Online Advertising Incrementality Testing

Practical Lessons, Paid Search 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

Paid Search Evaluation

Testing Lower Funnel Advertising

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Demand Captured vs Demand Generation Channels

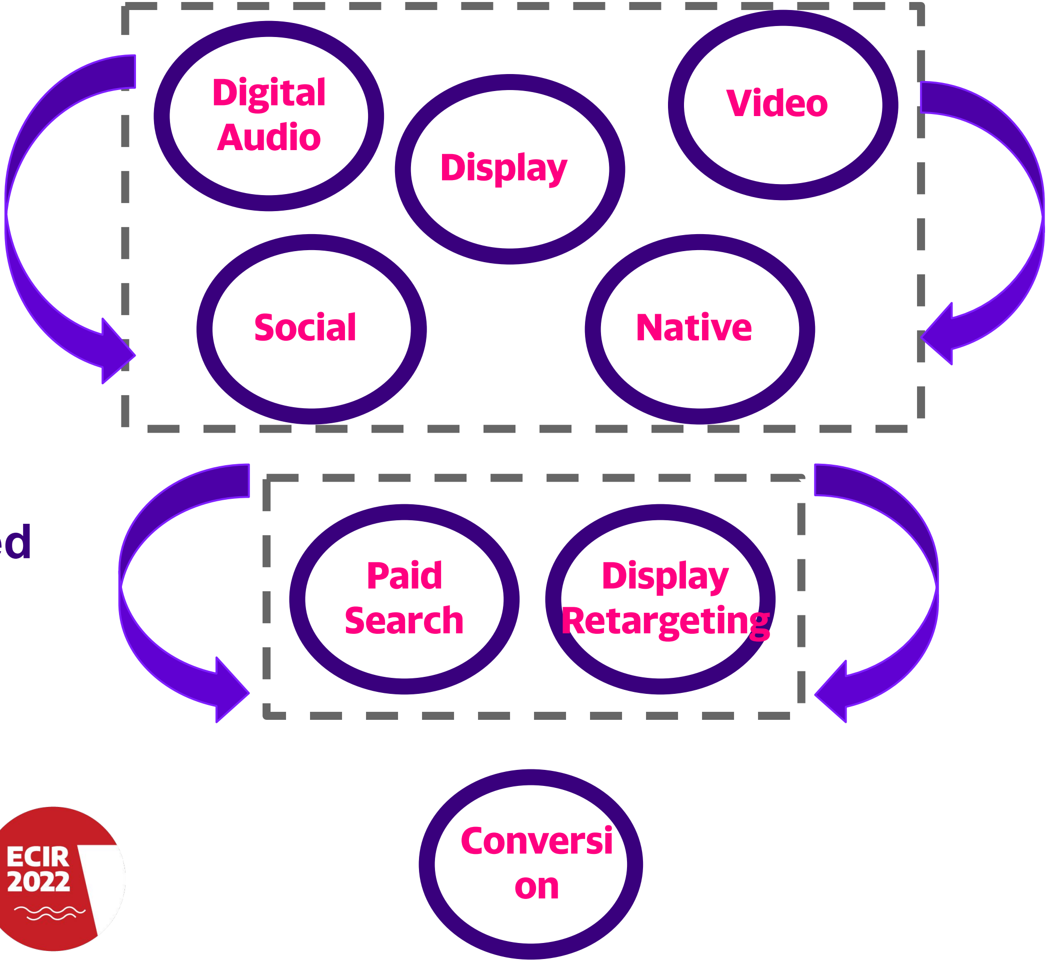
Li and Kannan (2014)

