GROWTH THAT COMPOUNDS

A marketing attribution model needs a counterfactual

A marketing attribution model can describe observed touches. It cannot prove incremental demand unless the decision includes a credible counterfactual.

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MANAGEMENT SUMMARY

A marketing attribution model answers a question about observed paths: which touchpoints were present before a conversion, and how should credit be assigned among them? Budget owners often ask a different question: what would have happened if the touchpoint had not occurred? The second question needs a counterfactual. This article separates last-click, multi-touch, aggregate and experimental measurement, then shows how to give each instrument the decision rights it can support. It explains why high attributed return can coexist with little incremental demand, why model sophistication does not remove selection, and how to build a marketing measurement review that leaves observed credit and causal lift in different columns.

Keywords: Marketing attribution model · Marketing attribution · Incrementality testing · Budget measurement

A marketing attribution model can describe observed touches. It cannot prove incremental demand unless the decision includes a credible counterfactual.

That is the boundary between "which touch received credit?" and "which outcome would not have happened without the touch?" Both questions matter. They are not answered by the same instrument, even when the dashboard displays both as return on spend.

Why must commercial attribution shift from touchpoint tracking to causal incrementality?

Last-click attribution asks which recorded touchpoint was closest to the conversion. Multi-touch models distribute credit across the observed path. Aggregate models relate spend and outcomes over time. A holdout or lift test compares treated and untreated units under a designed intervention.

The first three can be useful descriptions. The fourth is designed to estimate a counterfactual under the tested conditions. The practical mistake is not using an attribution model. It is giving its output the decision rights of an experiment.

Table 1 Observed credit is not incremental lift

Question	Instrument	What it can support	What it cannot support alone
Which touch was recorded?	Last click or rule-based attribution	Path description and operational reporting	Causal lift
How should observed credit be shared?	Multi-touch model	A chosen allocation of observed credit	What would happen without the touch
How did aggregate demand move with spend?	Marketing mix modeling	Scenarios under model assumptions	A clean channel experiment
What changed relative to no treatment?	Holdout, lift or ghost-ad design	Incremental outcome under the test conditions	Universal transfer to every segment

Author's synthesis of Gordon et al. (2019), Blake, Nosko & Tadelis (2015), Lewis, Rao & Reiley (2011), and Lewis & Rao (2015).

Why do high reported ROAS metrics frequently disguise inframarginal organic baseline demand?

People who are already close to buying are more likely to search, visit a site, click an ad and convert. A model that sees the path can mistake the buyer's intent for the effect of the touchpoint. The touchpoint was present. The conversion may have happened anyway.

Blake, Nosko and Tadelis' paid-search experiment is useful because it tests the counterfactual by turning off non-brand search in selected markets. The result is not a universal rule about search. It is a demonstration that observed activity can overstate incremental response when the audience contains buyers who were already likely to purchase.

Lewis, Rao and Reiley show the same problem from the measurement side: correlated online behaviour can make advertising look more effective than it is. Lewis and Rao then show why even a real incremental effect can be expensive to estimate when the outcome is noisy.

The conclusion is not that attribution is useless. It is that attribution and causality should sit in separate columns. The incrementality illusion is the deeper reading of the evidence. This article is the shorter operating rule: do not let observed credit set a causal budget without a counterfactual.

How should marketing leadership assign distinct decision rights to attribution tools?

An attribution model can help a team find missing tracking, detect a broken campaign path, identify which touchpoints are associated with a segment and organise a conversation with sales. It can also be useful for allocating operational attention within a known budget.

It should not, on its own, decide whether to increase a channel, claim a return that will survive a budget cut or compare one campaign's causal productivity with another's.

The decision rights should be written down before the dashboard is opened.

Table 2 The marketing measurement decision rights

Output	Allowed decision	Required companion
Observed touch volume	Fix tracking, routing or creative coverage	A clear statement that the output is descriptive
Attributed conversion share	Compare observed paths inside the same reporting system	A test or bound before reallocating causal budget
Modelled channel contribution	Run scenarios and identify sensitive assumptions	Calibration data outside the model
Incremental lift	Scale, hold or stop under the tested conditions	Scope note for segment, period and intervention
Payback and contribution	Set a cash or margin ceiling	Cohort economics and cost boundary

Author's operating framework based on the cited measurement literature and the site's evidence-over-anecdote discipline.

How can commercial teams construct an empirical counterfactual before reading reporting dashboards?

The smallest useful review asks four questions:

1. What is the unit that could have been treated or withheld?
2. What outside event would move both treated and untreated units?
3. What outcome is measured, and over what window?
4. Which decision changes if the observed credit is not incremental?

The answer may be that a test is too small or too expensive. That is still useful. It moves the decision to a cash-payback or contribution-margin rule instead of allowing a precise-looking attribution number to impersonate evidence.

Evidence over anecdote makes the same request in a broader form: write down what a number would have to survive before it is used. A marketing attribution model should survive the loss of its most convenient interpretation.

The final question belongs in the operating review: what would we have seen if the campaign had not run? If the answer is only “a lower attributed number,” the model has not yet earned the right to answer a budget question.

Evidence base. The analytical frame also draws on these additional sources: Johnson et al. 2017. The links identify the exact works; they support the mechanisms and boundary conditions discussed here, not every claim in isolation.

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END OF ESSAY

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