Attribution externalities in advertising markets

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Doctoriales i^3 May, 27^{th} 2020
Research questions

- Thesis on empirical analysis of targeted advertising in CIFRE with Ekimetrics.
- Access to a lot of advertiser’s sales and advertising data.
- Implement microeconomic analysis in Ekimetric’s activity

Today’s research question:
- Is online advertising overpriced?
- How does offline advertising impacts online ads effectiveness?
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Online advertising Industrial trend

Digital now represents the majority of media ad spending.

Figure: Digital ad spending 2019 (eMarketer)

What drives this trend? Tracking of ad effectiveness, low targeting cost, price discrimination (Goldfarb, 2014).
### Table: Differences between online and offline ad markets

<table>
<thead>
<tr>
<th>Differences</th>
<th>Economic</th>
<th>Technological</th>
<th>Media</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Industrial Organization</td>
<td>Targeting capabilities</td>
<td>Format</td>
</tr>
<tr>
<td></td>
<td>Market power</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>Players</td>
<td></td>
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<tr>
<td></td>
<td><strong>Pricing:</strong> GRP vs ROI</td>
<td></td>
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<td></td>
<td></td>
<td>Effectiveness tracking</td>
<td></td>
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</tbody>
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Offline advertising IO

**Figure:** Offline advertisement (e.g. TV, radio, print, outdoor advertising) industrial organization.
Online advertising IO

Figure: IO based on Estrada-Jiménez et al. (2019). Several platforms provide spaces, targeting, pricing or management services to both sides.
Focus on pricing

Offline ads are priced at **audience**.

- Advertisers pays for a GRP (Gross Rating Point).
- Measure guaranteed by trustworthy third-party (Médiamétrie).
- **Pricing**: rate grids established by media and negotiated with each advertiser.

Online ads prices are based on an expected **return** (clicks in CPC, acquisition in CPA)

- Those insights are calculated by ad sellers themselves.
- **Pricing**: Advertisers compete on a Vickrey auction where each bids a fee per views, click or purchase.
Adstock (Broadbent, 1979): share $\lambda$ of ad expenditures $I_t$ still efficient after the diffusion period:

$$A_t = I_t + \sum_{n=1}^{t-1} \lambda^n I_{t-n}.$$ 

- **Halo** effect: advertising for a good may rise consumer’s utility for similar goods or brands.

Adstock & halo effects are **externalities**: neither advertisers or consumers pay for it.

The magnitude of advertising externalities depends on the **diffusion** of ad complement.
Advertising as a complementary good

(Becker and Murphy, 1993)

Advertising is *complementary* to the advertised product. Consumer values advertising according to its preferences.

- Advertising conveys *information* (Stigler, 1961; Nelson, 1974).
- But also *narratives*: subjective content.

<table>
<thead>
<tr>
<th></th>
<th>Information</th>
<th>Narratives</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Content</strong></td>
<td>Objective</td>
<td>Subjective</td>
</tr>
<tr>
<td><strong>Utility distribution</strong></td>
<td>Uniform</td>
<td>Heterogeneous</td>
</tr>
<tr>
<td><strong>Differentiation</strong></td>
<td>Vertical</td>
<td>Horizontal</td>
</tr>
<tr>
<td><strong>Social utility</strong></td>
<td>Often none</td>
<td>Bandwagon effect*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Addiction</td>
</tr>
</tbody>
</table>

*Table: Economic characteristics of information and narratives.

* Bandwagon effect refers to Leibenstein (1950).
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Ad market players behavior

ROI: indicator of online advertising efficiency.

- Click and conversions are provided by (dominant) ad-sellers\(^1\).
- Cost of doing complementary analysis.
- Credence good? More like oligopoly market with high opportunity cost.

Attribution models determines:

- Advertiser’s media futur media investment. (Berman, 2018).
- Consumer’s welfare (Tucker, 2013).
- Competition, demand and price for online spaces (Li et al., 2016).

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\(^1\)Via consumer tracking technologies
What is **Misattribution**? 

1. Online ROI includes offline advertising positive externalities (adstock and halo).
   - *What brings consumers to search for a product/a brand on Google or Amazon?*

2. Online ROI captures competitor’s notoriety investment.
   - *A firm can buy its competitors keywords or audience on Google or Facebook: Interflora vs Florajet.*
   - Absence of Google’s competitors: Interflora can’t compete with Florajet elsewhere.
Misattribution problem

Measurement stake: quantifying the amplitude of misattribution externality via a causal relationship:

**Figure:** Hypothetical interaction between offline advertisement, online advertisement and sales.
Economic implications

Once the magnitude of misattribution externality have been quantified, correlating it to others indicators can help to understand market implications:

Table: Measuring market implication of misattribution

<table>
<thead>
<tr>
<th>Implication for:</th>
<th>Correlating misattribution to</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consumers</td>
<td>Retail prices</td>
</tr>
<tr>
<td>Advertisers</td>
<td>Audience price</td>
</tr>
<tr>
<td>Offline media</td>
<td>Advertiser’s offline investment</td>
</tr>
<tr>
<td>Online media</td>
<td>Slot prices</td>
</tr>
</tbody>
</table>
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### Data summary

