Cross-media externalities in advertising markets

Rémi Devaux
CERNA – MINES ParisTech (PSL Université)

Discussant: Daniel Herrera
Journée des Doctorants en Économie, Université Paris-Dauphine.
February, 2\textsuperscript{nd} 2021
A bit of context

- Digital now represents the majority of media ad spending...
- ...At the expense of traditional media advertisement

Figure: Digital ad spending 2020 (eMarketer)

Research question: externalities between advertising ecosystems.
Table of Contents

1. Theoretical framework: advertising ecosystem

2. Empirical strategy

3. Results and discussion

4. References
Table of Contents

1. Theoretical framework: advertising ecosystem

2. Empirical strategy

3. Results and discussion

4. References
Advertising: setting the stage

- Advertising as a commodity
  - Complementary to the advertised good \((Becker \text{ and } Murphy, 1993)\).
  - Whose effect are inter-temporal \((Joy, 2006)\).

- Two distribution channels for advertising
  - Offline media: audience-oriented media (GRP) \((Evans, 2009; Goldfarb, 2014)\).
  - Online media: targeting + action-oriented media (e.g. pay-per-clicks) \((Goldfarb, 2014; Hu \text{ et al., 2016})\).

- Economic relationship between both media?
  - Perfect substituability \((Goldfarb \text{ and } Tucker, 2011b, a; Bergemann and Bonatti, 2011)\).
  - VS Media synergies \((Naik \text{ and Peters, 2009}; Lewis \text{ and Reiley, 2013}; Kireyev \text{ et al., 2016})\).
Research intuition and results

Different **pricing models** for the same good.

- Pricing on an **hypothetical audience vs effectiveness**
- Unknown **vs** observable consumer’s utility.

Research questions

- Does consumers’ utility for traditional ads impact their behavior toward online ads?
  - E.g. Does TV, Radio or print GRPs generates Google clicks?
- Economic implications?

Results

- Offline expenditures impact online clicks (e.g. +1% Print ad stock → +1.1% Google clicks);
Table of Contents

1. Theoretical framework: advertising ecosystem

2. Empirical strategy

3. Results and discussion

4. References
We seek to estimate the impact of offline advertisement on online effectiveness

Firm-level data: 3 advertisers in 2 industries (hotel and perfume).

- Outcome variables: #clicks received on Google and Facebook ads.
- Exogenous features: advertising spending (in €) on multiple media: e.g. TV, radio, print, display
- Controls: monthly dummies, market prices, #impressions on Google and Facebook ads, competition.
Descriptive statistics I

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Mean</th>
<th>St. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>#Google Clicks</td>
<td>15 885</td>
<td>6 493</td>
</tr>
<tr>
<td>#Google impressions</td>
<td>75 171</td>
<td>35 454</td>
</tr>
<tr>
<td>#Facebook Clicks</td>
<td>661</td>
<td>1 354</td>
</tr>
<tr>
<td>#Facebook impressions</td>
<td>231 618</td>
<td>470 656</td>
</tr>
<tr>
<td>Price (EUR)</td>
<td>112</td>
<td>7</td>
</tr>
<tr>
<td>Social (EUR)</td>
<td>550</td>
<td>977</td>
</tr>
<tr>
<td>Display (EUR)</td>
<td>4 070</td>
<td>5 876</td>
</tr>
<tr>
<td>OOH (EUR)</td>
<td>1 265</td>
<td>5 671</td>
</tr>
<tr>
<td>Multi-brand offline (EUR)</td>
<td>18 384</td>
<td>82 076</td>
</tr>
<tr>
<td>Multi-brand Online (EUR)</td>
<td>2 372</td>
<td>21 657</td>
</tr>
<tr>
<td>Competitors (EUR)</td>
<td>475 099</td>
<td>501 766</td>
</tr>
<tr>
<td>TV (EUR)</td>
<td>3 271</td>
<td>23 258</td>
</tr>
<tr>
<td>Print (EUR)</td>
<td>258</td>
<td>2 595</td>
</tr>
</tbody>
</table>

\[n\] 190  
Period covered 01/2016 to 07/2019

Table: Summary statistics for brand A, (EUR) indicates a monetary investment whereas # indicates a count.
Descriptive statistics II

Figure: Brand A’s clicks on Google and Facebook ads through time
Figure: Brand A’s media investment through time
Key features

Why clicks?

- Measure online ad’s utility and price.
- Google-Facebook: an online ad duopoly (≈ 76% of online ad revenues in France).

Adstock $A_{m,t}$. For each media $m$, we compute the following discounted advertising disconted stock:

$$A_{m,t} = I_{m,t} + \sum_{\ell=1}^{t-1} \delta_m I_{m,t-\ell}$$

- $I_{m,t}$ is advertising expenditures, $\delta_m$ a carry-over rate.
- Take in account inter-temporal advertising effects
Estimation strategy

How the adstock on a given media affect affects online ad effectiveness?

