GUIDELINES FOR INCREMENTAL MEASUREMENT IN COMMERCE MEDIA

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Introduction

Incrementality is a core concept in marketing measurement, but it is often misunderstood. As budgets shift into commerce media, marketers are under greater scrutiny to prove that their investment is driving real business growth rather than just capturing outcomes that would have occurred anyway.

IAB DEFINES INCREMENTALITY AS:

Incrementality measures the causal impact of marketing by identifying the additional business outcomes directly driven by a campaign or tactic, compared to what would have occurred in the absence of marketing activity.

In practice, incremental measurement approaches vary widely. Some approaches rely on gold-standard experiments, others on modeled counterfactuals, econometrics, or proxy-based approaches. Each has strengths and limitations. Incrementality differs from attribution and ROAS: those methods show what happened, not whether marketing caused the result. Incrementality is also not static. Changes in competition, consumer behavior, and marketing tactics can shift outcomes. Incrementality provides a flexible way to understand both past performance and future drivers of impact.

The challenge marketers face today with incrementality is two-fold: choosing the right method and understanding the claims it supports and its causal reliability. This paper outlines the primary incrementality methods in commerce media, provides a framework for thinking through approaches, and defines what makes an incrementality model causal.

Incrementality methods vary in their approaches, strength of causality, and scope

Incrementality is in the spotlight in commerce media as marketers face growing pressure to justify increased media spend with retail and commerce partners. They must be able to demonstrate how marketing investment has driven and will drive measurable business outcomes such as sales, revenue, and profit. Unlocking these insights will accelerate commerce media's next growth trajectory.

The framework below summarizes four major categories of methods, their use cases, causal strength, and trade-offs.

Method type	Example of approaches	Justification for being an incremental method	Causal strength	Holistic scope	Strengths / Weaknesses
Experiment-based	Random Control Tests (RCTs), Hold out / Ghost Ads, Matched Markets	Explicit test vs. control for causal inference. Tests can be executed individually on each platform and potentially simultaneously across multiple platforms to measure platform-specific lift.	Strong	Low - usually confined to one platform unless usage of multi-platform holdouts.	**Strengths:** High rigor (especially user-level tests), geo-tests are highly scalable. **Weaknesses:** Costly, prone to data contamination without proper controls, time-intensive.
Model-based Counterfactual	Synthetic control, Machine Learning propensity models	Predicts the unobserved counterfactual via statistical or MLmodeling.	Strong to Moderate	Medium - possible to extend across platforms/channels if data sources are linked, but often limited to siloes.	**Strengths:** Highly scalable and can be applied retrospectively. **Weaknesses:** Prone to model bias (e.g. omitted variable bias, selection bias) and data quality issues.
Econometric	Marketing Mix Modeling (MMM), Time-Series Regression	Captures long-term, aggregate marketing effects across all business drivers and non-marketing factors (e.g. seasonality, competitor activity).	Moderate to Weak	High - designed to capture all measured channels and broad business impact.	**Strengths:** Highly comprehensive, can allocate budget across all media, can incorporate non-media factors. **Weaknesses:** Backward looking, lacks granularity, often suffers from multicollinearity not predictive for one-off campaigns or rapidly changing trends.
Hybrid Proxies	New-to-brand percentage, baseline vs. exposed analysis, platform-reported incrementality, Simple Multi-Touch Attribution	Provides directional evidence of lift by comparing performance indicators or relying on platform-specific attribution / modeling rather than an independent, true control group.	Weak	Low - narrow, often single platform or campaign-specific only.	**Strengths:** Easy, fast, scalable, always-on. **Weaknesses:** Lack causal rigor, limited actionability.

What kind of business use cases align best with incrementality approaches?

The usage of incrementality as a measurement approach should be guided by the business goal in mind - not by the availability of a specific measurement method. Different questions require different levels of causal rigor, data access, and time horizons. In practice, marketers can combine multiple approaches to triangulate insights and build confidence in their decisions.

