be included in MMM. If its impact is lower than the variance in sales data, its impact can't be modelled. A rule of thumb is to include channels with a percentage of spend of over 5%. A channel might also have a subjective importance; a marketing manager might be specifically interested in its impact. The actual impact of the channel is also an indicator. Deciding whether to include a channel based on its impact might sound paradoxical because its impact is exactly what we are trying to determine, but sometimes that's exactly what we do: we include a certain channel and estimate it's effect just to see whether it needs to be included in the first place.

We recommended creating a separate regression model per online channel and conversion dimension. Creating separate models accounts for the fact that media can have a different effect on different online channels and conversion dimensions.

DEEP DIVE – MMM Model for Different Channels

Instead of using a single regression model with one sales KPI, we define a separate model per online channel:

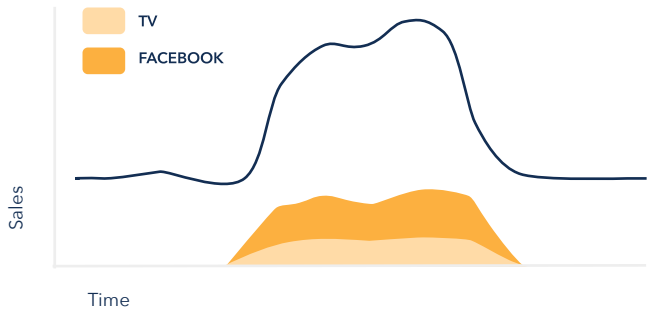
In our paper, the media mix regression model is defined as follows:

$$y_{cd} = \beta_0 + \sum_{i=1}^{m} \beta_i X_i + \varepsilon$$

y becomes ycd = the conversions of dimension d attributed to channel c

3. Multicollinearity

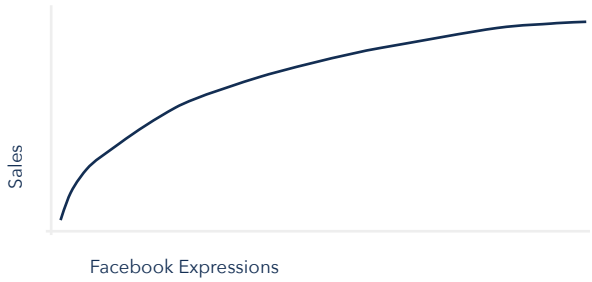
When marketeers use different channels simultaneously, it is difficult for a model to determine which channel caused uplift. Imagine a marketeer who advertises for one week a year, and nothing throughout the remainder of the year. During this period, he advertises on TV and Facebook. During his week of advertising there is also a huge peak in conversions. Using a simple model, it's impossible to determine which channel caused the peak. Maybe Facebook was fully responsible, or maybe TV contributed to 50% of the conversions, or any other combination of the two. Purely based on the data, each scenario is equally plausible. This problem, when multiple channels or variables occur at the same time, is called multicollinearity.



Before carrying out MMM, check for multicollinearity issues. This can be done by inspecting the correlations or by calculating the variance inflation factor (VIF) of the different variables.

4. Diminishing returns of media spend

It is commonly known that there are diminishing returns to marketing and media spend. At some point, the media budget becomes less effective because the complete target audience might be have been reached several times already. Or the budget within search becomes less effective because you are already in a high position for all relevant search terms. The relationship between investment and returns is nonlinear – every additional euro you invest will not yield a unit increase in returns. For each channel, it holds that at some point the next euro invested will return less than the spend. When making investment decisions, it is good to consider the cost of an additional conversion (incrementality).



Input variables need to be transformed to capture diminishing returns. For every additional euro spent the return will gradually taper off, resembling a logarithmic scale. A common method to model diminishing returns is thus to take the natural logarithm (ln).

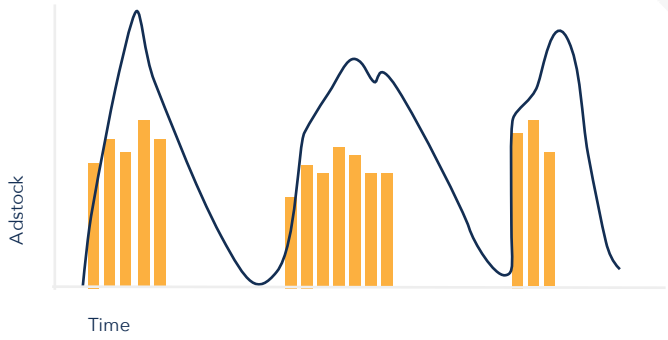
DEEP DIVE – Diminishing returns

Instead of using the spend variable Xi directly in the regression, we transform Xi to capture the diminishing effect of media spend on the KPI of interest.