Upper Funnel

Lower Funnel

Advertiser Initiated Ads: Demand Generation

Customer Initiated Ads: Demand Captured

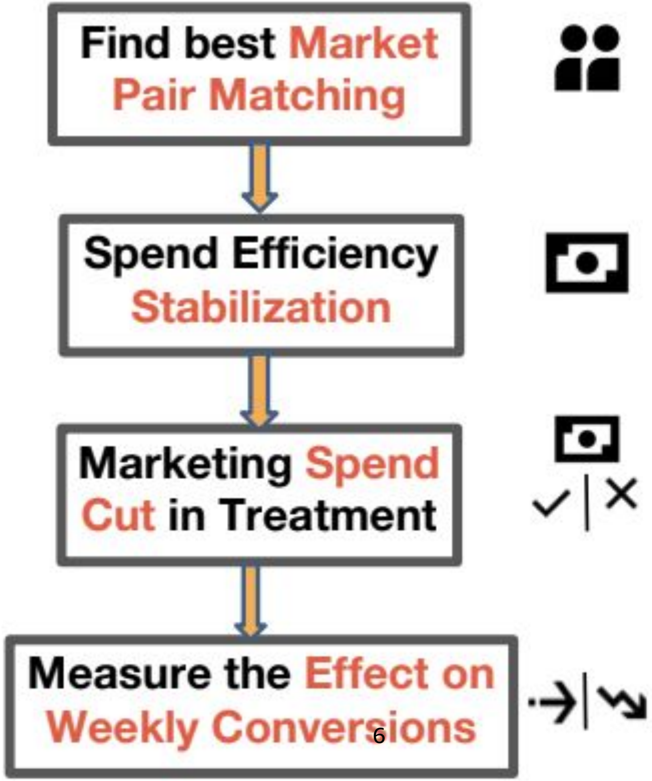


Testing Challenge: No User-level holdout
Blake et al. (2015), Barajas et al. (2020)

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**

Same concepts applied to hold out users in paid-search: e.g. display retargeting

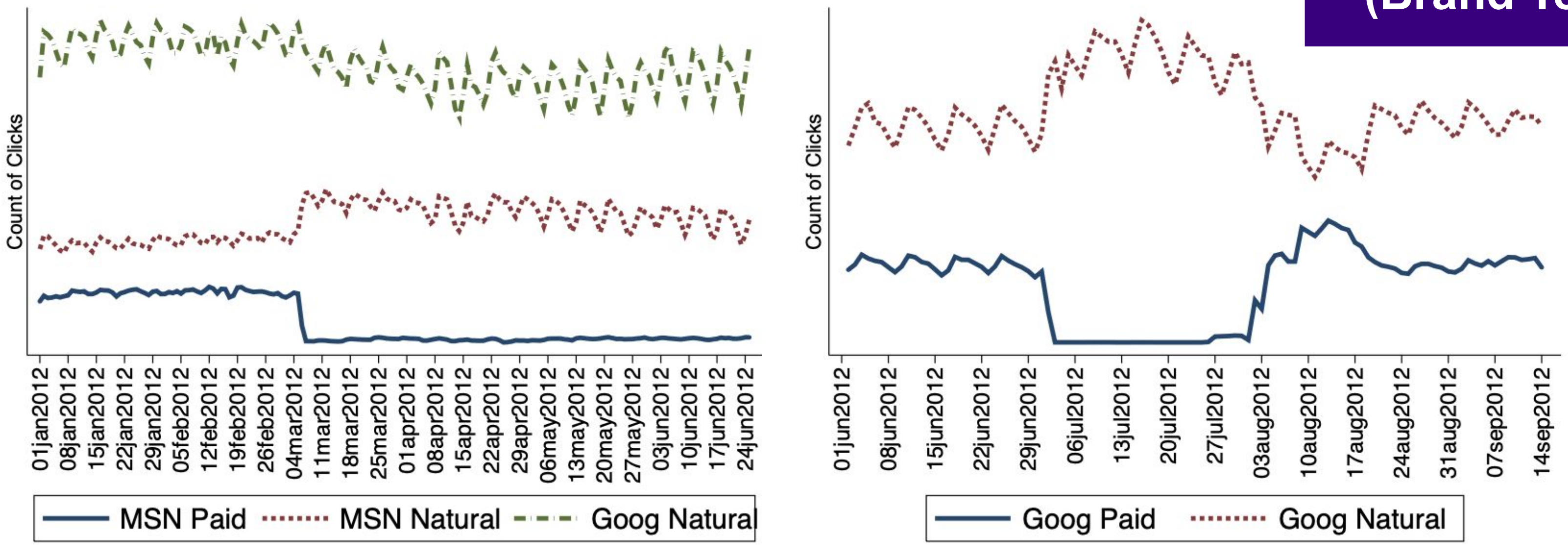


The Effects of Lower Channels: Organic vs Paid Search

Blake et al. (2015)

