# Impact of Bias in Incrementality Measurement Created on Account of Competing Ads in Auction Based Digital Ad Delivery Platforms

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**Abstract**
Incrementality measurement, often conducted via randomized control trials (RCTs), is widely recognized as the gold standard for assessing digital advertising effectiveness. These measurements aim to quantify the true causal impact of advertising campaigns by isolating incremental outcomes from baseline behaviors. However, auction-based ad delivery platforms, which rely on complex real-time bidding (RTB) mechanisms, introduce substantial biases that compromise the validity of incrementality results. These biases stem from competitive dynamics, including intra-advertiser (self-competition) and inter-advertiser (rival) effects, which distort treatment-control group comparisons through mechanisms such as bid inflation, cannibalization of conversions, and contamination of control groups. Moreover, these biases are exacerbated by temporal and spatial variations in auction intensity and user behavior.
This study explores the mechanisms through which auction dynamics skew incrementality measurements, with a focus on biases affecting cost-efficiency metrics like incremental Return on Ad Spend (iROAS) and incremental conversions. Using theoretical models and empirical analyses, we highlight the role of bid overlap, sequential exposure effects, and auction pressure in distorting results. The paper also proposes methodological interventions, including advanced experimental designs, collaborative data frameworks such as cleanrooms, and auction-dynamics-aware metrics.

**Keywords:** Privacy enhancing technologies, Multi-party computation, Causal inference, Digital Ad platforms, Auction based RTB's, Data encryption and retrieval, Randomized control trials, Competing Ads Bias, Cleanroom protocols

## 1. Introduction

Platforms such as Google Ads, Meta Ads Manager, and Amazon DSP leverage advanced algorithms to conduct real-time bidding (RTB) for ad placements. These systems dynamically allocate ad impressions by evaluating bids, relevance scores, and predictive metrics based on user behavior. While these mechanisms optimize revenue for platforms and deliver precision targeting for advertisers, they introduce significant complexities that can distort key measurement frameworks.
Incrementality, a fundamental metric for evaluating digital advertising effectiveness, measures the causal impact of a campaign by comparing outcomes between treatment and control groups. Randomized control trials (RCTs) or A/B tests are considered the gold standard for this measurement, isolating the incremental effects of advertising from baseline behaviors or external factors. However, the competitive and dynamic nature of auction-based platforms introduces biases that undermine the validity of these measurements.

Both self-competition, where an advertiser's campaigns bid against each other, and external competition, where rival advertisers vie for the same impressions, alter ad delivery dynamics in a manner that skews the observed outcomes.

This paper delves into the mechanisms of these biases, offering a detailed analysis of how auction dynamics interact with incrementality measurement. We aim to provide advertisers with actionable insights and propose robust methodological refinements to mitigate these distortions, ensuring more reliable causal inference in digital advertising evaluation.

## 2. Bias Mechanisms in Auction-Based Platforms

### 2.1 Self-Competition Bias

Self-competition bias arises when multiple campaigns from the same advertiser target overlapping user segments. Since these campaigns operate independently within the auction ecosystem, they may inadvertently bid against one another, creating inefficiencies that distort incrementality measurement. The key manifestations include:

- **Cannibalization of Conversions:** When multiple campaigns from the same advertiser engage a shared audience, conversions may be attributed to the wrong campaign. For example, a user exposed to ads from two campaigns may convert due to one campaign but be incorrectly attributed to another, thus reducing the measured incremental impact of either campaign.
- **Bid Inflation:** Self-competition artificially increases the cost per impression (CPM) or cost per click (CPC), as the advertiser's bids drive up auction prices. This escalation inflates campaign costs and distorts efficiency metrics such as incremental Return on Ad Spend (iROAS).
- **Over delivery in Control Groups:** Many ad platforms, such as Meta's Conversion Lift studies, implement randomized control trials at the user level. Due to reduced competition within control groups (as treatment campaigns are excluded), competing campaigns from the same advertiser may disproportionately overdeliver ads in control groups. This artificially inflates control group conversion rates, leading to underestimation of true incrementality.

### 2.2 Rival Competition Bias

Rival competition bias occurs when external advertisers target overlapping audiences, influencing auction outcomes for both treatment and control groups. This bias manifests through:

- **Control Group Contamination:** Users in control groups, while excluded from the tested advertiser's campaigns, may still encounter ads from competing advertisers. This exposure can drive conversions that otherwise might have been attributed to the tested campaign in treatment groups, resulting in an underestimation of incremental effects.
- **Auction Pressure Effects:** The presence of rival advertisers alters auction dynamics by increasing competition for high-value impressions. For instance, rival bids may crowd out the tested advertiser's treatment group impressions, reducing their volume and quality. This dynamic skews comparative analyses between treatment and control groups, leading to biased incrementality results.

