Proving Efficacy of Marketing Mix Modeling (MMM) through the Difference in Difference (DID) technique

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Abstract

This report presents a novel approach to validate the efficacy of Marketing Mix Modelling (MMM) using Difference-in-Difference (DID) technique. We use DID to measure the impact of MMM by comparing outcomes from two markets—one receiving increased marketing investments and the other maintaining existing strategies. The results confirm the causal effects of MMM interventions, demonstrating DID's utility in showing MMM's practical benefits and encouraging its broader adoption.

Keywords: Marketing Mix Modelling, Difference in Difference, Econometrics, Causal Inference

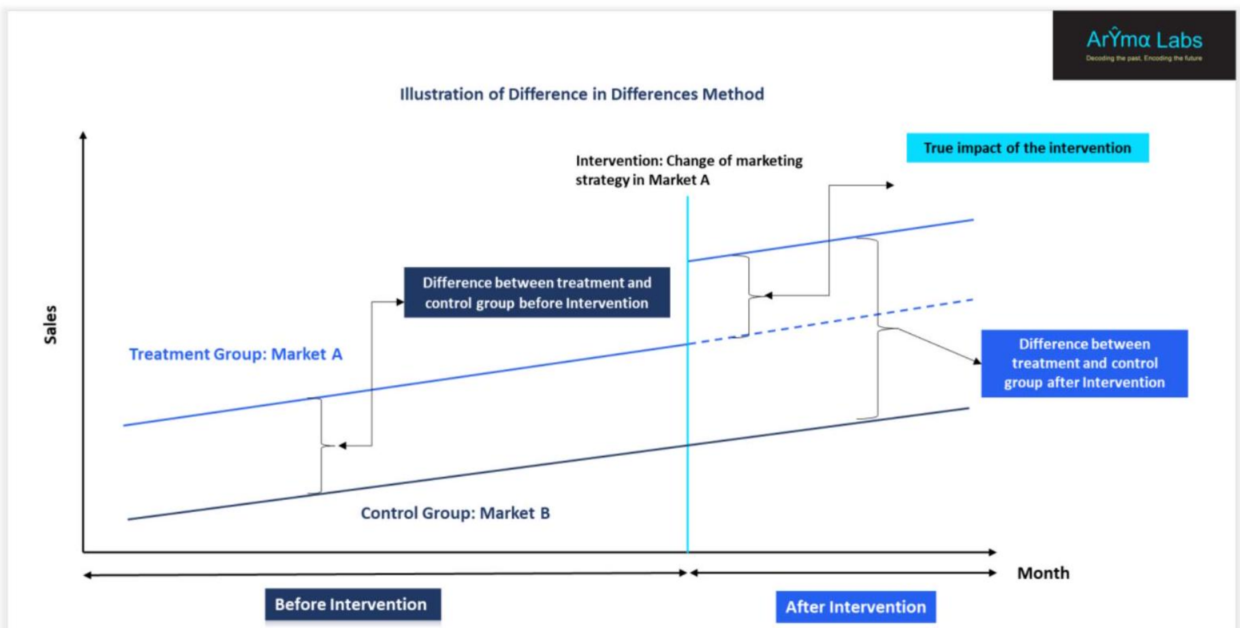

Figure 1: Illustration of Difference in Difference Method

1. Introduction:

Marketing Mix Modelling (MMM) adoption is increasing globally. This renaissance of MMM can be attributed to reasons such as:

- Third party cookie deprecation as mentioned in [1]

- Data privacy updates like iOS 17
- Data Compliance and regulations like GDPR

As the adoption of MMM is permeating into domains which previously had no exposure to them, a lot of curious questions and natural scepticism is natural.
The million-dollar questions on the mind of any client post building the MMM models are:

- How do we know the MMM model is working on the ground?
- If it is working, can we causally prove it and quantify the efficacy of the MMM Model?

To answer these questions, we already used the lens of KL Divergence and Chebyshev Inequality in [4]. Now, we propose a novel approach of using Difference in Difference technique to prove the efficacy of MMM, on the lines of the approaches outlined in [6].

2. Purpose of this paper

Generally, MMM metrics like $R^\wedge 2$, adj. $R^\wedge 2$, AIC, MAPE, RMSE etc. only convey information about goodness of fit or the performance of MMM on holdout data.
The real test of efficacy of MMM is when it is implemented on the ground. The question then arises, how do we measure the efficacy on the ground.
We propose a novel application of Difference-in-difference method to prove the efficacy of MMM on the ground.

