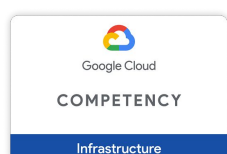
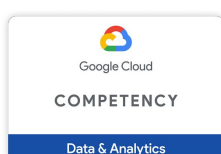
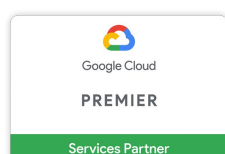




TRKKN Meridian Playbook

Calibrating Meridian with Causal Experiments

A practical guide to turning experimental evidence into stronger priors and more reliable ROI estimates.





Escaping the Iteration Trap

At TRKKN, our data science team has successfully deployed multiple advanced Marketing Mix Models (MMM) using Meridian across a diverse portfolio of clients, helping them transition from fractured attribution to a unified, data-driven media strategy.

Through these extensive, real-world implementations, we have identified a recurring challenge in the MMM ecosystem: **the endless cycle of subjective tuning.**

When launching a baseline Meridian model (Iteration 1¹) using default priors, the algorithm frequently struggles to untangle highly correlated channels, leaving performance marketers with wide credible intervals, over-attributed branded campaigns, and hesitant budget allocations.

The solution to this "Iteration Trap" is not more algorithmic tuning; **it is empirical ground truth.**

This playbook provides **a standardised, technical workflow for fusing Bayesian modelling with Causal Impact analysis.** By running continuous, parallel Causal Impact experiments – via tools like **Causmos** – alongside your Meridian modelling window, you can replace subjective assumptions with validated, strictly calculated incremental lift.

Auditing Iteration 1: Leveraging Historical Budget Shifts

After preparing your dataset and running your initial Meridian iteration with default priors, the model outputs often present a mathematically plausible but commercially unrealistic view of your marketing mix.

Common indicators of an unsatisfactory Iteration 1 model include:

LEARN IN THIS PLAYBOOK:

✓ Strategic Test Design

How to structure a concurrent Causal Impact analysis to target your most ambiguous, highly-saturated channels without pausing your MMM timeline.

✓ Mathematical Translation

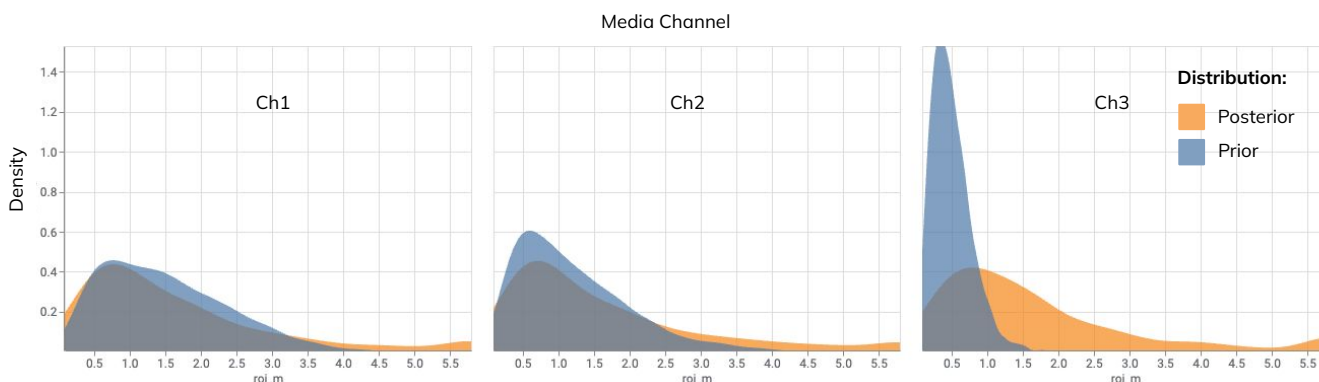
The exact step-by-step formulas required to convert linear causal data into Meridian's strictly positive Log-Normal distribution.

- **Unrealistic ROI concentration:** Highly correlated, lower-funnel channels (like Branded Search or Retargeting) capture an outsized, improbable percentage of revenue contribution, starving upper-funnel channels of credit.
- **Unusable credible intervals:** A major channel exhibits such a wide variance between its upper and lower bounds that performance marketers cannot confidently use the data to adjust future budgets.
- **Contradictory attribution:** The model assigns near-zero incrementality to a channel that the business historically knows drives baseline volume.

When you encounter these red flags, the solution isn't to launch a new, expensive hyperparameter experiment. Instead, you should examine your historical data for instances when you naturally disrupted the baseline, such as a sudden budget scale-up for a promotion or a temporary pause in spending.

1. Iteration 1 is the initial baseline run of the model using default Meridian priors.

Example. Unresolved Meridian output for channel Ch2 successfully grounded the dataset, providing the exact diagnostic evidence required to justify a causal intervention.



