Advertising Incrementality Measurement using Controlled Geo-Experiments: The Universal App Campaign Case Study

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ABSTRACT
Measuring the incremental effectiveness of advertising is a critical task for advertisers for financial planning and optimal budget allocation among different online channels. Recent literature has consistently recommended the use of experiments to estimate advertising effectiveness reliably. Closed Ad networks often prevent advertisers from having direct access to user-level traffic for business privacy reasons. As a result, running experiments by randomizing users is rarely feasible for advertisers. We present a controlled experiment design and an effect estimation framework focused on advertisers’ side by leveraging geo-targeted spend interventions at market-level. Our method is based on the selection of the best pair of markets for testing, conditional on a pre-determined effect estimation method, preventing any model tuning bias. We use a Bayesian structural time series to predict the treatment conversions counterfactual based on the observed control market conversions. We present the results of a field experiment of a Universal App Campaign (UAC), a recent mobile ad campaign format. We find evidence that this advertising format causes incremental conversions, despite the limited campaign customization options. We measure a 6.57% decrease of conversions (statistically significant) when UAC spend is suspended. To our knowledge, our work is one of the earliest studies that successfully measures the incremental value of UAC with controlled experiments.

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1 INTRODUCTION
Advertisers often run a portfolio of media channels, including programmatic native advertising, social advertising, sponsored search, video advertising, among others. In these heterogeneous ecosystems, relying on last-touch attribution poses significant issues because of the bias towards channels closer to conversion in the funnel (demand capture channels), e.g. sponsored search, versus demand generation channels, e.g. display advertising. Thus, measuring the incrementality of advertising spend is critical for advertisers’ financial planning and optimal budget allocation [14].

Previous literature in the evaluation of online campaigns has focused mainly on the effectiveness of display advertising [11], how ad targeting incentives play a role in the evaluation [2], and the difficulty of measuring the effect of this advertising format [15]. Other studies have evaluated paid search [12], and social advertising [9]. Most of these results rely on the ability to randomize users and detailed user tracking data in all treatment groups. Another stream of research to solve this problem is running user-level observational-based methods, including propensity score-based methods [16], from logged data post-campaign. However, Gordon et al. concluded that these methods, even in the presence of rich user-level data, do not provide a reliable estimate of the advertising effectiveness [9]. The most widely accepted approaches by the research community, as well as by the ad tech industry, to measure advertising incrementality are to use controlled experiments [4, 8, 11].

Evaluating campaigns for optimal budget allocation implies measuring the incremental value using advertiser side data and interventions. Product conversions (user responses) are generally well-identified within markets by advertisers. However, in the online advertising ecosystem, ad networks typically manage user-level targeting and ad delivery. Thus, advertisers are often prevented from having direct access to user level traffic, especially when campaign ads are not displayed. As a result of this limited access, running incrementality experiments by randomizing users is rarely feasible outside the ad network. Therefore, advertisers are left with aggregated time series response signals and spend intervention levers, which can be targeted at the market level. This time-series data lead to the deployment of Media Mix Models, which suffer from the lack of rigorously controlled experiment results in the estimation of the advertising budget effectiveness [7].

Designed Market Area (DMA) based targeting in the US is a testing strategy that uses aggregate time series and counterfactual prediction [4, 13]. DMAs are geographical regions in the US designed based on marketing similarities1. Kerman et al. and Blake et al. recommend to randomize DMAs, or any other geo segmentation outside the US, aggregate the observed responses overall regions, and perform a pre/post-intervention analysis based on difference-in-differences [4] or Bayesian Structural time series [13].

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One fundamental limitation of this design is the need to pause the advertising strategy in a given country for the test. Since the audience for an advertising channel format (e.g. social advertising) is likely to overlap with other media channels in the media mix (e.g. programmatic display), the risks of channel cannibalization might bias the experiment. Pausing the advertising strategy in the entire country is rarely feasible in ongoing advertising spend planning.

Blake et al. address geographical spillovers among DMAs, and the difficulties from merely randomizing DMAs leading to a simple correlation analysis to identify the best control group, i.e., not at random. Also, the experiment required close to two-thirds of DMAs. However, the authors do not address the bias of other media channels spend, and the spend levels heterogeneity of the markets before the experiment intervention.

1.1 Our Contribution
We introduce a controlled geo-experiment design and an effect estimation framework focussed on advertisers’ needs. We model the treatment effect using a Bayesian structural framework with time series and a regression component (matched control market conversions), to predict the treatment conversions [5] within the family of synthetic control based methods [1].

