Online Advertising Incrementality Testing

Industry Practical Lessons And Emerging Challenges

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Who we are ...

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Tutorial Parts

1. The basics: context and challenges
2. Incrementality Testing: concepts, solutions and literature
3. From concept to production: platform building, challenges, case studies
4. Deployment at Scale: test cycle and case studies
5. Emerging trends: identity challenges, industry trends and solutions

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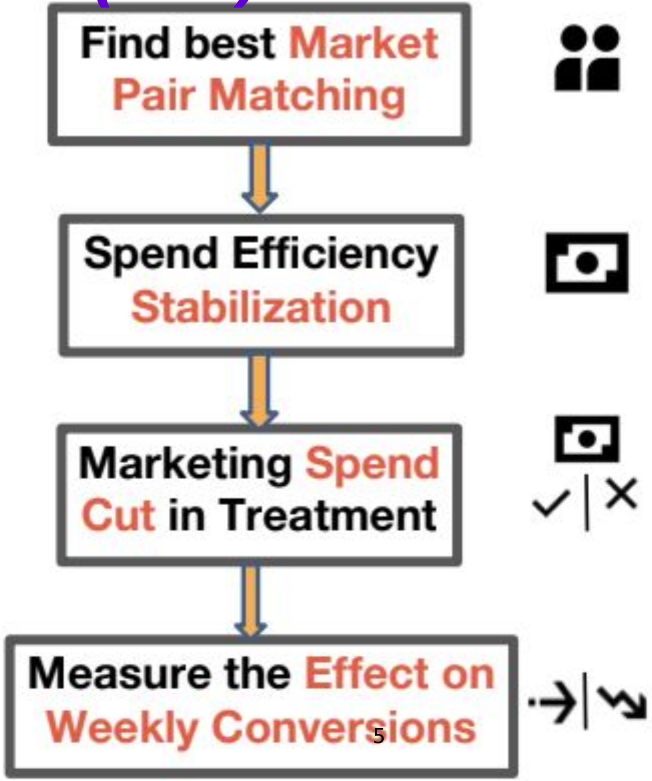
Geo-Testing

Testing with aggregate time series and geo testing units

Controlled Geo-Experiment + Synthetic Control

Barajas et al. (2020), Blake et al. (2015), Abadie et al. (2010)



Without user level holdout, market pair testing is a viable solution

- Typical incrementality testing for advertisers when the ad network **does not support user-level holdouts**

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Causal Estimation: Synthetic Control

Barajas et al. (2020)

Bayesian Structural framework with **time series and a regression component** from the control market conversions to predict the treatment conversions (**synthetic control**).

Structural Equation

$$
\begin{aligned}
y_t^{(treat)} &= \overbrace{F_t \theta_t}^{\text{Time Series trend}} + \overbrace{x_t^{(control)T} \beta}^{\text{Control Market Predictor}} + \epsilon_t, \qquad \epsilon_t \sim N(0, \sigma^2), \\
\theta_t &= G_t \theta_{t-1} + \omega_t, \qquad \omega_t \sim N(0, W),
\end{aligned}
$$

Market Best Match: A/A tests

Barajas et al. (2020)

Best Pair selection given the conversion and estimation method

Algorithm 1 Control/Treatment Market Pair Selection

Ω: Set of Markets to consider
Φ: Set of placebo intervention times
Δ_t: Time length of historical data
Δ_{t_i}: Time after placebo intervention
for all treatment market: $m \in \Omega$ **do**
  for all control market: $n \in \{\Omega - m\}$ **do**
    for all intervention time: $d \in \Phi$ **do**
      Fit the synthetic control model of Eq 1:
      Find Θ^s, $s = 1, \ldots, N_s$, given $\{y^{(m)}_{d-\Delta_t:d-1}, x^{(n)}_{d-\Delta_t:d-1}\}$
      Predict $\hat{y^s}^{(m)}_{t_i}$, $\forall s \in \{s = 1, \ldots, N_s\}$ after intervention, $\forall t_i \in \{d, \ldots, d + \Delta_{t_i}\}$
      Estimate Credible Intervals (CI) $lift_{cum(d+\Delta_{t_i})}$, Eq 3
    end for
  end for
  $n^*, d^* \leftarrow$ tightest CI that include $lift_{cum(d+\Delta_{t_i})} = 0$
  Append best control/treatment/time $V = \{V, (m, n^*, d^*)\}$
end for
return V

