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# Challenges and Prospects of Using Synthetic Control Groups in Measuring Digital Advertising Effectiveness: A Data Quality Perspective

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## Abstract

*The article examines the potential of using the synthetic control group method to measure the incremental effect of digital advertising in fragmented ecosystems and under conditions of limited feasibility for classical experiments. The relevance of the work is driven by the rapid growth of the share of digital media in global advertising budgets and, consequently, the high cost of systematic errors in assessing the contribution of campaigns to business outcomes. The study aims to provide a critical analysis of the methodological and operational challenges in applying synthetic control, clarify its scope of applicability, and formulate requirements for data, campaign design, and procedures for diagnosing the robustness of estimates. The novelty of the article lies in shifting the focus from the abstract properties of the method to the concrete conditions of digital advertising practice: it is demonstrated how panel structure, tracking quality, the extent of spillover effects, and the choice of data aggregation level may reinforce or, conversely, undermine the identification assumptions of synthetic control. Particular attention is devoted to comparing synthetic control with alternative causal methods, discussing typical scenarios of estimation bias, and proposing practical heuristics for donor pool selection and for configuring diagnostic placebo procedures in real-world projects. This approach should be regarded as a complementary instrument to randomized geo-experiments and media mix models, and its use requires a prespecified research protocol, unified modeling standards, and transparent communication of estimation uncertainty to stakeholders. The article is intended for researchers in marketing analytics, media measurement specialists, and digital communications managers responsible for building and developing advertising effectiveness measurement systems across industries.*

**Keywords:** *Digital Advertising, Panel Data Quality, Incremental Effect, Synthetic Control Method, Counterfactual Analysis.*

## INTRODUCTION

The rapid growth of advertising expenditures in digital environments has dramatically increased the stakes for accurately measuring their impact. According to industry estimates, by 2024, digital and other new media accounted for approximately 52% of total global advertising and marketing spending, up from 40% in 2019, and their share continues to grow (The Marketing Explainer, 2025). Under these conditions, any systematic error in assessing campaign contributions not only leads to statistical inaccuracies but also to a persistent redistribution of multi-billion-dollar budgets across channels and formats. The widespread availability of user data and platform analytics has created an illusion that effectiveness can be measured via simple correlation-based metrics. In contrast, the key managerial demand is the assessment of a genuinely causal, incremental effect: how audience behavior would have changed in the absence of exposure to advertising, rather than merely which touchpoints preceded the target action.

Classical approaches are poorly suited to solving this problem. Attribution models based on sequences of touchpoints typically redistribute observed conversions across channels but almost always remain correlation-based constructs that struggle to account for endogenous ad serving, unobserved variables, and the influence of non-measured contacts (El Mekkaoui & Benyoussef, 2025). This has been noted both in practice-oriented work on causally motivated attribution for online advertising and in more recent reviews of multichannel attribution.

Simple before/after schemes are susceptible to trends, seasonality, and parallel activities. In contrast, randomized split experiments, although they remain the gold standard, are often challenging to implement due to ecosystem fragmentation, constraints on identifiers, and the breakdown

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of familiar targeting channels, as discussed in detail in studies on the use of causal inference methods in advertising attribution (Digitale et al., 2021). Against this backdrop, the synthetic control method, initially proposed for evaluating the consequences of large-scale aggregated interventions, offers a constructive way to approximate the unobserved counterfactual outcome: it constructs a synthetic control group as a weighted combination of unexposed units whose pre-campaign dynamics are as close as possible to the dynamics of the treated group (Bonander et al., 2021). Further developments of the method, including generalized variants with interactive fixed effects, demonstrate its potential as a modern tool for measuring incremental effects in situations where classical difference-in-differences designs and standard experiments are inapplicable or insufficiently robust.

The purpose of this article is to critically analyze the challenges and prospects of using the synthetic control method to assess the effectiveness of digital advertising: to discuss data requirements and donor pool selection, the robustness of results to violations of assumptions and to changes in market conditions, to compare this approach with alternative causal inference methods, and on this basis to formulate practical recommendations and directions for further research for building scalable systems to measure incremental effects in digital communications.