We focus primarily on the controlled geo-experiment design. Thus, given the causal effect estimation method, we perform several placebo tests (i.e., A/A tests) using the experiment response signal and the typical markets for the advertiser. Based on these tests, we select the best market matched pairs, as opposed to a simple correlation analysis proposed by Blake et al. [4]. This process guarantees unbiased model selections or tuning post-experiment since we design the controlled experiment specifically for the user response of interest and the given causal effect estimation.

We present the results of a controlled experiment of a Universal App Campaign (UAC), a recent mobile ad campaign format. In this format, the ad network manages and optimizes UAC campaigns within its properties. However, advertisers often expressed concern about limited settings and transparency. The current experiment was performed by Uber as an advertiser, where Uber cities were used as geo-market units. We provide evidence that this advertising format is effective in driving incremental customer acquisition conversions, i.e., signups. To our knowledge, our work is one of the earliest studies to be published that successfully measures the incremental value of UAC with controlled experiments.

Running market matched controlled experiments comes with a significant amount of experiment design tuning and recommendations to improve the precision of the measurement. Challenges include confounding factors such as spend in other media channels, different effects of holidays on target markets, decreased marginal effects of additional spend (diminishing returns [7]), among others. We provide detailed recommendations and discussions about the practical challenges.

2 METHODOLOGY
We propose a controlled market match based experiment design where we identify the best market pair matching. This design is based on the causal estimation of placebo tests (A/A tests) and their credible intervals. Thus, we first describe the causal estimation methodology followed by the controlled experiment design.

2.1 Causal Estimation
Given a pair of markets, we use the conversion time series in both. We consider these markets as treatment and control cells and use the control cell as a predictive variable of the treatment cell.

We model the treatment effect using a Bayesian structural framework with time series and a regression component (matched control market conversions), to predict the treatment conversions (synthetic control). We consider the following structural equation:

\[
g_t^{(\text{treat})} = F\theta_t + x_t^{(\text{control})} \beta + \epsilon_t, \quad \epsilon_t \sim N(0, \sigma^2), \quad \omega_t \sim N(0, W),
\]

where \(t\) is the week index, \(g_t^{(\text{treat})}\) is the weekly number of conversions in the treatment market, \(x_t^{(\text{control})}\) is the weekly number of conversions in the control market, \(\theta_t\) is the time series latent state of \(g_t^{(\text{treat})}\), \(F\) and \(G\) are the state design matrices, \(\beta\) is the regression parameter vector of control conversions, and \(\sigma^2, W\) are the variance parameters. This state-space time series modeling is flexible to integrate various seasonal and trend components based on model superposition in the definition of \(F\) and \(G\). Different components have been modeled before in the effect estimation of online display campaigns [3]. We note the flexibility of the estimation framework and the family of model selections it covers.

We model a local linear trend, a spike-and-slab prior distribution for \(\beta\), diagonal covariance matrix \(W\), and standard non-informative conjugate inverse gamma priors of the variance parameters. The model is fitted using a Markov Chain Monte Carlo (MCMC) sampling approach for \(\beta\) [10], and a faster alternative to the standard forward-filtering, backward-sampling approach in state-space models [5]. The spike-and-slab prior distribution for \(\beta\) provides an automatic variable selection for cases when the control time series is approximately uncorrelated to the treatment series.

We consider historical conversion time series for both treatment and control groups to fit the model. Then, at the time of intervention, we predict the treatment conversions by the evolution of the time series components and the control conversion observations. Let \(\Theta = [\sigma^2, W, \beta]\) be the model parameters to be fitted, given pre-intervention historical conversions, \(D_{1:T-1} = \{g_{1:T-1}^{(\text{treat})}, x_{1:T-1}^{(\text{control})}\}\), where \(T\) is the time of intervention. After fitting the model, we have the posterior distribution \(\Theta^s\) given \(D_{1:T-1}\) where \(s = 1, \ldots, N_s\) and \(N_s\) is the number of MCMC samples. We predict the treatment conversions after intervention as follows:

\[
g_s^{(\text{treat})} = F\theta_T + x_T^{(\text{control})} \beta_s^{(D_{1:T-1}, x_T^{(\text{control})})}
\]

for \(\forall s \in \{s = 1, \ldots, N_s\} \) and \(\forall t \in \{T, \ldots, T_i\}\), where \(t_i\) is the time index after intervention and \(T_i\) is the latest observation. Based on these \(g_s^{(N_s, T_i)}\) posterior samples, and the actual observations for the treatment group after intervention \(g_T^{(\text{treat})}\), we estimate
Algorithm 1 Control/Treatment Market Pair Selection