### 2.3 Bid Overlap and Sequential Exposure Effects

Auction algorithms optimize ad delivery based on user behavior, ad quality scores, and contextual factors. Consequently, users often encounter sequential exposure to multiple ads from competing advertisers, diluting the observed impact of any single campaign. Key challenges include:

- **Bid Overlap:** Shared audience segments create scenarios where multiple advertisers bid for the same impressions. This overlap intensifies auction competition and introduces noise into incrementality measurements by making ad delivery patterns more variable.

- **Sequential Exposure Effects:** Users exposed to ads from multiple advertisers may exhibit diminished response rates due to ad fatigue or attribution ambiguity. For example, a user who engages with a rival's ad before seeing the tested advertiser's ad may convert due to a combined influence, complicating causal attribution.

This section sets the stage for a deeper exploration of methodological challenges and mitigation strategies, emphasizing the necessity for refined experimental designs and analytical tools to address these biases effectively.

## 3. Methodological Challenges in Measuring Incrementality

### 3.1 Variance in Ad Delivery Dynamics

Even with random assignment, auction variability can lead to significant differences in ad delivery between treatment and control groups. For example:

- Treatment groups may face higher competition, reducing impression volume and skewing outcomes.
- Control groups may inadvertently be targeted by rival ads, introducing noise(known as Rogue Ads) into the measurement of true incremental effects. This effect is seen here in Fig 1. over as a generalized curve seen across over 60 incrementality studies at a major Ad platform where the true lift understatement increases as the magnitude of measured lift increases (wider the difference in test vs. control the greater the bias)

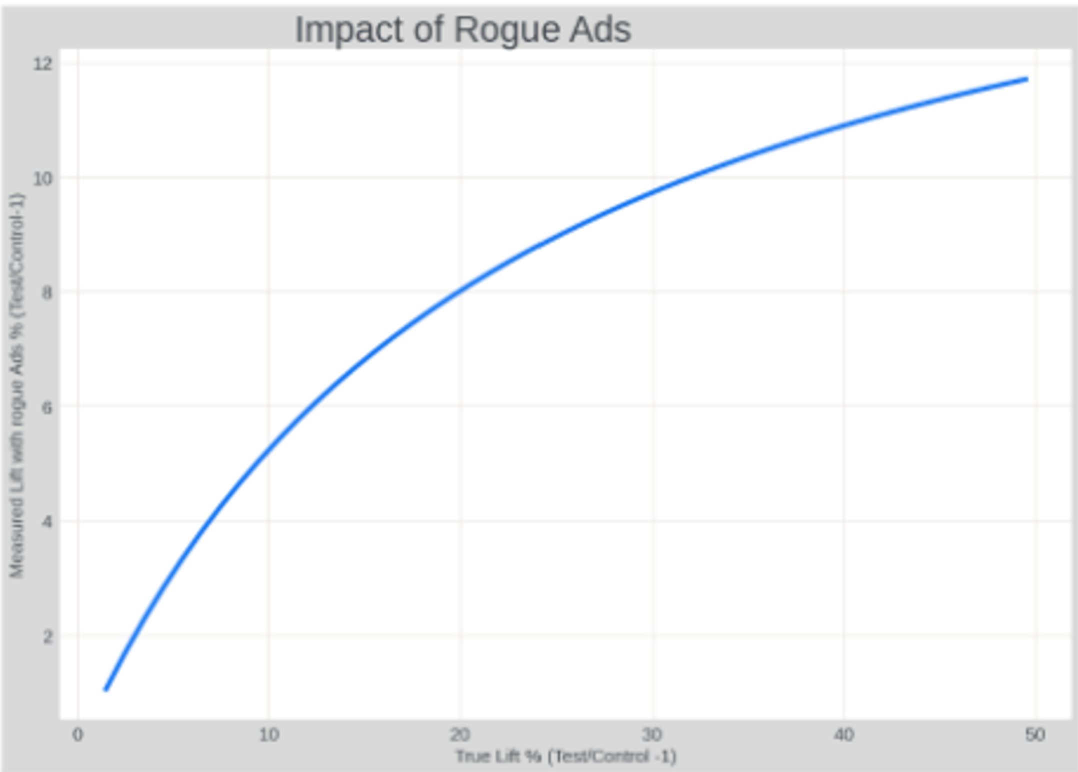


**Fig 1.**

### 3.2 Temporal and Spatial Competition

Auction dynamics can vary across time (e.g., peak vs. off-peak hours) and geography, further complicating the attribution of incremental effects.

## 4. Mitigation Strategies

Addressing biases in incrementality measurement on auction-based platforms requires a multifaceted approach that combines experimental design, advanced analytics, and collaborative frameworks. The following strategies aim to minimize distortions caused by competitive dynamics and enhance the reliability of causal inference in digital advertising evaluations.