3. About Difference-in-Difference (DID)

The difference-in-differences (DiD) method is a statistical tool used to estimate the causal effect of a treatment or intervention by comparing changes in outcomes over time between a control group and a treatment group. This method is especially valuable in observational studies where random assignment to treatments is unfeasible, and it relies on the assumption that both groups would have followed similar trends in the absence of the intervention. Thus, it is a quasi-experimental method heavily utilised in the econometrics and social sciences' domain, especially when an experimental set-up is not possible.
The difference in differences methodology helps us to estimate the impact of an intervention by comparing the treatment and the control group. The primary assumption of this method is the parallel trends assumption. It is assumed that the treatment group and the control group are changing in the same way over time, i.e., both the groups have similar trend over time.
The difference in differences method accounts for two differences:

- First difference: The difference between the treatment and the control group
- Second difference: The difference before the intervention and after the intervention

4. Novel application of DID in MMM

Traditionally in DID, the treatment is binary, i.e., either a policy is applied or not. In the case of MMM, there is no straightforward binary treatment that can be applied.
Hence, we decided to take a novel approach and decided to consider the strategy recommendations of MMM itself to be a treatment.

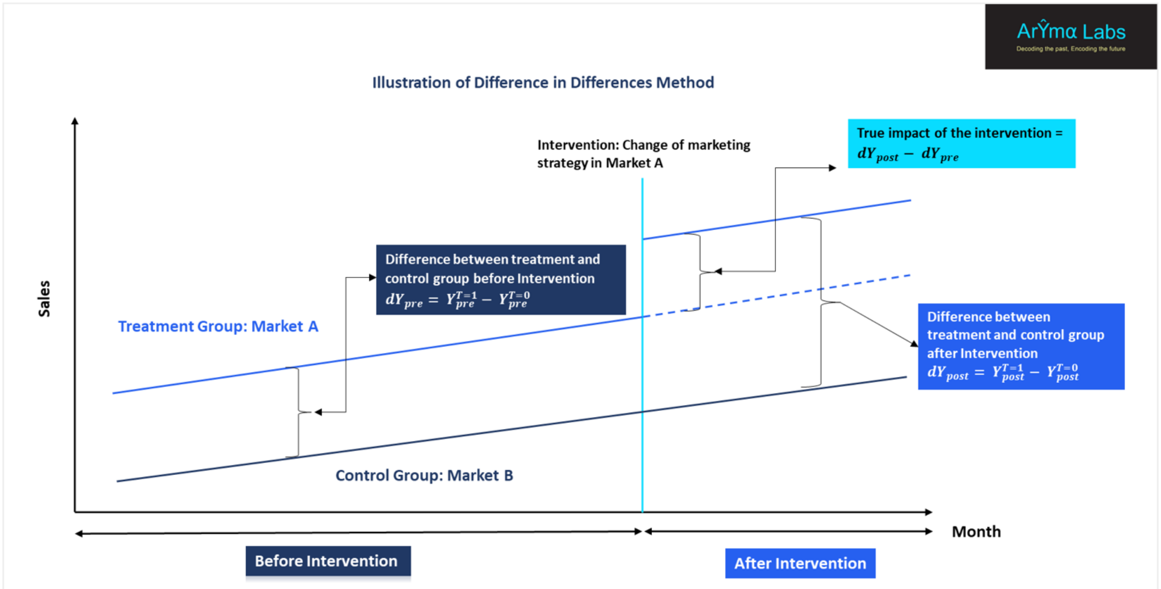

Figure 2: Illustration of Difference in Difference with formulae

5. Approach in detail

5.1. The MMMs

Assume, one has built MMMs for 2 markets - Market A and Market B.
Let's say that market A and Market B are very similar in terms of the pattern of sales (or other KPI) as well as in terms of marketing spend pattern and by and large have the same top drivers of sales.
The primary goal of MMM is first attribution. On having correctly attributed the change in KPI to the respective marketing channels, the next question that arises is - which of the variables are the key drivers of the KPI?
Through the ROI analysis of marketing channels, we could identify 4-6 channels. These would be the key drivers of the KPI and could account for nearly $70\% - 80\%$ change in the KPI. We term these channels as 'Heroes'.
We could implement MMM based increased spends strategy in one market (Market A) and increase spends on the "hero" channels.
For example: Increase spends of channels ch1, ch2, ch3, ch 4 , ch 5 by 30%.
The other market - Market B could continue with the current strategy, i.e., maintaining the current spend pattern across all the marketing channels without any shift in marketing spends/pattern of spends.
Hence, Market A, could be considered as the Test Market where the MMM based suggestion of increased spends would be applied.
And
Market B, could be considered as the Control Market as there is no change in marketing spends.

5.2. The Utility of DID

Assuming that our MMM model is specified correctly, we hypothesize that there will be a positive effect on the KPI in Market A as a result of applying the MMM based strategy of 30% marketing spends increase on the 'heroes'.

Now the question arises, what is the correct way to measure the lift in Market A only due to the treatment.
Why not just use incrementality testing, i.e., measure post and pre levels of the Market A post treatment? Why use DID?
Well, the answer is that if there is a natural trend (which is almost always there) in Market A, then this effect confounds with the treatment (30% increase in marketing spends).
It then becomes difficult to discern only the treatment effect. For this reason, a control group is required. But one has to make sure that the control group has similar natural trend as that of the Market A. Through DID, we subtract off these effects and are hence only left with the treatment effect. Thus, we can prove that the incremental sales are due to the marketing efforts only and not due to any other external factors.