Cannibalization of Organic Search (Brand Terms)

Figure 2: Brand Keyword Click Substitution



(a) MSN Test

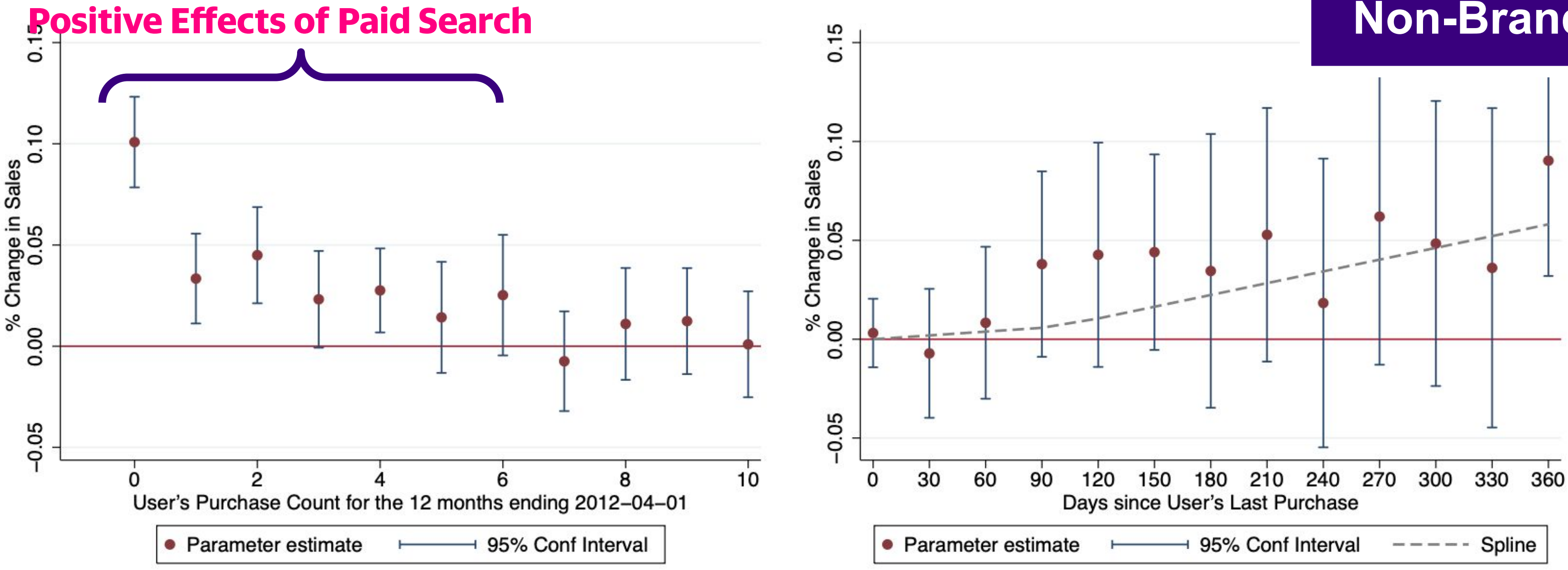
(b) Google Test

Paid Search: Positive effect on new/infrequent users

Blake et al. (2015)

Positive Effect on Least-Active Users: Non-Brand Terms

Figure 4: Paid Search Impact by User Segment



(a) User Frequency

(b) User Recency

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Paid Search effect on Yelp Metrics

Dai and Luca (2016)

Dai and Luca (2016)

- **Randomizes Restaurants** (Advertisers) in Yelp
- Assigns **paid search packages to treatment** restaurants only (no ads to control restaurants)
- Positive effects on **upper-funnel metrics**:
  - Page views: 25%
  - Purchase intention metrics (directions to restaurant, browsing, etc): 9% - 18%
  - Number of reviews: 5%