The table below outlines how various incrementality methods can be applied to answer key marketing questions within the context of commerce media. It also illustrates when to rely on each method and how they can complement one another.

How to read this table:

Each cell is color-coded to indicate how well a given approach fits a specific business need:

- 🟢 **Strong fit:** The method is well-suited to answering this question with credible, actionable results.
- 🟡 **Conditional fit:** The method can help if data, design, or context allow, but limitations should be understood.
- 🔴 **Limited fit:** The method is not well-suited for this need or should only be used directionally.

Business need	Experiment-based approaches	Model-based counterfactual approaches	Econometric approaches	Hybrid proxy approaches
Optimize always-on campaigns	🟡 Effective for validating optimizations via small holdouts; limited scalability for ongoing programs.	🟢 Strong for continuous counterfactual estimation, marginal lift analysis and rapid post-update recalibration.	🔴 Too slow for short-term optimization.	🟢 Quick directional reads for in-flight tuning; however, lacks causal rigor and can mislead without corroborating tests.
Allocate commerce media budget across channels	🟡 Can inform allocation rules through controlled tests but may not be scalable and lacks efficiency for frequent optimization.	🟡 Useful if cross-channel data is unified; accuracy depends on model specifications and unbiased input data.	🟢 Designed for budget allocation and long-term cross-channel planning.	🔴 Platform-level proxies don't support channel tradeoff analysis and often exclude competitive overlaps.
Compare performance across commerce media networks	🟡 Rarely practical given ecosystem silos and identity fragmentation.	🟢 Possible but complex; may require probabilistic matching with higher uncertainty; data access and assumptions limit accuracy.	🟡 Best suited – MMMs provide unified, cross-channel perspective.	🔴 Not suited – platform-bound and incomplete coverage.

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Validate ROI of commerce media investment	🟢 Gold standard for proving causal lift through RCTs or matched markets.	🟢 Scalable complement to experiments between cycles.	🟡 Useful for long-term ROI validation but lacks granularity.	🟡 Quick directional validation when causal testing isn't feasible, but prone to bias.
Demonstrate commerce media's impact on sales	🟢 Ideal for proving lift on specific products or promotions.	🟢 Extends experimental findings to broader campaigns.	🟢 Captures cumulative long-term sales effects and brand halo.	🔴 Confined to short-term, self-reported outcomes without external validation.
Plan and measure full-funnel commerce media campaign	🟡 Effective for testing upper/mid-funnel elements individually. Harder to link to lower-funnel KPIs without extended tracking.	🟢 Integrates multi-signal modeling across funnel stages, including brand equity.	🟢 Captures long-term brand + conversion interplay.	🔴 Lower-funnel directional read only. Misses mid/upper funnel contribution.
Test new tactics, formats, or partnerships	🟢 Best-in-class for innovation testing; provides clean causal readouts and high credibility.	🟡 Extends learnings from test environments to forecast broader impact, but sensitive to extrapolation error.	🔴 Not built for discrete short-term creative or tactic tests.	🔴 May indicate engagement or reach shifts but not incrementality.
Calibrate and validate platform-reported lift estimates	🟢 Serves as ground truth to benchmark platform claims.	🟢 Reconciles modeled vs. platform lift estimates for triangulation; enables bias detection.	🟡 Useful for macro-level benchmarking over longer cycles.	🟡 Starting point but requires validation from proven causal methods to avoid false confirmation.

Technical Deep Dive: What makes an incrementality model causal?