## MATERIALS AND METHODOLOGY

The study materials were formed based on a targeted sample of academic and applied works on measuring incremental effects in digital advertising, including contemporary reviews on attribution (El Mekkaoui & Benyoussef, 2025), studies of the limitations of quasi-experimental designs in fragmented ecosystems (Digitale et al., 2021), and fundamental contributions to the development of the synthetic control method (Abadie, 2021; Arkhangelsky & Hirshberg, 2023). Methodological recommendations from studies on constructing synthetic groups and diagnosing the robustness of counterfactual estimates (Bonander et al., 2021) were also critically important, enabling the formulation of a consolidated set of data and panel structure requirements typical for advertising problems.

Methodologically, the study is designed as a comparative-analytical work that juxtaposes synthetic control with alternative causal methods and assesses its applicability to real-world campaign data. The analytical sequence included: (1) identifying key limitations of traditional effect measurement methods and determining their relevance in the context of digital advertising; (2) constructing a conceptual framework of requirements for the donor pool, the structure of time series, and the level of data aggregation; (3) conducting a content analysis of applied use cases in which synthetic control was employed to evaluate the impact of interventions under conditions of incomplete control over identifiers; (4) developing diagnostic procedures, placebo tests, sensitivity analyses with respect to the length of the pre-campaign window, and variation of the donor set, based on practices proposed in the econometric literature (Bonander et al., 2021).

## RESULTS AND DISCUSSION

The synthetic control method rests on a counterfactual framework: the effectiveness of an advertising intervention is determined not by the outcome's trajectory in the treated group per se, but by the difference between the observed trajectory and the trajectory that would have been observed in the absence of the campaign. Because such a world without advertising is not directly observable, it must be approximated using comparable observational units that were not subject to the intervention. The synthetic control method formalizes this idea by proposing, instead of a single control group, the construction of its synthetic analogue, a weighted combination of several unexposed units (regions, audiences, inventory sources), with weights chosen so that in the pre-campaign period the synthetic construct closely reproduces both the level and dynamics of the target unit.

This synthetic group serves as an estimate of the counterfactual outcome, and the divergence of trajectories after the campaign launch is interpreted as the causal effect. This approach was initially proposed for evaluating the consequences of large-scale politico-economic interventions. It demonstrated its ability to approximate an unobserved counterfactual by combining multiple donors rather than selecting a single ideal analogue (Arkhangelsky & Hirshberg, 2023). Subsequent works developed generalized versions of the method that connect synthetic control to interactive fixed-effects models, expanding its domain of applicability and enabling a flexible representation of latent factors that jointly influence different units and time points (Wang, 2024).

Such a construction imposes strict yet transparently interpretable requirements on data and assumptions. First, a sufficiently long and clean pre-campaign period is required: weights are estimated on this period, and any large shocks or regime shifts before the intervention degrade the quality of the counterfactual trajectory approximation. Second, relationships between the target unit and the donor pool must be relatively stable over time: the method relies on the hypothesis that the latent factors shaping the joint dynamics of the outcome continue to operate after the campaign begins and that their influence is adequately captured in the pre-intervention phase.

Third, the absence of strong spillover effects is assumed. If advertising in one region substantially alters consumer behavior in neighboring areas designated as the control region, the synthetic counterfactual becomes biased. Empirical reviews of synthetic control applications emphasize that when these conditions are violated, the method either loses identification power or requires additional robustness checks and placebo analyses (Abadie, 2021).

In the context of assessing advertising campaign effects in digital environments, these requirements are, somewhat paradoxically, more attainable than in classical macroeconomic applications: platforms and advertisers possess long panel series across numerous geographic areas, audience segments, or inventory sources, which facilitates the construction of a rich donor pool and enables the identification of stable relationships between units.

At the same time, the synthetic control method is attractive because it approximates causal estimation without conducting a fully randomized user-level experiment: it suffices to have aggregated time series in which some units experience changes in advertising activity while others do not. Figure 1 shows the Feasibility and Applicability of the Synthetic Control Method.