1: $\Omega$: Set of Markets to consider
2: $\Phi$: Set of placebo intervention times
3: $\Delta_t$: Time length of historical data
4: $\Delta_{t_i}$: Time after placebo intervention
5: for all treatment market: $m \in \Omega$ do
6: for all control market: $n \in (\Omega - m)$ do
7: for all intervention time: $d \in \Phi$ do
8: Fit the synthetic control model of Eq 1:
9: Find $\Theta^s$, $s = 1, \ldots, N_s$, given $\{y_d^{(m)}(t_{\Delta_t}) - y_d^{(n)}(t_{\Delta_t})\}$
10: Predict $\hat{y}_t^{(m)}$, $\forall s \in [1, \ldots, N_t]$ after intervention, $\forall t_i \in \{d, \ldots, d + \Delta_{t_i}\}$
11: Estimate Credible Intervals (CI) $\text{lift}_{\text{cum}}(d + \Delta_{t_i})$, Eq 3
12: end for
13: end for
14: $n^*, d^* \leftarrow$ tightest CI that include $\text{lift}_{\text{cum}}(d + \Delta_{t_i}) = 0$
15: Append best control/treatment/time $V = \{(V, (m, n^*, d^*))\}$
16: end for
17: return $V$

intervention attribution change as:

$$
y_{\text{Attr}}^{v}(t_{i}) = y_{\text{treat}}(t_{i}) - y_{\text{control}}(t_{i}),$$

$$y_{\text{cumAttr}}^{v}(t_{i}) = \sum_{t \in T, \ldots, t_{i}} y_{\text{Attr}}^{v}(t),$$

$$\text{lift}_{\text{cum}}^{v}(t_{i}) = \frac{y_{\text{cumAttr}}^{v}(t_{i})}{\sum_{t \in T, \ldots, t_{i}} y_{\text{treat}}(t_{i})},$$

(3)

where $y_{\text{Attr}}^{v}(t_{i})$ is the conversion change attributed to the treatment intervention at time $t_{i}$, $y_{\text{cumAttr}}^{v}(t_{i})$ is the cumulative attributed conversions up to time $t_{i}$, and $\text{lift}_{\text{cum}}^{v}(t_{i})$ is the cumulative lift up to $t_{i}$ all for the $s$ sample. Posterior credible intervals are estimated based on the $N_f$ effect estimate samples. For the effects of the current experiment analysis, we use the CausalImpact implementation in the interest of result replicability [6].

Compared to the time-based regression approach for analyzing geo experiments proposed by Kerman et al. in [13], which uses only the control markets in the treatment prediction, we also integrate the time series predictive components. We note that these components reduce the variance introduced by noisy observations in the control market time series. Compared to the difference-in-difference based approach deployed by Blake et al. in [4], we integrate time series components and rely on the control predictive power of the treatment observations. Brodersen et al. provide evidence where state-space methods are more accurate than difference-in-difference techniques to measure the effect of interventions [5].

2.2 Controlled Experiment Design

We identify control and treatment groups based on market-level weekly conversions and market-pair matching combinations. For a given market pair matching, we find the treatment effect without intervention (placebo tests), as described in section 2.1.
popularity of UAC as a different advertising media, evaluating the incrementality of this channel becomes increasingly relevant to the industry.

3.2 Treatment Intervention

To estimate the effectiveness of the UAC media channel, we design the experiment to cut the channel spend in the treatment markets from the ongoing regular advertising strategy. UAC provides the ability to target spend at the DMA level and zip code level. For the current study, we use Uber-cities market design based on the zip codes each one covers. Therefore, we, as an advertiser, have control over weekly spend based on the geo-targeting capabilities of the channel.

Assuming diminishing returns of additional advertising spend [7], we determine that we have a more substantial probability of measuring the channel effects by cutting the spend than by increasing it. This strategy gives us a direct estimation of the incremental conversions generated by the channel, similar to the experiment run by Blake et al. for paid search [4].

Due to the UAC mixture of demand-generating and demand-capture media types, changes in UAC spend are likely to have an effect on other channels in the firm advertising media mixture. These spillover effects occurred because there is a significant overlap of audiences among media channels. Thus, other channels’ spend is likely to increase to cover the gap of the spend cut from the focal channel, i.e. UAC, decreasing the power of the test and under-estimating the value of the channel. Therefore, to avoid spillover effects from other channels, we control the other channels spend to keep the same levels, i.e. constant cost-per-attributed-signup (CPA), during the stabilization period in both market groups. We also carefully control the UAC channel spend in both market groups by setting a similar bidding and intra-channel allocation strategy. These potential confounding factors are overlooked in previously proposed geo-experiment designs [4, 13].