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Min</th>
<th>Median</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sales $Y_t$</td>
<td>256</td>
<td>28 869</td>
<td>12 032</td>
<td>9 625</td>
<td>28 185.5</td>
<td>93 060</td>
</tr>
<tr>
<td>Price $P_t$</td>
<td>256</td>
<td>42</td>
<td>8</td>
<td>26</td>
<td>42</td>
<td>120</td>
</tr>
<tr>
<td>Number of stores $S_t$</td>
<td>256</td>
<td>53</td>
<td>11</td>
<td>54</td>
<td>63</td>
<td>73</td>
</tr>
<tr>
<td>Offline ad investment</td>
<td>256</td>
<td>71 868</td>
<td>114 606</td>
<td>0</td>
<td>13 042</td>
<td>563 746</td>
</tr>
<tr>
<td>Online ad investment</td>
<td>256</td>
<td>33 406</td>
<td>44 893</td>
<td>0</td>
<td>19 550.5</td>
<td>349 099</td>
</tr>
</tbody>
</table>

**Table:** Sales and advertising data from an **iconic** jean brand. Data available on a weekly basis from 2015 to 2019. Sales and prices are available per product (e.g. Jeans, T-shirts). Offline and online investment are also available by media (e.g. TV, Radio, Facebook, Display). However, for this preliminary analysis, we used aggregated sales, price and advertising data.
Importance of adstock

Table: Ad-sales relationship before and after taking in account a negative exponential lagged adstock ($v = 0.1$ and $\lambda$ depends on each media):

\[
A^{Off}_t = 1 - e^{-vI_{t-2}} + \lambda A_{t-3}
\]

\[
A^{On}_t = 1 - e^{-vI_{t-1}} + \lambda A_{t-2}
\]
A basic sales-ad regression

Computing a simple sales-advertising regression:

\[ Y_t = \alpha + \beta_1 \log(P_t) + \beta_2 S_t + \beta_3 A_{t}^{off} + \beta_4 A_{t}^{on} + \beta_5 (A_{t}^{on})^2 + \theta M + \gamma Y + \varepsilon_t \]

- \( M \) and \( Y \) are vectors for month and year dummies.
- \( \beta_1 \) is price elasticity.
- \( \beta_3 \) and \( \beta_4 \) are offline and online advertising marginal effectiveness.
- With a quadratic term, marginal online ad effectiveness is measured by \( \beta_4 + 2\beta_5 \).
## Basic results

<table>
<thead>
<tr>
<th></th>
<th>Sales</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \log(P_t) )</td>
<td>(-27,895.3^{**} )</td>
</tr>
<tr>
<td></td>
<td>(3,681.785)</td>
</tr>
<tr>
<td>( S_t )</td>
<td>(797.9^{**} )</td>
</tr>
<tr>
<td></td>
<td>(286.426)</td>
</tr>
<tr>
<td>( A_{t}^{off} )</td>
<td>(461.1^{**} )</td>
</tr>
<tr>
<td></td>
<td>(209.225)</td>
</tr>
<tr>
<td>( A_{t}^{on} )</td>
<td>(1,452.1^{**} )</td>
</tr>
<tr>
<td></td>
<td>(582.317)</td>
</tr>
<tr>
<td>( (A_{t}^{on})^2 )</td>
<td>(-140.3^{**} )</td>
</tr>
<tr>
<td></td>
<td>(56.700)</td>
</tr>
<tr>
<td>( \alpha )</td>
<td>(80,566.2^{***} )</td>
</tr>
<tr>
<td></td>
<td>(17,067.600)</td>
</tr>
</tbody>
</table>

| Observations         | 256            |
| Adjusted R\(^2\)    | 0.77           |

- Positive and significant adstock coefficients.
- Diminishing marginal effect of online advertisement: \((A_{t}^{on})^2 < 0\).
- Saturation threshold reached at:

\[
A_{t}^{on} = \left| \frac{\hat{\beta_4}}{2\hat{\beta_5}} \right|
\]
We are interested in quantifying the effect of offline media on online advertising effectiveness.

- Proxy for effectiveness: local online advertising elasticity:

$$\eta_t = \frac{\Delta Y_t / Y_{t-1}}{\Delta A_{on}^t / A_{on}^{t-1}}.$$ 

- How offline adstock affects the positive part of $\eta$?

$$\eta^+_t = \alpha + \beta_1 A_{off}^t + \beta_2 P_t + \theta M + \gamma Y + \varepsilon_t.$$
Positive relationship between offline adstock and online ad elasticity of demand!

However: low $R^2$ and significance threshold.

May be due to the aggregated level of the analysis.
Discussion

Findings

- Adstock modeling is decisive in advertising’s empirical analysis. Must be based on microeconomic assumptions.
- Adstock allows to calculate saturation effects in online advertising.
- For an iconic brand: offline adstock seems to influence online ad effectiveness.

Limitations

- Limited *causal* analysis and dataset.
To be done, next:

- Incorporating causal modeling: e.g. Path modeling, IV, Backdoor adjustment, Bayesian networks.
- Using more complete datasets to compute: Offline adstock $\rightarrow$ Clicks (or conversion).
- Implementing competitor’s investment in modeling.
- Robustness check: $\varepsilon$’s heteroskedasticity and autocorrelation.
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