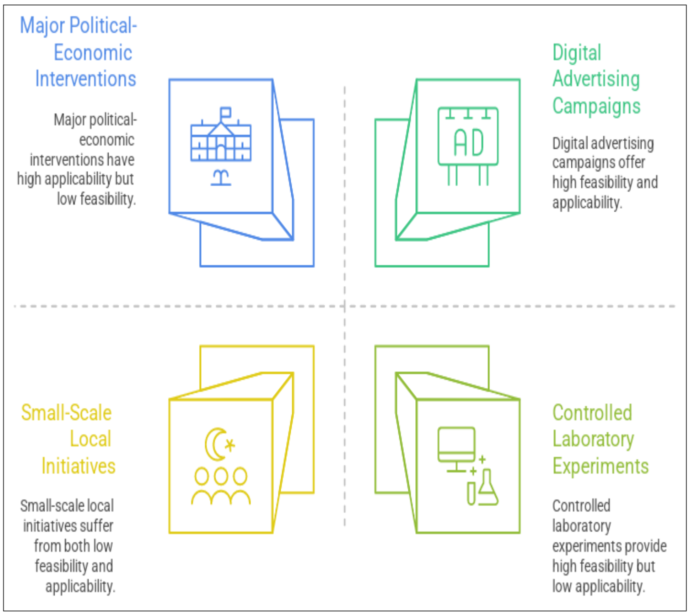


**Fig. 1.** Feasibility and Applicability of the Synthetic Control Method

Under contemporary conditions of tightening privacy requirements and constraints on individual identifiers, it is imperative that such analysis can be performed using aggregated indicators (for example, at the level of regions or clusters of inventory sources), while preserving interpretability of the incremental effect and comparability with the results of geo-experiments described in the statistical and marketing literature (Chen & Au, 2022).

Despite the attractiveness of synthetic control as an instrument for measuring incremental effects, its application in digital advertising immediately encounters issues of data quality and structure. In real campaign scenarios, advertising reach often becomes practically universal: large brands go live simultaneously across countries, cities, and types of inventory, leaving very few genuinely clean zones unaffected by communication. Under such conditions, the donor pool is either extremely narrow or implicitly contaminated by indirect exposures, as audiences frequently cross regional boundaries or switch between inventory sources formally assigned to the control group. As a result, the synthetic control group ceases to be a convincing counterfactual, and the divergence of trajectories begins to reflect not only the effect of advertising but also residual differences in hard-to-compare units.

Even when the set of potential donors is sufficiently broad, data on user behavior and campaign outcomes are rarely smooth and continuous. Tracking failures, changes in tagging systems, migration to new pixels, modifications to consent procedures for data processing, and ad blocker configurations all lead to breaks in time series and artificial spikes and drops. Synthetic control, which relies on matching pre-campaign dynamics, becomes sensitive to such artifacts: weights are chosen to explain noise rather than stable dependencies, and the counterfactual trajectory is distorted from the outset. An additional complication arises from the choice of aggregation level: working at the level of individual geographic zones, device types, or audience segments yields a fine-grained picture but amplifies random fluctuations and makes the model unstable, whereas coarser aggregation into large clusters smooths noise but conceals substantial heterogeneity in advertising response.

The methodological risks relate primarily to the assumptions underpinning effect identification. The key assumption for synthetic control to hold is that, in the absence of the campaign, the treatment and synthetic control follow parallel trends and that the latent factor structure has not changed. This assumption is more likely to fail in digital media because of frequent changes to major platforms' algorithms, the emergence of new ad product types, reallocations of spending among competitors, or changes in user behavior between the campaign and its run-up, rendering the latter a poor counterfactual for the former. In such situations, precise pre-campaign fit creates an illusion of accuracy, whereas unanticipated structural breaks undermine the causal interpretation of the effect.

The mechanism of selecting and weighting donor units is likewise problematic. The more flexible the weighting scheme, and the more tuning parameters and auxiliary predictors are incorporated into the procedure, the higher the risk of overfitting: the model begins to reproduce historical fluctuations driven by randomness and measurement error, and transports these idiosyncrasies into the counterfactual forecast. Under overly restrictive constraints, by contrast, the risk of bias increases. Excessively rigid donor selection rules and weight restrictions result in the target unit being matched with regions or segments that are essentially dissimilar, generating an inherently flawed baseline. The situation becomes even more complex in the presence of multiple treated units and staggered campaign rollout, when different regions or inventory sources are exposed to communication at other times: overlapping treatment waves and interactions between units must be accounted for, and the classical single treated unit–synthetic control pair no longer suffices to describe the underlying process. Estimates are additionally affected by the nonlinearity and heterogeneity of advertising effects: diminishing returns at higher pressure levels, and differential sensitivity across segments, creatives, and touchpoints, distort the straightforward interpretation of the trajectory difference as a single constant effect.