At its core, incrementality is about answering a causal question: *What changed because of the marketing action, versus what would have happened without it?*

For a model to credibly answer this counterfactual and claim causality, it must successfully adhere to three core requirements:

1 A CREDIBLE COUNTERFACTUAL OR INTERVENTION

- **Definition:** Establish a valid "what if not" scenario or a clearly defined intervention that separates test and control groups. The counterfactual represents what outcomes would have looked like in the absence of the marketing action. Interventions creates the necessary conditions for comparing treated versus untreated groups (e.g., user-level or geo-level separation).
- **Why it matters:** Without a credible counterfactual, measured differences may reflect correlation rather than true campaign impact. The rigor of this initial design is the primary factor determining the causal strength of the entire model.
- **Examples:** Randomized control groups (RCTs) (for user-level rigor), Holdouts / Ghost Ads (for platform-specific controls), Matched Markets (for geo-level testing), or Synthetic Control Groups (for model-based counterfactuals).
- **Limitations:** Establishing a credible counterfactual can be costly and time-intensive. Furthermore, with proper controls and isolations (especially in multi-platform scenarios), the counterfactual is prone to data contamination (e.g., control group exposure to the ad on an unmeasured platform).
- **Traits connected:** *Interventional orientation* (asking a "what if" question) and *Estimand-first discipline* (precisely defining the effect to measure).

2 CONTROLLING FOR BIAS

- **Definition:** Ensure the measured effect reflects the campaign's impact rather than other hidden factors that influence the outcome. In practice, it is rarely possible to remove all sources of bias, but well-designed causal methods can reduce it to a level where results are still actionable and useful.
- **Why it matters:** Bias can easily distort results, leading to misallocation of budget. Factors like seasonality, pricing, promotions, competitor activity or unmeasured concurrent campaigns can make results misleading if not accounted for (omitted variable bias).
- **Critical sources of bias:** *Model Bias* (e.g., selection bias in observational data), *Multicollinearity* (especially in aggregated models like MMM where media channels are correlated), and *Data Quality Issues* (inaccurate or incomplete linkage of cross-platform exposure data).
- **How to address:** Use explicit identification assumptions, control for confounders (including non-media factors in the model), test for parallel trends (in time-series data), or use geo-randomization and instrumental variables when appropriate.

- **Traits connected:** *Explicit identification assumptions* and *Bias-and-validity tests* (as necessary commitment to proving the model's structure is sound).

3 SEPARATION OF SIGNAL FROM NOISE

- **Definition:** Distinguish true incremental effects from randomness, sampling variability, or insufficient data. Noise can never be fully removed, but well-designed studies can reduce its influence and quantify the uncertainty around results.

- **Why it matters:** Even if the design is conceptually sound, a lift estimate that is statistically insignificant (e.g. falls within the noise floor) is not reliable for decision making. A failure to detect a real effect due to small sample size represents inefficient allocation of testing budget.

- **How to address:** Require statistical robustness — e.g., confidence intervals that exclude zero, bootstrapping, falsification tests, and sensitivity analyses to verify results. Critically, the time dimension often helps separate real effects from noise and short-term variance: repeated measurement across periods can reveal whether observed lift persists or was random fluctuation. This underscores that incrementality is not a one-and-done test but an ongoing process that adapts to changing market and consumer dynamics.

- **Traits connected:** *Bias-and-validity tests* (robustness checks) and *Counterfactual simulation* (ability to project alternative actions with uncertainty quantified).

Approaches that satisfy these principles — whether experiment-based, model-driven, or econometric — can claim causal validity. Others may still be useful as directional proxies but fall short of causal rigor.

Conclusion

Incrementality is not a single technique but a family of approaches, ranging from rigorous randomized experiments to directional proxies. What unites them is the goal of isolating the true business impact of marketing activity. But not all methods are equal in their ability to establish causality, and not all use cases demand the same level of rigor.

Marketers should align the method to the decision at hand:

- For high-stakes strategic questions - such as budget allocation, cross-channel planning, or proving ROI to the C-suite - use methods with stronger causal foundations.

- For fast, tactical optimization or operational decisioning, lighter-weight proxies may be acceptable, provided their limits are acknowledged.

Ultimately, causal measurement requires three elements: a credible counterfactual or intervention, control of bias, and separation of signal from noise. As commerce media grows, adopting a shared framework will allow marketers, agencies, platforms, and retailers to measure consistently, compare results fairly, and connect investment to genuine business growth.

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