Xi then becomes ln(Xi)

5. Advertising Adstock

Consumers don't always convert immediately upon seeing an advertisement. The idea could linger in their head for a while before they convert. The prolonged or lagged effect of advertising on consumer purchase behavior is called adstock.



An advertisement has a certain 'stock' in people's minds which depletes over time. Imagine that a person sees a TV ad, and the stock for this ad depletes with a rate of 0.5. This implies the stock will be halved by the following day, halved again the day after that, and so on. As illustrated by the graph, the adstock builds up when GRPs are shown and then depletes over time.

To capture the lagged effect of media it is important to include adstock in your MMM model. The rate at which the media depletes can be found in your data.

DEEP DIVE –Adstock

To incorporate the effect of lagged purchasing behaviour, we incorporate an adstock term into our modelling.

We calculate adstock as follows:

$$A_t = X_t + \gamma A_{t-1} \quad for\ t = 1, \ldots, n$$

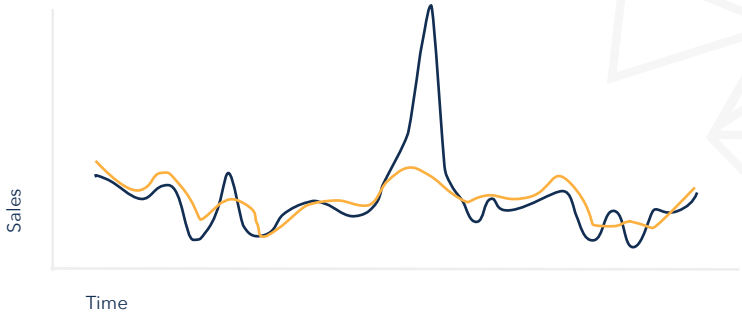
Where

At = Adstock at time t,

Xt = the value of the advertising variable at time t γ = is the 'decay' or lag weight parameter

6. External Factors and Special Events

Controlling for special events is essential for MMM. Marketers often plan media activities around special events. Failing to incorporate these factors can have a major impact on media effectiveness findings. Consider the following situation:



a telco has an always-on strategy for Facebook, but only advertises on radio when there is a product launch, such as the release of the newest iPhone. The product launch will most likely cause a huge spike in sales but the model will think this is only due to the radio campaign. From the model's perspective, sales are relatively constant when there are Facebook ads, and there is a huge spike when there is a radio campaign. In this way, the model will overvalue the impact of radio. Including a dummy variable allows you to control for this situation.

In order to correct for special events or other external factors, these variables should be incorporated in the MMM model. This can be done by including a dummy variable. This is a binary variable with values 0 and 1 to indicate the absence or presence of a special event.

DEEP DIVE – Dummy Variables

To incorporate the effect of external variables and special effects, we include dummy variables in our model. The dummy variables are defined as follows:

$$X_i = \begin{cases} 1 & \text{if the event occurs} \\ 0 & \text{otherwise} \end{cases}$$

Case Study: The Impact of Facebook Advertising Among the Dutch Telecom Providers Researched

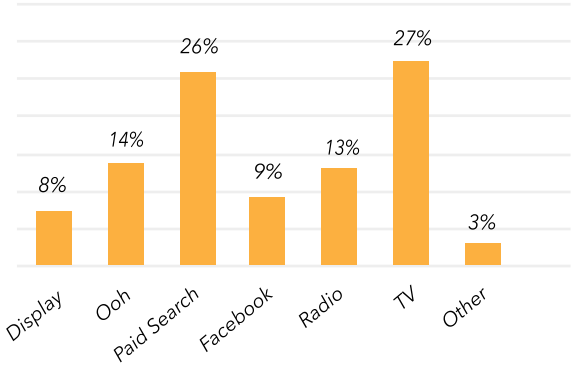
Taking into account these six considerations or best practices for MMM, we can now use MMM to attribute revenue and conversions to Facebook and measure the impact of Facebook advertising. We will investigate its impact based on a case study of the Dutch telecom industry and according to the following question:

How impactful is Facebook in driving key outcomes: sales and search volume?