We note that the overall controlled experiment design is resource-consuming and potentially expensive. Controlling for other channels’ spend to diminish the risk of spillovers requires pausing the complete advertising strategy for the treatment and control markets. That is, spend optimization should be suspended to maintain similar pre-experiment spend levels in both markets. Also, the spend cut intervention needs to be significantly large to be detectable in the aggregate conversion (signups) time series. Thus, the spend cut intervention needs to be performed in some of the top-spending markets for the firm. That is likely to represent a sizable strategic price of the test. Despite the cost and effort, this design maximizes the likelihood of successfully measuring the effect of the media channel. Even when we expect an incremental effect of the channel a priori, in practice, proving channel incrementality rigorous estimates is challenging (see [9, 15] for empirical evidence of the difficulties). As a result, special care needs to be taken in the intervention design.

4 SETUP AND VALIDATION

To identify the best market matchings, we run placebo tests (Algorithm 1) for a sample of 50 most representative Uber markets (Ω), leading to 2,450 market matching combinations. We consider a set of different intervention dates and training periods to decrease the effect of arbitrary choices of an intervention date for placebo treatments. We test for 5 intervention times (Φ): winter, spring, summer, fall, and holidays. We consider 6 months of historical data prior to the intervention date for training (Δt) and 2 months of experiment duration after the intervention (Δτ). Figure 2 shows the distribution of lift effect point estimates of Algorithm 1 lines 8-11. We observe a large variability of effects, including values different from zero. This process illustrates the need for a more sophisticated market matching than a simple correlation analysis (as proposed by [4]).

We identify that holidays are often problematic as conversions behave differently for each market. These different behaviors increase the variability of our estimates, making it more challenging to measure the effectiveness of the channel accurately. To avoid the impact of holidays, we execute the experiment intervention on March 19th, 2018, after stabilizing the channel spend in both cells starting on January 15th, 2018. The experiment ended on May 15th, 2018. Figure 3(a) shows the historical spend for both markets, the spend stabilization period, and the spend cut at the time of intervention.

Based on Algorithm 1 lines 14-15, we optimize the market pair selection to minimize the probability of a false positive effect detection. For the current experiment, we find a minimum detectable lift of 0.83% based on the best control for the selected treatment market, and the settings we set above.

5 RESULTS

Figure 3 shows the experiment spend intervention, the treatment conversions against the predictive control conversions, and the cumulative effect of the treatment, based on the metric definitions of Equation 3.

We observe in Figure 3(b) noisier observations before the spend normalization period. Here, the treatment scaled conversions show slight differences with the predicted scaled conversions without intervention. Reasons for these variations include different historical spend from other channels and the Christmas holidays. Testing based purely on synthetic control solutions need to handle this variability and increase of variance in the effect estimation [1]. We note that during the spend stabilization (01/15/18 - 03/12/18) observed and predicted treatment scaled conversions are closely aligned. This stabilization is one of the primary benefits of our controlled experiment design because it decreases the variance of the effect estimations improving the power of the experiment design.
We report an effect on spend of - would have been observed in the average. We observe in Figure 3(a) that the spend is not completely zero. That is because of tailing drop is within the credible intervals of the predicted treatment scaled conversions. The smaller the exposed population of a given market, the more diluted the spend effect is. Adding any filter on the users who we are confident are not exposed to ads improves the likelihood of successfully measuring a significant effect. As a result, the proposed design and estimation framework require interventions with large expected effects. Since the incremental value of additional spend stabilization and the dependence on historical spend in the predictive markets, despite the usage of more conversion time series predictors. This increase in the precision of the results shows the value of spend stabilization to successfully measure the effect of the campaign with statistically significant results.

### 6 LIMITATIONS

Accurately measuring the effect of advertising on a given conversion metric is critical for successful advertising spend planning. Identifying these effects is hard, and often leads to a large percentage of inconclusive campaign experiments [15]. Comparisons between aggregate market conversions require large intervention effects. Without user-level data, we are unable to identify the user population exposed to the campaign ads and isolate their conversions. The smaller the exposed population of a given market, the more diluted the spend effect is. Adding any filter on the users who we are confident are not exposed to ads improves the likelihood of successfully measuring a significant effect. As a result, the proposed design and estimation framework require interventions with large expected effects. Since the incremental value of additional advertising spend over ongoing spend levels is smaller, assuming

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**Table 1: UAC Campaign Controlled Experiment Results.**