Short-term top-funnel metrics: All effects droop to zero after test

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Limitations and Caveats

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Limitations and Caveats

1. Paid search studies suggest the channel **to be effective for short-term effects within the search marketplace** .

2. Ongoing research suggests a more **complex set of effects on marketplace prices** in e-commerce sites (see **Moshary (2021)**)
   a. The study suggests a potentially negative effect on total sales in the platform

3. More studies need to be developed

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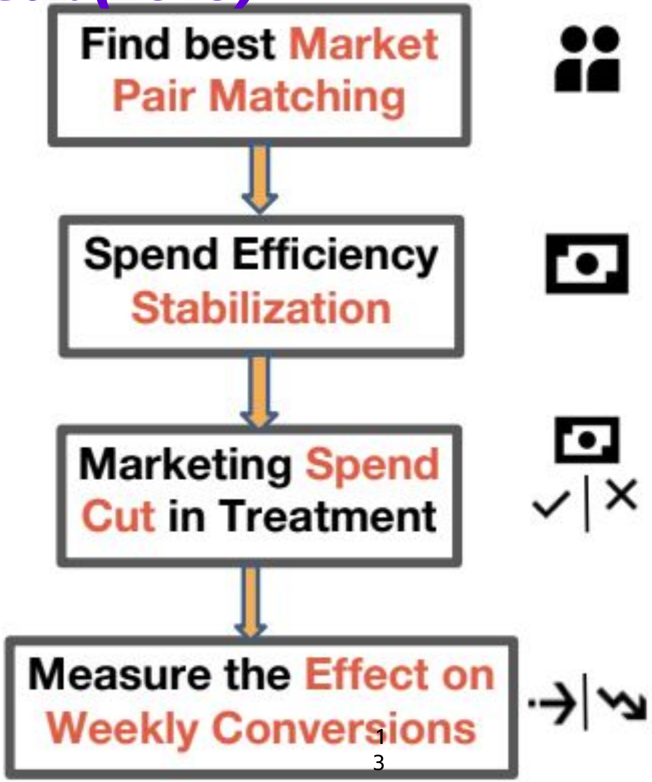
Geo-Testing

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)



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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

Time Series trend

Control Market Predictor

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

Market Best Match: A/A tests

Barajas et al. (2020)