The Dutch Telecom Industry

The Dutch telecom industry is dominated by several large players and is highly competitive. As in many industries, telecom markets are heavily influenced by pricing and important events such as handset launches. These factors are thus important to incorporate in any media modelling effort.

Testament to the competitive nature of this market is the substantial media spend. An overview of the share of media spend per channel for an average Dutch telco in 2018 is given below:

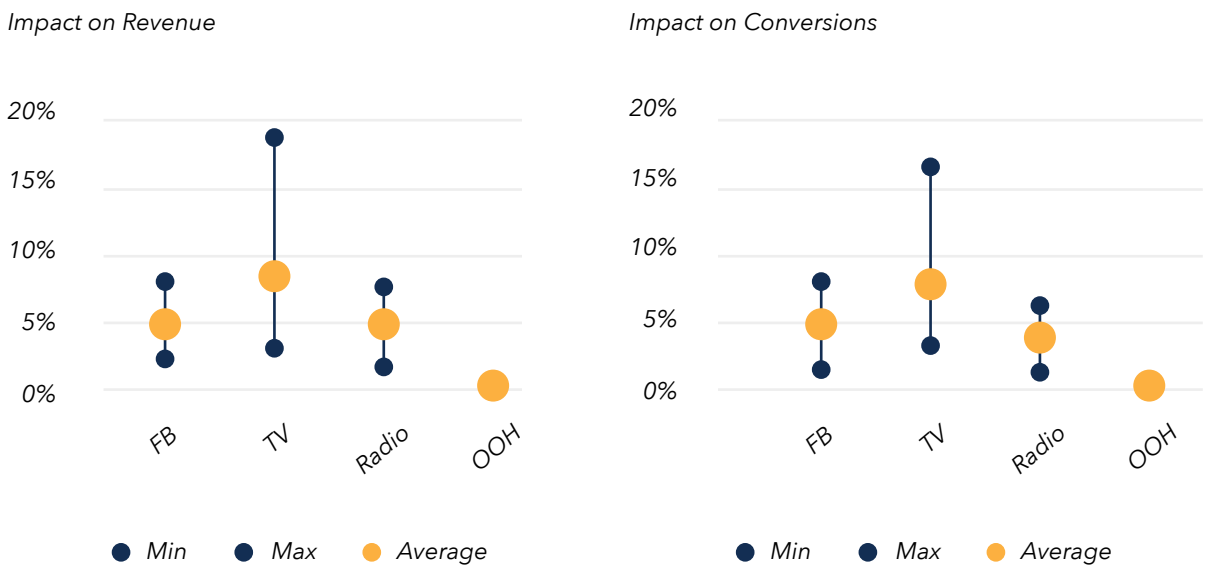


The largest spends are in TV and Paid Search. On average, 9% of media budget is spent on Facebook. As the Facebook spend is growing yearly, it becomes increasingly important to include Facebook in MMM analyses.

Using MTA, only click outs from Facebook to your website can be measured. Aggregated data such as Facebook impressions can be measured using MMM. Knowing the impact of Facebook impressions allows you to optimize investments in Facebook in comparison to both on- and offline media.

Media Effectiveness

So does the spend on Facebook deliver? Which share of revenue and conversions can be explained by Facebook and which share is explained by the other channels?



The graphs above show the MMM results for all the aggregated channels: Facebook, TV, radio and OOH. They show how much of the total revenue and conversions can be explained by each channel. The black dots indicate the average impact across telcos and the grey lines indicate the variation (min, max). In total, the impact of all media channels on revenue or conversions adds up to roughly 20%. The remaining 80% of revenue or conversions consists of base sales plus sales caused by user-level channels which were analysed using MTA.

The difference in channel impact between revenue and conversions can be explained by the type of advertisement. The impact of TV on revenue is relatively high compared to its impact on conversions. This could indicate that telcos advertise for more expensive products (i.e. handsets) on TV compared to other channels.

Telcos spend roughly 9% of their marketing budget on Facebook. This is less than they spend on other channels such as TV, radio and OOH. Telcos spend three times more on TV than on Facebook, but that only leads to about 1.75 times more revenue and conversions. Facebook has a similar effect on revenue and conversions to radio, but on average telcos spend 30% less on Facebook than on radio. And finally, Facebook is significantly more effective than OOH. With 35% less budget than OOH, Facebook generates more than ten times the amount of revenue and conversions.