Estimation Parameters: Markets, Intervention times, Train/follow-up Length

A/A test estimation: Given Causal Estimation Framework

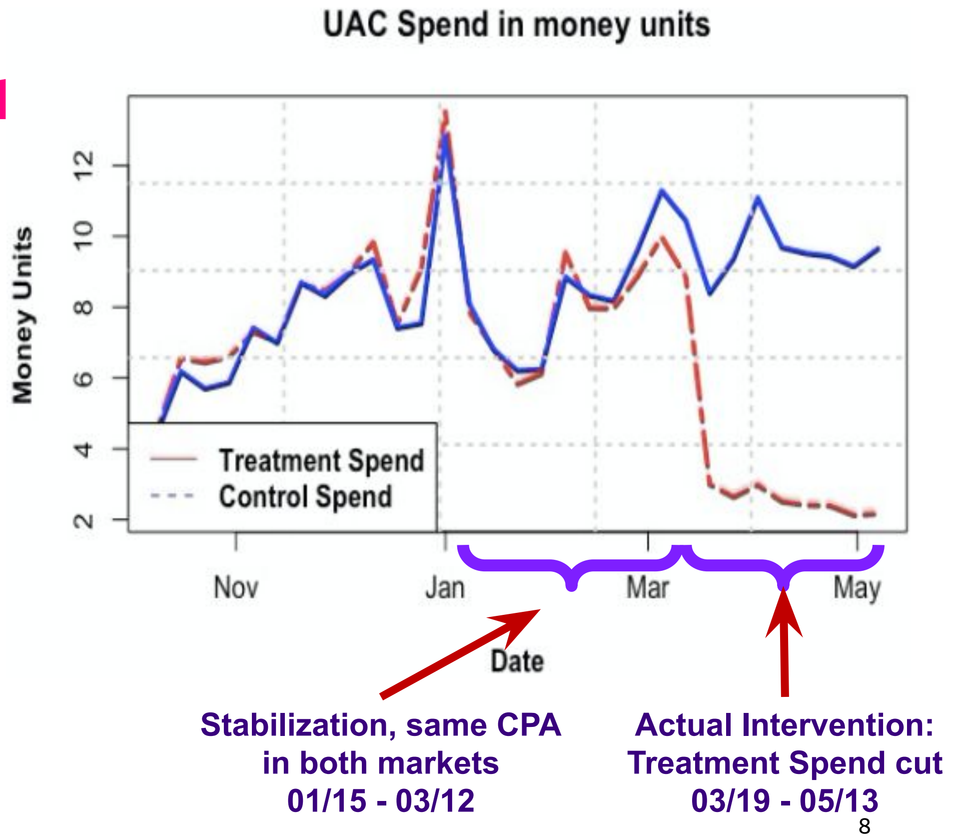
Filter Best Pairs and Parameters: tightest and interval with zero effect

UAC Incrementality: Intervention
Barajas et al. (2020)

Given **treatment/control pairs and the estimation method**, we execute the experiment

1. Cost-per-attributed-signup (CPA) **stabilization** both groups

2. **Suspend** spend for treatment market



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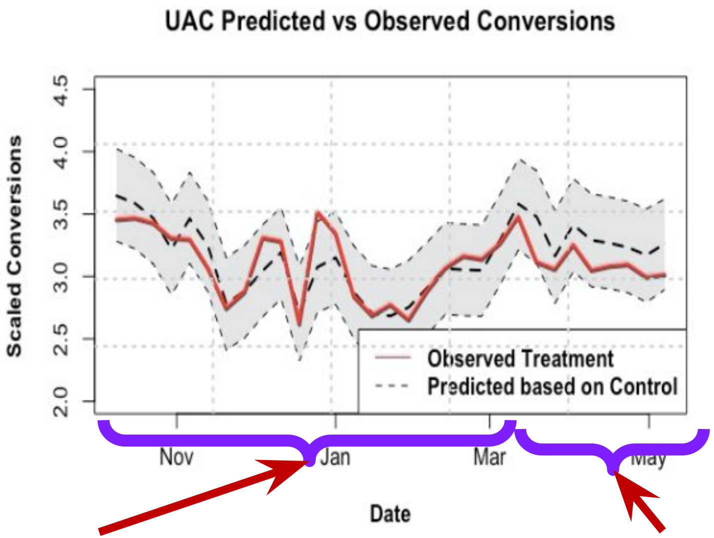
UAC Incrementality: Effect on Weekly Conversions

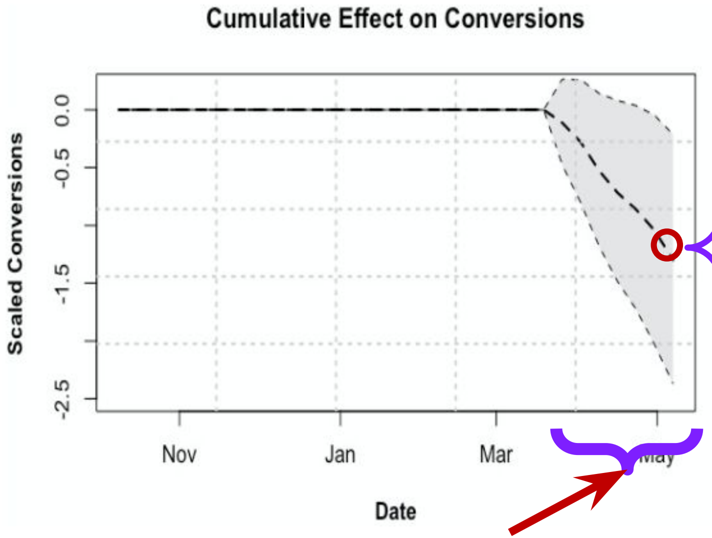
Barajas et al. (2020)

Consistently lower predictive (synthetic control) treatment conversions than observed



Training period:
09/09 - 03/12

Intervention period.
Predictive vs observed
03/12 - 03/15



Cumulative effect and 95% credible intervals

Conversion Lift:
-6.57%

Spend Lift:
-72.33%

Cost per Incremental Scaled conversion:
39.30 money units

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Limitations and Caveats

Limitations and Caveats

1. Comparisons between aggregate market conversions **require large intervention effects (spend)** since we are **unable to identify users not exposed to the ads** leading to less precision.

2. Rigorously designed experiments provide **valuable data to build channel cost curves of incremental conversions** and to calibrate Media Mix Models for optimal spend allocation

3. **Testing during holidays is noisy and problematic**, which is a big limitation compared to user holdout testing

Thank you!!!

Feedback welcome.

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