- Regression of $i \in \{Google, Facebook\}$’s clicks on adstocks and time+control features:

$$\ln(\text{Clicks}_{it}) = \alpha_i + \beta \ln(I_t) + \sum_m \gamma_{im} \ln(A_{mt-1}) + \Phi D_t + \theta X_t + \epsilon_{it}$$ (2)

- Coef. of interest: $\gamma_{im}$, i.e. click elasticity of $i$ to past advertising stock $m$.

- $\beta$ accounts for immediate effects, $\Phi$ controls for time and $\theta$ for retail prices and $i$’s impressions.
1. Theoretical framework: advertising ecosystem

2. Empirical strategy

3. Results and discussion

4. References
Results: some coef. \( \gamma \) for brand \( A \)

<table>
<thead>
<tr>
<th>Media</th>
<th>Google clicks</th>
<th>Facebook clicks</th>
</tr>
</thead>
<tbody>
<tr>
<td>TV</td>
<td>0.006*</td>
<td>-0.03</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>Print</td>
<td>0.011**</td>
<td>0.052</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.062)</td>
</tr>
<tr>
<td>Display</td>
<td>0.012**</td>
<td>0.111***</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.038)</td>
</tr>
<tr>
<td>Google</td>
<td>0.134***</td>
<td>-0.175***</td>
</tr>
<tr>
<td></td>
<td>(0.030)</td>
<td>0.062</td>
</tr>
<tr>
<td>Facebook</td>
<td>0.005</td>
<td>0.116**</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.053)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Pseudo ( R^2 )</th>
<th>.95</th>
<th>.35</th>
</tr>
</thead>
<tbody>
<tr>
<td>( n )</td>
<td>190</td>
<td></td>
</tr>
</tbody>
</table>

**Table:** Regression coefficients. Google: Poisson. Facebook: Negative-binomial.
Implications of externalities among ad media

Managerial implications

- **Advertisers** Positive cross-media effects may result in higher costs online: $+TV \rightarrow +\text{Clicks} \rightarrow +\text{CPC}$
- **Media** are not compensated for the effects they generated on Google & Facebook.

Regulation

- Offline and online may be as much complementary as they are substitutes: two different relevant markets?
- Change in the nature of advertisement.
- Market power of dominant ad sellers on firms’ adstock: essential facility?
Robustness checks

- Lagged adstock \((t - 1)\) to counter endogeneity between online consumer’s response and advertising investment.
- ML estimation with robust standard errors to correct autocorrelation.
- Robustness checks on \(A_{mt-1}\) and \(\delta_m\)
  - Control regression with \(A_{mt-3}\): similar results
  - Control regression with a carry-over rate \(\delta'_m = 1 - \delta_m\). No loss in overall significance.
Conclusion

Contribution

- Empirically assess the externalities of offline media on online ads’ effectiveness.
- Challenge the definition and regulation of advertising markets.

Limitations

- Low number of observations.
- Correlation-based study.
- Sparse (skewed?) Facebook data.
Table of Contents

1. Theoretical framework: advertising ecosystem

2. Empirical strategy

3. Results and discussion

4. References
References I


References II


Correlation matrix: Brand A

Figure: Correlation between modeling features
Results: some coef. $\gamma$ for brand $B$

<table>
<thead>
<tr>
<th>Media</th>
<th>Google clicks</th>
<th>Facebook clicks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Outdoor</td>
<td>0.008*</td>
<td>$-0.151^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.046)</td>
</tr>
<tr>
<td>Radio</td>
<td>0.019**</td>
<td>$-0.054$</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.072)</td>
</tr>
<tr>
<td>Google</td>
<td>0.046***</td>
<td>$-0.025$</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.079)</td>
</tr>
<tr>
<td>Facebook</td>
<td>0.014***</td>
<td>0.136**</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.058)</td>
</tr>
</tbody>
</table>

Pseudo $R^2$  .94  .55
$n$              190

**Table:** Regression coefficients. Google: Poisson. Facebook: Negative-binomial.
Results: some coef. $\gamma$ for brand $C$

<table>
<thead>
<tr>
<th>Media</th>
<th>Google clicks</th>
<th>Google Shopping clicks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Outdoor</td>
<td>$-0.011^*$</td>
<td>$-0.05$</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Print</td>
<td>$0.017^*$</td>
<td>$-0.012^{**}$</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Google</td>
<td>$0.165^{***}$</td>
<td>$0.042$</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.079)</td>
</tr>
<tr>
<td>eMail</td>
<td>$0.055^*$</td>
<td>$-0.036$</td>
</tr>
<tr>
<td></td>
<td>(0.031)</td>
<td>(0.029)</td>
</tr>
</tbody>
</table>

Pseudo $R^2$ | .89 | .92  

$n$ | 118  

**Table:** Regression coefficients. Google: Poisson. Facebook: Negative-binomial.