This shows that Facebook has a relatively high impact on revenue and conversions, especially when taking costs into consideration. The results clearly indicate that there are significant differences in the impact of different channels on conversions and revenue. This highlights the importance of including all these channels in an MMM analysis, instead of simply assuming increased media spend leads to more sales. That last point doesn't seem to be the case for OOH, for example. However, it must be noted that we only measure the impact on performance metrics (i.e. revenue and conversions). It is possible that OOH has a significant effect on brand metrics such as brand awareness.

DEEP DIVE – Ideal Facebook Adstock Rate for Telcos

To find the best adstock rate, we tested a range of different adstock rates for Facebook. In most cases an adstock rate of 0.75 leads to the best model fit.

An adstock rate of 0.75 means that Facebook impressions have a half-life time of about three days.

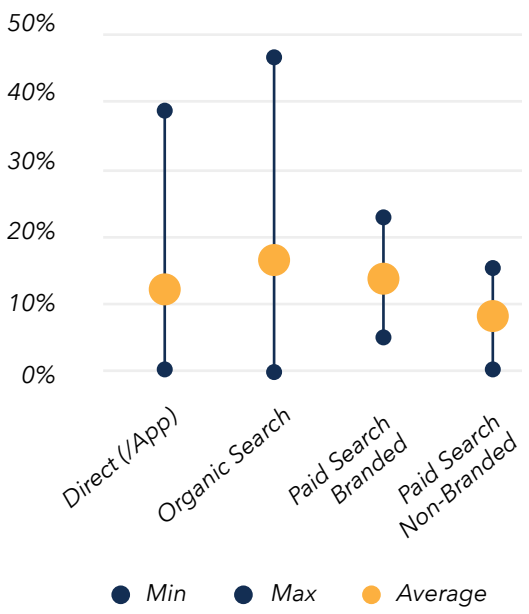
This seems like a clear pattern. It must be noted, however, that the differences in the model for different adstock rates are very small; on average the difference between the best and the worst adstock rate only causes a 1,3% difference in the model fit (adj. R squared).

The Effect of Facebook on Other Online Channels

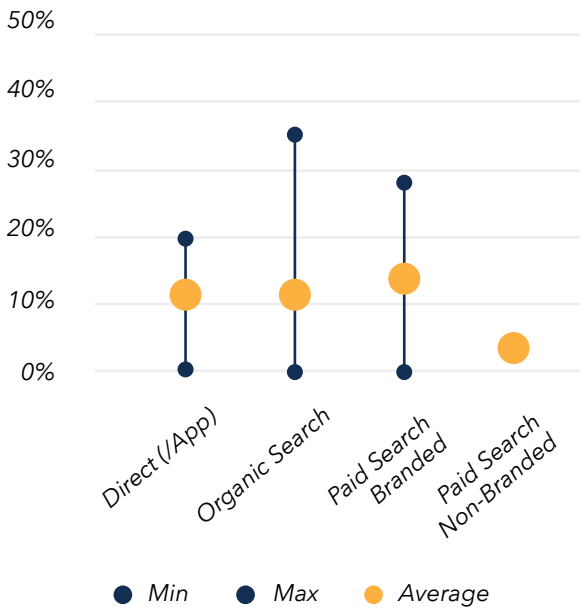
As shown above, Facebook explains 4.9% of revenue and 4.7% of conversions. These sales do not only consist of direct click outs via Facebook. We also observe significant indirect effects of Facebook advertising, such as an increase in conversions via paid search. In other words, when a consumer sees a Facebook ad, he can click on the add, which we call the direct effect, but he can also decide to later search for the product or visit the advertiser's website directly, which we call the indirect effect.