Understanding Causal Impact Analysis

Before building the configuration, it is critical to understand how we will measure this historical disruption.

Causal Impact Analysis is a time-series methodology that estimates the true effect of a specific event (the budget adjustment) on your primary KPI (like daily revenue or conversions).

It works by analyzing the period before the budget shift to build a synthetic control – a highly accurate prediction of what your primary KPI would have been if the budget had never changed. By comparing the actual KPI against this synthetic baseline during the event, the analysis isolates the exact incremental lift or drop.

To run this analysis successfully, you need three core elements:

1. A specific intervention date (when the budget changed).
2. Historical time-series data for your primary KPI.
3. Control variables (covariates) that share the same historical seasonality as your KPI but were entirely unaffected by the budget change.



Beliani Uses Causmos to Prove Demand Gen Drove Gross Profit

TRKKN Client Story | E-commerce

Beliani wanted to isolate the true incremental impact of its Demand Gen campaigns beyond standard attribution. Together with TRKKN, the retailer used Causmos on Google Cloud to compare test and non-test markets and estimate how performance would have developed without Demand Gen. The analysis revealed:

26%

Max. incremental lift
in gross profit in
validated market

99.9%

Probability of
causal impact

[LEARN MORE ↗](#)



While you can build these Bayesian structural time-series models from scratch, we use Causmos to accelerate the workflow. Causmos streamlines data ingestion, automates the complex selection of covariates, and instantly generates the exact causal lift metrics required to calibrate Meridian.

Here are three steps to achieve the Meridian calibration with Causmos:

- **Pinpoint a historical budget adjustment:** Review your historical media spend for the specific channel exhibiting poor results in Meridian. Identify a specific, isolated date range where a significant budget adjustment occurred (e.g., a sharp decrease, a brief pause, or a major scale-up). This date range serves as the intervention period for your causal analysis.
- **Set up your variables in causmos:** Input your primary target KPI data into Causmos covering the period before, during, and after the historical budget adjustment. Next, supply the tool with your control covariates, metrics like organic traffic, industry search volume, or sales from an unrelated region. Causmos uses these unaffected variables to accurately model the counterfactual baseline.

- **Execute the analysis and extract results:** Run the analysis across the exact date range of your historical budget shift. Causmos will output the true incremental impact caused solely by that intervention. Review the final summary to extract the exact point estimate (incremental ROI) and the standard error of that estimate, which you will carry over to Meridian.

Mathematical Translation of Causal Insights

Injecting a raw experimental result directly into a long-term Marketing Mix Model creates a temporal mismatch. Your Causmos analysis isolated the exact incremental lift for a small historical window, but Meridian is trying to calculate the average ROI across a larger historical window of fluctuating market conditions.

The "Prior Domination" Problem

In Bayesian statistics, the standard error (σ) acts as a "confidence dial." Because Causal Impact analyses often produce highly precise results with a very small standard error (σ -test), feeding that raw, tiny number into Meridian tells the algorithm: *"I am absolutely certain this ROAS applies to the entire two-year period, don't argue with me."*

Example. For Ch2, we had increased the budget during week 60 of our data. We used this information as input to Causmos to analyse the incremental impact of the budget increase on our main KPI, and the results were positive.


Causmos^{BETA}

✎ Edit Analysis

📊 Data ▾

🔍 Validation Tests ▾

Analysis Quality

Trend: Uplift

Quality Score: 10/10

- + Pre-period validation doesn't show any causal impact before the intervention date
- + Unaffectedness validation shows your covariate csv_Cov2 has no causal impact
- + Main test shows a significant uplift based on your parameters



If you do this, the former will dominate the model. Meridian will ignore its own observational data and simply regurgitate your Casumos' result, preventing the model from accounting for ad fatigue, competitor shifts, or seasonality changes that occurred outside your historical test window.

The Extrapolation Discount (Variance Inflation)

To solve this, data scientists apply an "extrapolation discount" by multiplying the experimental standard error by an inflation factor (e.g., 1.2x to 2.0x). Mathematically, this widens the probability distribution. It acts as a safety valve, telling Meridian: *"This Causmos result is a highly accurate anchor, but because the test happened in the past, treat it with mild skepticism. Allow the broader observational data to flex the final ROI up or down if there is strong evidence."*

The exact multiplier you choose is not a rigid mathematical law; it is a heuristic based on temporal relevance:

- **1.2x Multiplier (recent & highly relevant):** Use this multiplier if the budget shift occurred within the last three months and the market has not fundamentally changed. It provides a tight anchor with minimal flexibility.
- **1.5x Multiplier (moderate decay):** The standard default. Use this if the test is three to six months old. It acknowledges that consumer behaviour or seasonality has shifted slightly since the intervention.
- **2.0x to 3.0x Multiplier (stale data):** Use this multiplier if the budget shift occurred six to 12 months ago. This flattens the prior significantly, using the historical test only as a directional guidepost to prevent the model from drifting into completely unrealistic territory.