<table>
<thead>
<tr>
<th>Estimation Method</th>
<th>Metric</th>
<th>Treatment Lift</th>
<th>P-Value</th>
<th>Credible Interval</th>
<th>Incremental Units</th>
<th>Cost per Incremental Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed Estimation</td>
<td>Scaled Signups</td>
<td>-6.57%***</td>
<td>0.0064</td>
<td>-11.66% -1.43%</td>
<td>-1.29</td>
<td>39.30 money units</td>
</tr>
<tr>
<td>Synthetic Control</td>
<td>Scaled Signups</td>
<td>-5.03%</td>
<td>0.2180</td>
<td>-13.73% 3.66%</td>
<td>-1.01</td>
<td>50.20 money units</td>
</tr>
<tr>
<td>Proposed Estimation</td>
<td>Spend Units</td>
<td>-72.33%***</td>
<td>0.0010</td>
<td>-82.40% -61.28%</td>
<td>-50.70</td>
<td>-</td>
</tr>
</tbody>
</table>

For comparison, we use an internal synthetic-control based method off-the-shelf\(^3\). This method uses a standard synthetic control approach [1] based on the control market conversions used by the proposed method. Based on the results of Table 1, we observe that this synthetic-control based estimation provides a similar point estimate but with larger p-value, without achieving statistical significance. We attribute the more substantial variability to the lack of spend stabilization and the dependence on historical spend in the predictive markets, despite the usage of more conversion time series predictors. This increase in the precision of the results shows the value of spend stabilization to successfully measure the effect of the campaign with statistically significant results.

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\(^3\)Under the Hood of Uber’s Experimentation Platform. Published: https://eng.uber.com/xp
We have presented a controlled experiment design and effect estimation framework with advertiser side spend levers when user level randomization is not possible. We have detailed and discussed the day-to-day constraints faced by advertisers to effectively measure advertising channel incrementality with experiments. These constraints contrast with the majority of the current literature in ad effectiveness which assumes the ability to randomize users.

We approached the incrementality testing problem with a market matched based experiment and by targeting advertising spend at the market level. We have provided practical recommendations to successfully measure channel incrementality with advertiser spend levers without user level exposure data. We have demonstrated that the proposed method is more effective in detecting and estimating the effect of channel spend than standard synthetic control based approaches.

We have provided evidence from a large-scale field experiment that UAC, a recent online advertising format, shows incremental advertising effectiveness when compared to the control market during the spend stabilization period. There are cases where a market match test is preferred over a randomized A/B experiment. Cases when negative brand perceptions are likely to spread if users without access to the advertising offer become aware that they have been excluded. We recommend randomized A/B experiments with user-level exposures and responses whenever possible. Unfortunately, often ad networks do not provide this capability, and UAC exemplifies these constraints.

7 CONCLUSION AND MANAGERIAL IMPLICATIONS

We have presented a controlled experiment design and effect estimation framework with advertiser side spend levers when user level randomization is not possible. We have detailed and discussed the day-to-day constraints faced by advertisers to effectively measure advertising channel incrementality with experiments. These constraints contrast with the majority of the current literature in ad effectiveness which assumes the ability to randomize users.

We approached the incrementality testing problem with a market matched based experiment and by targeting advertising spend at the market level. We have provided practical recommendations to successfully measure channel incrementality with advertiser spend levers without user level exposure data. We have demonstrated that the proposed method is more effective in detecting and estimating the effect of channel spend than standard synthetic control based approaches.

We have provided evidence from a large-scale field experiment that UAC, a recent online advertising format, shows incremental value as a media channel, despite the limited customization levers. We hypothesize that the diversity of the media type within UAC is one of the main reasons the channel is effective. The combination of demand-generating and demand-capturing advertising media suggests a powerful set of advertising levers. Also, the use of app store within UAC is a powerful tool to automatically blacklisted users who have been acquired, when compared to other media types. As future work, we encourage more testing of UAC marketing campaigns. Measuring the effects of this channel in other types of conversions, apart from customer acquisition, would shed light on the effectiveness of UAC more broadly.

Testing without user-level randomization is expensive, but it is the only option without user randomization. Although some ad networks provide incrementality tools, particularly in ad exchanges and programmatic display, the fragmented nature of the online advertising industry still poses significant constraints. In ongoing advertising evaluation and optimization planning, rigorously designed experiments provide valuable data to build channel response curves for incremental conversions and to Media Mix Models. We recommend running experiments to calibrate those models. Making rigorous experimentation for advertisers more effective and across multiple media channels remains an open research topic.

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