This section investigates which channels are influenced by Facebook ads, in other words the indirect effect of Facebook ads. The results are shown below:

FB impact on channels - revenue



FB impact on channels - conversions

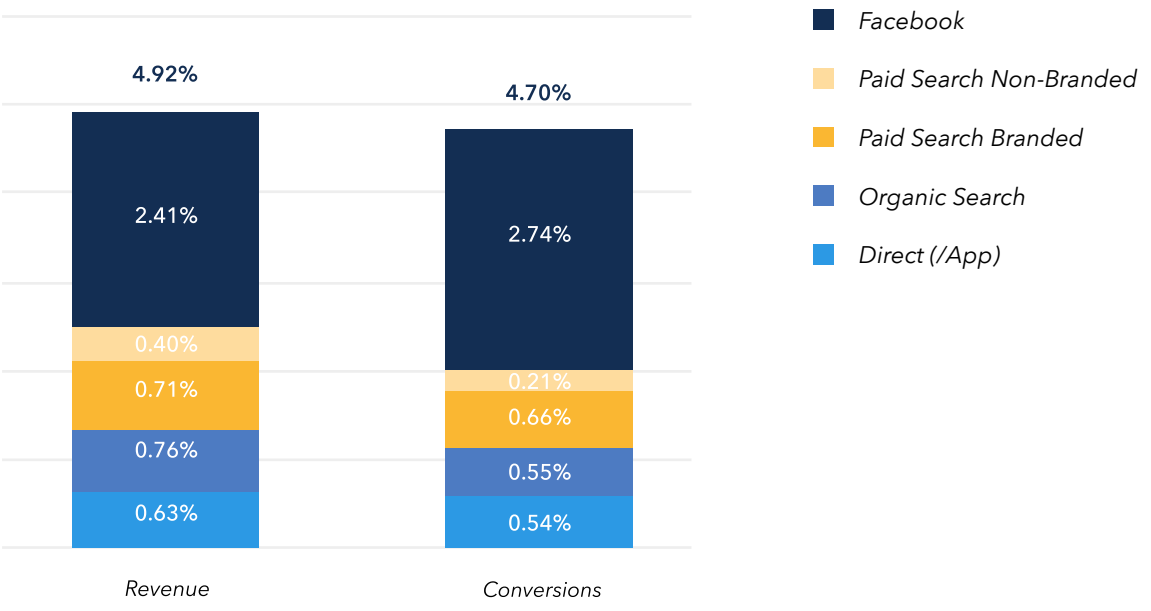


The graphs show the effect of Facebook on the other media channels as measured by our media mix model. The variation is high, and some telcos showed channels that were not influenced by Facebook: the display and email channels. These results are very intuitive: Facebook ads cause a viewer to search for the brand in question or to go directly to the website, but do not necessarily cause the viewer to click on an email or banner.

All this can be summarized in the visual below. In total, 4.9% of revenue can be attributed to Facebook. This revenue is generated via various media channels: 13% via Direct/App, 16% via Organic Search, and 22% via Paid Search. The remaining 49% is the direct effect of Facebook click outs. And 13+16+22=51% of the Facebook effect is indirect. Thus, 4.9% * 51% ≈ 2.5% of total sales are caused by Facebook but occur via other channels.

If Facebook had not been included in the attribution model, for example if only MTA were used, these other channels (direct, organic search, paid search) would have been credited with 2.5% of total sales, which were actually caused by Facebook. MMM can essentially be simplified to "credit where credit is due".

Facebook effect on Revenue and Conversions



Conclusion

This case study of the Dutch telecom industry was commissioned by Facebook and reviews the impact of Facebook advertising. The study incorporates six important considerations for MMM, including diminishing returns, adstock rates and special events.

We found a significant indirect effect of Facebook on other channels. Of all conversions attributed to Facebook, about half (49%) are via direct Facebook click outs. The rest of the effect is indirect, and Facebook causes an uplift in other channels: 22% via paid search, 16% via organic search and 13% via direct website sessions. If Facebook is omitted from your MMM analysis, this indirect effect is not measured and all the credit goes to the other channels. This means that Facebook will be undervalued and the other channels will be overvalued, showing the importance of incorporating Facebook in your MMM analysis.

On average, Facebook is responsible for 4.92% of all revenue whereas TV, radio and OOH are responsible for 8.38%, 4.91% and 0,24%, respectively. These percentages are similar for conversions. When looking at this, especially in combination with media spend per channel, Facebook advertising is effective in driving revenue and conversions. Tv spend is almost three times as high, on average, but not three times as effective as Facebook. It is only roughly 1.75 times more effective. The effect of Facebook is similar to the effect of radio, but Facebook spend is more efficient.

With the telco industry only looking at click outs, half of the Facebook effect went unnoticed and Facebook was undervalued. Using a proper MMM analysis revealed Facebook's actual impact. In conclusion, our MMM analysis revealed Facebook to be much more effective than previously measured using click outs. Facebook is the most cost effective channel in our analysis.

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