By calculating your adjusted standard error ($\sigma\text{-adj} = \sigma\text{-test} * \text{Multiplier}$), you strike a perfect balance, anchoring the model to empirical reality without suffocating its ability to read the full dataset.

Meridian requires all ROI priors to follow a Log-Normal distribution. This statistical constraint ensures the Bayesian algorithms never calculate a negative return on ad spend – a mathematical impossibility, as spending money on media cannot physically subtract baseline revenue.

Because Causmos outputs its point estimate ($\mu\text{-test}$) and standard error ($\sigma\text{-test}$) in a standard linear space, passing them directly into Meridian will crash the model or produce wild distortions. You must mathematically translate your adjusted linear metrics into Log-Normal parameters ($\mu\text{-log}$ and $\sigma\text{-log}$).

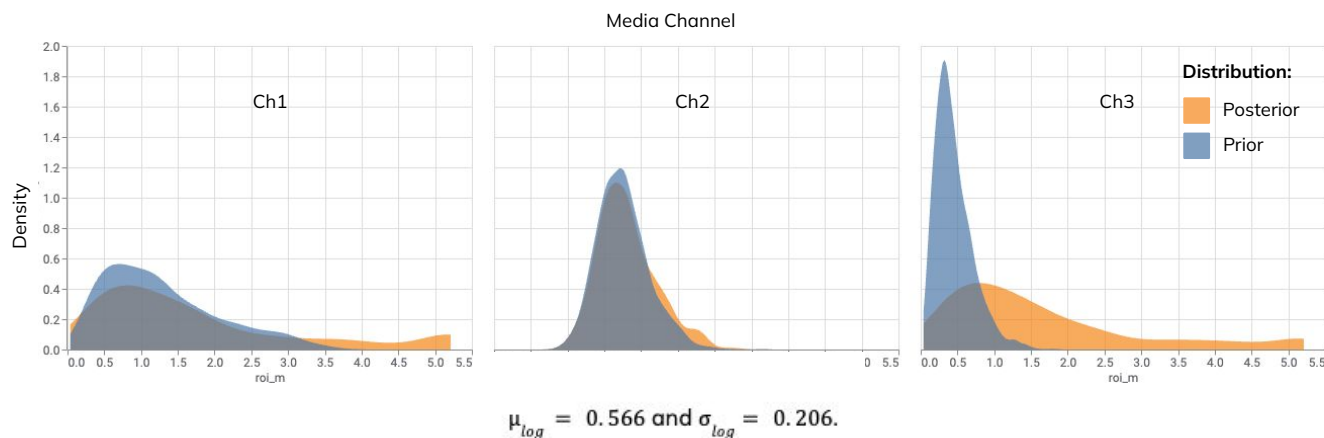
- **Solve for the Log-Normal Standard Deviation:** The standard deviation in log-space ($\sigma\text{-log}$) dictates the shape and spread of the distribution. It is calculated using the ratio of your adjusted standard error ($\sigma\text{-adj}$) to your causal point estimate ($\mu\text{-test}$).

$$\sigma_{log} = \sqrt{\ln\left(1 + \frac{\delta_{adj}^2}{\mu_{test}^2}\right)}$$

- **Solve for the Log-Normal Mean:** Once you have $\sigma\text{-log}$, you can calculate the log-space mean ($\mu\text{-log}$). This formula ensures that the peak of the Log-Normal distribution perfectly aligns with the linear point estimate Causmos generated.

$$\mu_{log} = \ln(\mu_{test}) - \frac{\delta_{log}^2}{2}$$

Example. By using our formula, the new prior for Ch2 are:



From Model Assumptions to Empirical Confidence

Marketing Mix Modelling does not have to be an exercise in endless, subjective tuning.

When Iteration 1 yields unrealistic ROAS distributions or unusable credible intervals, the answer is not to blindly tweak parameters until the output looks acceptable. The answer is to anchor your model in empirical reality.

By auditing your historical data for natural budget disruptions and running a Causal Impact analysis via tools like Causmos, you bridge the gap between pure data science and real-world media buying.

By adopting this workflow, data science teams can deploy Iteration 2 with mathematical confidence, and performance marketers can finally base their highest-stakes budget allocations on a validated single source of truth.

Ready to Calibrate Your Marketing Mix? Stop guessing your priors and start building a continuous, data-driven feedback loop.

Need to Prove Your Marketing Impact? TRKKN Can Help!