Even if the methodological issues are formally resolved, operational barriers remain when integrating synthetic control into an actual measurement stack. Large advertisers already employ complex analytics ecosystems: marketing media mix models, platform experiments with control-group allocation, recurring tests that hold out parts of the audience from exposure, and various user-path-level attribution schemes. Synthetic control should not displace these approaches but rather complement and calibrate them, which requires careful alignment of metric definitions, time windows, and research questions. Misaligned problem formulations across methods lead to conflicting effect estimates and erode confidence in the new instrument, even when its assumptions are better satisfied than those of familiar techniques.

A further layer of complexity arises from skills and tooling. Implementing synthetic control in an applied digital advertising setting requires not only proficiency in statistical and time-series methods but also an understanding of causal reasoning, identification vulnerabilities, typical pitfalls of overfitting, and specification errors. Off-the-shelf software implementations are often provided as generic libraries designed for academic contexts and require non-trivial adaptation to the specifics of advertising data: complex seasonality, sharp outliers, and asymmetric distributions. In the absence of robust expertise, the method easily becomes yet another black box, whose conclusions are difficult to interpret and defend in decision-making processes.

Finally, even a correctly constructed effect estimate loses value if its results cannot be communicated transparently. For many business stakeholders, the very idea of a synthetic control group is counterintuitive: it is necessary to explain why a combination of different regions or segments is used instead of a single clear control area, how weights are determined, and why such a counterfactual is preferable to a simple comparison with the nearest analogue. This calls for informative visualizations that demonstrate the quality of pre-campaign fit, the robustness of estimates to changes in assumptions and donor composition, and comparisons with alternative measurement methods. Proper statistical inference is also crucial: it is necessary to clearly show the range of uncertainty around the estimated effect, to use placebo scenarios and permutation tests, and to demonstrate how conclusions change when varying the length of the pre-campaign period, the set of explanatory variables, and donor filtering rules. Without such transparency, synthetic control is perceived as a fragile, poorly understood experiment rather than a robust element of the digital advertising effectiveness measurement system (see Figure 2).

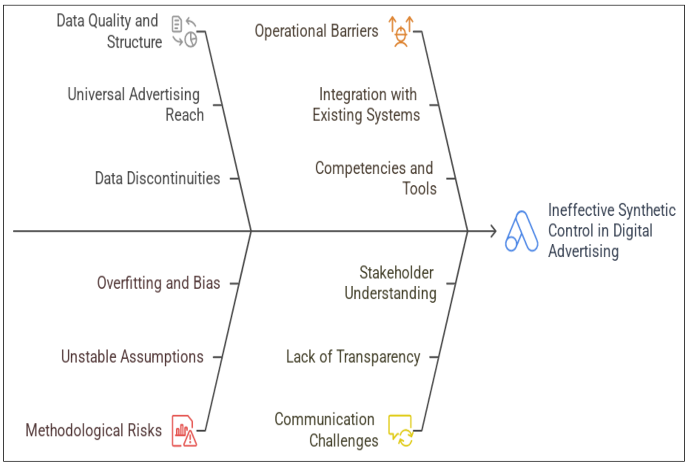


**Fig. 2.** Challenges in Applying Synthetic Control in Digital Advertising

The practical application of the synthetic control method in digital advertising begins well before campaign launch and is powerfully shaped by the rigor of the research design. At this stage, it should be explicitly agreed with the business stakeholders (not just formally, but also about audience behavior, channel overlap, and product distribution capability) which units will be treated as exposed to advertising, and which units will be treated as potential donors. It should also be checked that the historical profiles of critical metrics, such as sales, traffic, conversions, and reach, for the pre-campaign period are sufficiently similar to support a credible counterfactual comparison. In parallel, measures to reduce spillovers between treated and donor units should be considered: where possible, refraining from launching communication in neighboring regions, minimizing audience overlap, and accounting for user mobility and inventory source intersections. From a research perspective, it is essential to pre-specify how the influence of other channels and external shocks will be addressed, including parallel offline activities, seasonal promotions, changes in pricing policy, or macroeconomic events; this may require incorporating additional covariates, introducing exclusion periods, or explicitly defining subgroups in which interventions minimally overlap. Such a pre-analysis protocol disciplines the analysis and reduces the degrees of freedom for ex post selection of a favorable model specification.