5.3. Illustration

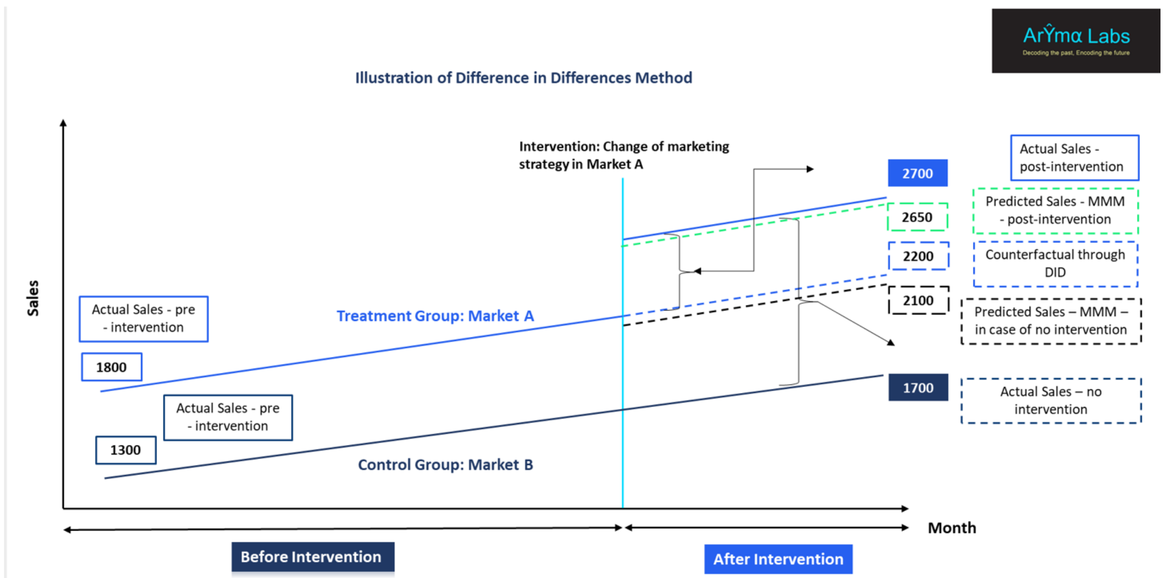

Figure 3: Illustration of Difference in Difference in the Context of MMM

Figure 3 shows the different monthly sales for Market A and Market B before and after the intervention. The intervention here being - increased spend in hero channels by 30%.
If we were to attribute incremental sales for Market A due to intervention (increased spends) using MMM predictions, we could say that the intervention led to (2650 2100) = 550 additional sales.
However, the increment of 550 is a prediction, and we need to prove whether this increase can be causally attributed to the intervention.
This is where DID comes into the picture.

- We can create a counterfactual for Market A using the sales of the control Market B.
- This counterfactual indicates that Market A could have got sales of 2200 , in case no intervention would have taken place.
- Now the difference between the actual sales of Market A (2700) and counterfactual for Market A (2200) is the true impact of the intervention = 500 units.

Hence, we can prove causally that there is an increment in sales of 500 units due to the intervention alone.
One should also note that the treatment and control lines drawn in the image are for illustration purposes only. In reality, these may not be perfectly straight lines. Also, the parallel trend may be directionally parallel but not perfectly parallel.

6. Addressing statistical concerns

6.1. The Parallel Trends Assumption

The parallel trends basically means that the treatment group, in the absence of the treatment, would have evolved like the control group.
The parallel trends assumption is considered to be one of the important assumptions in DID. Violation of parallel trends could lead to biased estimates.
However, there is no statistical tests to confirm the violation of parallel trends assumption.
One would have to rely on visual checks.
In a real MMM setup, perfect parallel trends may not be realistic. Hence one could relax these assumptions a bit. Many alternative solutions have been proposed. For a more detailed discussion, we refer the reader to [2] and [5].

6.2. The autocorrelation concern

Presence of autocorrelation in DID leads to inaccurate standard errors and thus lowers the power of the test, as mentioned in deail in [3].
However, if MMM is built using robust econometric principles such as taking care of autocorrelation, multicollinearity and endogeneity; then the autocorrelation problem is not a problem anymore.
We could make sure that while specifying the MMM model, the autocorrelation effect is studied thoroughly through tests like Durbin-Watson.
Hence the way the MMM is generally architected, the problem of autocorrelation is already solved.

7. Conclusion

Through this novel approach of DID, we believe any MMM's efficacy could be proved conclusively. Overall, causally proving the efficacy of MMM would lead to larger and quicker adoption of MMM worldwide.

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