Best Pair selection given the conversion and estimation method

A/A test estimation: Given Causal Estimation Framework

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

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

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 ∈ Ω do
    for all control market: n ∈ {Ω − m} do
        for all intervention time: d ∈ Φ do
            Fit the synthetic control model of Eq 1:
            Find Θ^s, s = 1, ..., N_s, given {y^(m)_{d−Δ_t:d−1}, x^(n)_{d−Δ_t:d−1}}
            Predict ŷ^{s(m)}_{t_i}, ∀s ∈ {s = 1, ..., N_s} after intervention,
            ∀t_i ∈ {d, ..., d + Δ_{t_i}}
            Estimate Credible Intervals (CI) lift_{cum(d+Δ_{t_i})}, Eq 3
        end for
    end for
    n*, d* ← tightest CI that include lift_{cum(d+Δ_{t_i})} = 0
    Append best control/treatment/time V = {V, (m, n*, d*)}
end for
return V
```

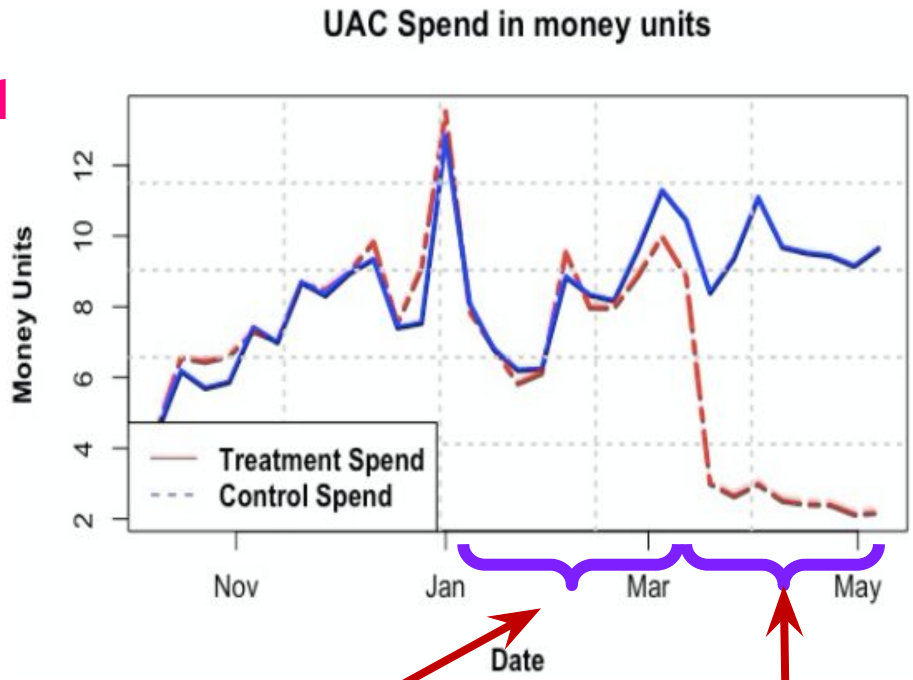
UAC Incrementality: Intervention

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



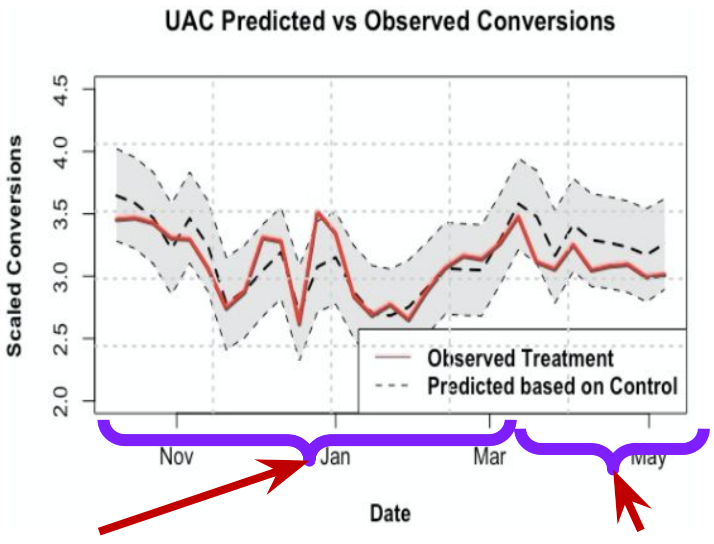
Stabilization, same CPA in both markets 01/15 - 03/12

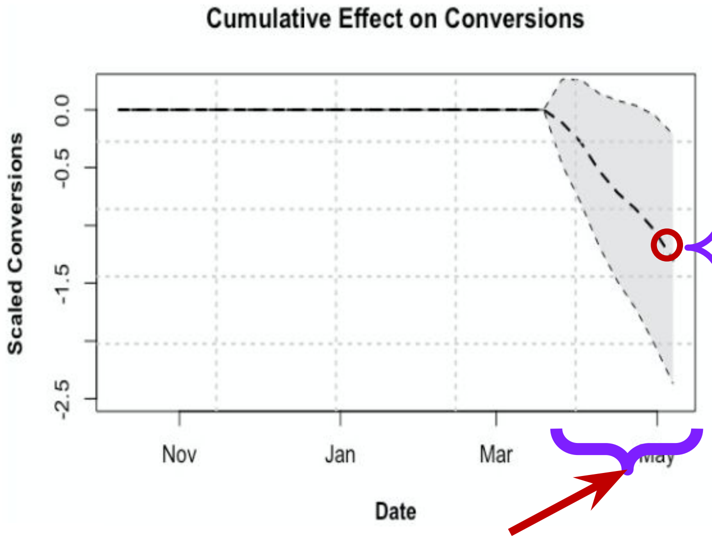
Actual Intervention: Treatment Spend cut 03/19 - 05/13

UAC Incrementality: Effect on Weekly Conversions

Barajas et al. (2020)

Consistently lower predictive (synthetic control) treatment conversions than observed





Conversion Lift:
-6.57%

Spend Lift:
-72.33%

Cost per Incremental Scaled conversion:
39.30 money units

Training period:
09/09 - 03/12

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

Cumulative effect and 95% credible intervals

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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