It is equally essential to establish unified standards for modeling, diagnostics, and interpretation of results so that the synthetic control method does not devolve into a one-off exploratory trick. It is advisable to fix a baseline model configuration: the set of key indicators to be matched in the pre-campaign period, the admissible set of covariates, regularization rules to limit overfitting, and criteria for excluding donors with anomalous behavior. On top of this, quality checklists are helpful: evaluation of pre-intervention fit accuracy, placebo analyses with redefinition of the treated unit, sensitivity to the length of the pre-campaign window and donor pool composition, and assessment of weight plausibility. When presenting results to business stakeholders, the emphasis should shift from internal technicalities to intuitive visualizations and managerial implications: trajectories of the actual and synthetic outcomes before and after the intervention, the contribution of individual donors to the counterfactual curve, and the uncertainty range of the estimated effect. The Synthetic Control Method in Digital Advertising is shown in Figure 3.

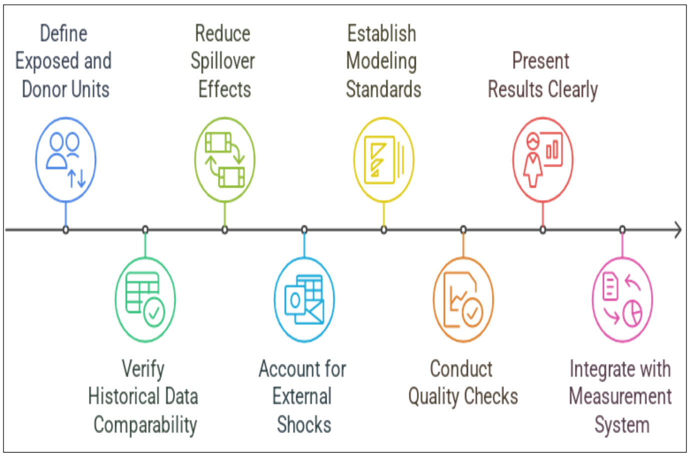


**Fig. 3.** Synthetic Control Method in Digital Advertising

The obtained difference should be translated into terms of incremental revenue, return on investment, and concrete decisions on budget reallocation, rather than confined to abstract percentage lifts. Finally, synthetic control should be regarded as part of a broader measurement system, with its conclusions compared with those of randomized controlled experiments, media mix models, and other causal inference approaches. Consistency, or at least an explainable divergence, among these sources yields a multidimensional view of advertising effects and enhances confidence in decisions guided by measurement outcomes.

## CONCLUSION

Taken together, the analysis demonstrates that the synthetic control method for measuring the incremental effect of digital advertising is a promising yet conceptually and operationally demanding approach. The central strength of the approach lies in its ability to approximate an unobserved counterfactual outcome when randomized experiments are absent or only partially feasible, which is particularly important in contemporary digital environments characterized by a shortage of independent control groups, fragmented identifiers, and persistent constraints on the use of individual-level data. However, its practical value depends entirely on adherence to strict assumptions, the stability of the structural relationships in the data, and the proper construction of the donor pool; without these, the causal interpretation loses its foundation.

The examination of challenges reveals that even when long panel series are formally available, advertisers face numerous sources of instability: incomplete and noisy tracking, systematic shifts in platform algorithms, heterogeneous user behavior, and ongoing changes in the competitive landscape. These factors not only complicate weight estimation and degrade the quality of pre-campaign matching; they also create the risk that the synthetic trajectory will begin to reflect noise patterns and data breaks rather than stable regularities in audience behavior. Against this background, methodological constraints, the need for stable latent factors, the absence of substantial spillovers, and the validity of parallel trends become not abstract conditions but critical tests of the entire causal construction's soundness. Consequently, synthetic control in digital advertising should be viewed not as a universal replacement for experimental designs or media mix models but as a complementary tool that expands the analytical arsenal in situations where classical methods are inapplicable or insufficiently robust. Its successful implementation requires a combination of strict methodological discipline, careful data engineering, and integration with other causal inference approaches.

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