### 4.1 Cross-Advertiser Collaboration and Cleanroom Protocols

**Collaborative measurement frameworks**, such as data cleanrooms, enable advertisers and platforms to jointly analyze aggregated data while adhering to privacy-preserving standards. Cleanrooms facilitate the identification of competitive biases by providing:

- **Holistic insights into audience overlap:** Cleanrooms aggregate impression and conversion data across multiple advertisers to evaluate shared audience targeting and its influence on auction dynamics.
- **De-biasing through comprehensive competition modeling:** By understanding the extent of rival ad exposures within treatment and control groups, cleanrooms allow for more accurate attribution of incremental effects.

  However, operational challenges, such as the complexity of integrating multi-party data and maintaining compliance with privacy regulations (e.g., GDPR or CCPA), remain significant barriers. To overcome these, industry-standard cleanroom technologies (e.g., Google Ads Data Hub, Amazon Marketing Cloud) must evolve toward greater scalability and transparency in reporting competitive metrics.

### 4.2 Incrementality Isolation with Holdout Groups

One way to isolate true incrementality involves creating holdout groups that exclude all ad exposures, including those from rivals. This method offers an untainted baseline for comparing the causal effects of advertising but introduces operational and technical complexities:

- **Challenges in implementation:** Excluding users from all ad exposures may require cross-platform collaboration and advanced targeting capabilities to ensure the holdout group remains representative.
- **Trade-offs in feasibility vs. accuracy:** While holdout groups improve baseline accuracy, they reduce the scale of the testable audience, potentially leading to higher variance and longer test durations.

  Despite these challenges, advanced solutions, such as **synthetic holdout group modeling**, which simulates exposure patterns, may serve as practical alternatives to fully isolated groups.

### 4.3 Controlling for Auction Dynamics in Experimental Design

Mitigating auction-related biases necessitates meticulous adjustments to experimental setups:

- **Auction Environment Normalization:** Ensuring treatment and control groups face comparable auction environments minimizes variability due to bid competition. Strategies include:
- **Standardizing bid strategies:** Employing uniform bid caps across groups to reduce discrepancies in impression volumes.
- **Targeting uniformity:** Avoiding overlapping audience definitions across campaigns to limit self-competition.
- **Bias-Aware Metrics:** Introducing metrics that explicitly account for auction dynamics provides a more nuanced view of campaign performance. Examples include:

- **Cost-per-Incremental Conversion (CPIC):** Combines auction costs and observed incremental outcomes to better reflect cost-efficiency.
- **Normalized Incremental Return on Ad Spend (iROAS):** Adjusts for competitive effects by incorporating auction-specific variables such as bid density and impression scarcity.

### 4.4 Advanced Modeling Techniques

**Sophisticated statistical approaches** can enhance bias mitigation by leveraging external data and machine learning models:

- **Instrumental Variable (IV) Approaches:**
- IV techniques utilize exogenous shocks (e.g., platform outages, policy changes) as instruments to isolate the causal impact of ad campaigns. These external events act as natural experiments, breaking the correlation between auction dynamics and user outcomes. For example, a temporary disruption in rival bidding patterns could be used to assess the unconfounded effect of the tested campaign.
- **Multi-Touch Attribution (MTA) Adjustments:**
- MTA models incorporate sequential exposure data to account for interactions between competing ads. By attributing conversions proportionally across touchpoints, MTA reduces biases from rival and self-competition, offering a more accurate representation of ad effectiveness.
- Advanced MTA frameworks, such as **deep learning-based attention models**, allow for dynamic weighting of ad exposures, reflecting their varying influence on user behavior across time and context.

These methods require significant computational resources and domain expertise but hold immense potential for improving the precision of incrementality evaluations.

## 5. Discussion and Future Directions

### 5.1 Implications for Advertisers

Advertisers must recognize the limitations of current incrementality measurement approaches in auction-based platforms and adapt their strategies to account for competitive biases. Investing in advanced attribution models and collaborative measurement solutions will be crucial for accurate performance evaluation.

### 5.2 Role of Platforms

Platforms should provide greater transparency into auction dynamics and enable more robust incrementality measurement tools. For example, offering anonymized insights into rival ad exposure could help advertisers better contextualize their incremental outcomes.

### 5.3 Future Research

Further research is needed to quantify the magnitude of biases introduced by auction dynamics across platforms and industries. Additionally, developing standardized methodologies for addressing these biases would benefit the digital advertising ecosystem.

## 6. Conclusion

Competing ads in auction-based digital advertising platforms introduce significant biases in incrementality measurement. By understanding and addressing these biases, advertisers can enhance the reliability of their campaign evaluations and optimize their strategies in increasingly competitive environments. Continued advancements in privacy-preserving technologies and collaborative measurement frameworks will be essential for mitigating these challenges.

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