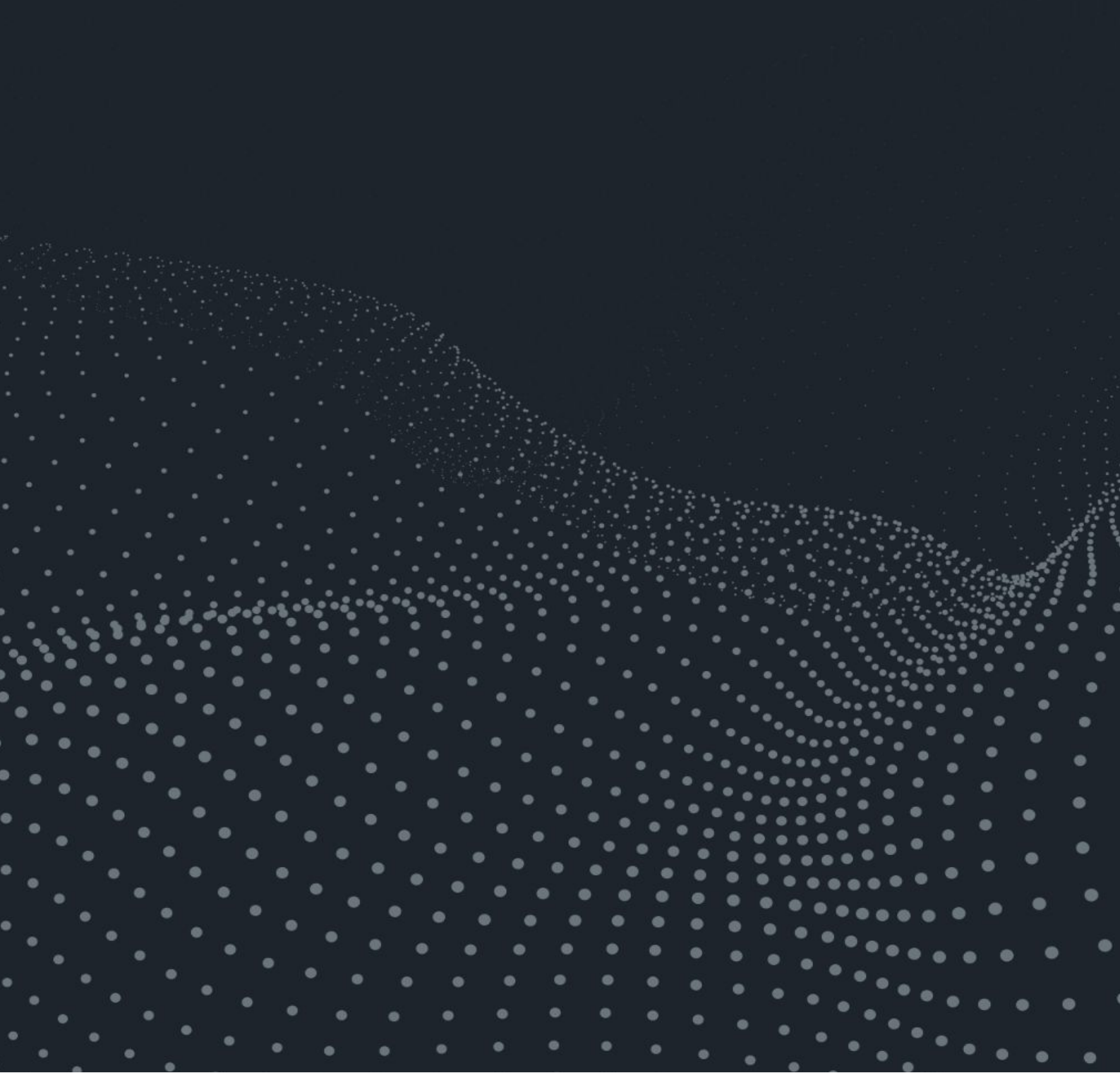
At TRKKN, our advanced measurement expertise spans the complete marketing analytics spectrum – from building predictive Marketing Mix Models using Meridian to deploying data-driven attribution frameworks based on Shapley value algorithms. We solve complex incrementality challenges by designing rigorous causal impact analyses and geo-experiments across a variety of industry-leading tools. This multi-layered approach ensures brands can triangulate their true media performance and make critical budget decisions based on validated empirical evidence.



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TRKKN is a full-service provider of Analytics, Marketing, Cloud & AI Technology, and Digital Experience Optimization. As one of the leading Google Marketing Platform Sales Partners and Google Cloud Premier Partners, TRKKN enables businesses to drive business outcomes through AI-powered digital transformation and marketing technology. Operating in multiple locations worldwide, TRKKN supports leading brands across industries in leveraging the Google tech stack and beyond to advance digital maturity in an AI-driven and privacy-centric world.

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Last updated: October 2026.