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Externalities across advertising markets

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ABSTRACT

This paper analyzes externalities generated by offline advertising campaigns on the performance of online ads. Using advertising data on a panel of firms in the hotel industry, we estimate how a firm's offline, display, and competing ad campaigns impact the effectiveness of Google and Facebook advertising. We find a positive effect of traditional mass-media campaigns on Google clicks. Advertising from competitors does not affect Google ad performance but it increases advertising prices, suggesting keyword poaching. Further analyses hint that Google's monopoly power and auction system allow free-riding on advertising externalities. Although we find similar positive effects on Facebook ads, they are not significant.

Introduction

Online advertising now accounts for the majority of media spending: with a growth rate of 29% in 2021, it amounted to 63% of total advertising expenditure (eMarketer, 2021). A number of economic studies have argued that online advertisements generate efficiency by dramatically decreasing the costs of targeting consumers and measuring ad effects (Goldfarb, 2014). However, these arguments may fail to consider externalities between advertising media. For example, offline advertising may directly affect the effectiveness of online ads.

Such externalities are important. On the one hand, online advertising slots are often priced based on effectiveness metrics such as clicks or purchases. Yet, these outcomes may be partly generated by offline media campaigns that raise awareness for the product. Thus, given that offline ads impact online advertising effectiveness, who benefits from this externality? On the other hand, the existence of significant externalities between both media may suggest that offline and online advertising are two distinct, complementary, markets. The definition of a relevant advertising market is still in debate in the literature and underlies regulations such as offline media mergers (VideoWeek, 2022).

Our analysis treats the effect of advertising from an industrial organization perspective. We argue that advertising generates externalities on consumers and competing firms. While traditional campaigns are priced based on their audience and yield unobserved returns, online ads are often priced according to directly observable effectiveness metrics (e.g., clicks). Given the existence of such externalities between offline and online advertising, we cannot expect their direction (positive, negative) and magnitude to be uniform across industries. Indeed, such effects depend on firms' propensity to advertise online as well as consumers' online searches and purchase behavior in a given market.

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This study proposes to test the existence of externalities across advertising media in a given industrial context, i.e., the market for hotels. We leverage firm-level data from five advertisers belonging to an international hotel group to study how a brand's offline and online display and competing ad campaigns impact Google and Facebook advertising outcomes. Using a fixed-effect regression with instrumental variables, we find offline investments have a positive impact on the effectiveness of Google search ads. For example, increasing the stock of offline advertising by 10% ($\approx$ €7200) increases clicks on Google ads by 0.5% ($\approx$ 135 clicks). Surprisingly, we find a negative effect of display ads on Google clicks, suggesting that both media compete for users' attention. Similar results are found for Facebook ads but they remain statistically insignificant.

The presence of offline-to-online effects opens the path to a more important question, i.e. who benefits from such externalities? Further analyses show that by increasing the volume of searches and the propensity to click, offline advertising increases the overall Google price paid by the advertiser. In the long run, the increase in Google advertising performance (clicks) negatively affects the offline share of advertising budget. Although they do not impact Google clicks, ads by competitors increase the Google cost for the focal brand, suggesting that firms compete in auctions to buy their competitors' branded keywords (Desai et al., 2014; Sayedi et al., 2014; Simonov et al., 2018). In other words, a firm can buy a well-known competitor's Google keyword in order to free-ride its notoriety. For example, a London-based hotel chain could buy the keyword "Airbnb London" to appear in the latter's search results. We refer to this strategy as *brand poaching*.

The literature on offline-online advertising effects is abundant and our contribution is both conceptual and empirical. First, the study demonstrates the existence of offline-to-online externalities affecting not only advertising performances, but also ad prices, and the media budget share. Second, to the best of our knowledge, we are the first to document the joint effect of offline ads on both Google and Facebook – the two biggest online advertising networks. Third, we study the simultaneous externalities generated by offline, online and competing ads by using a novel instrumental variable which exploits advertising on foreign markets.

Our results have several implications. (i) First, they suggest that online advertising's return on investments (ROI) may be biased in the presence of externalities between offline and online ads. Given the positive effect of traditional media campaigns on search advertising outcomes, the effectiveness of the latter is likely to be over-estimated. (ii) Second, as an online search monopoly, Google seems able to free-ride on such externalities. Indeed, the increase in queries and clicks generated by offline ads translates into additional revenues for Google since search ads are priced based on the quantity of consumer queries (cost-per-1,000 impressions model) or clicks (cost-per-click model). Thus when firms advertise offline, they affect Google advertising outcomes and pay additional search advertising costs. (iii) Third, brand poaching creates a prisoner dilemma for brands that increase their Google advertising costs. We argue that this strategy should be regulated. (iv) Finally, this study could suggest that offline and online advertising are complements rather than substitutes. While offline campaigns provide information and narratives to a mass of consumers, online ads guide consumers toward the purchase.

Although we only identify offline-to-online externalities in the hotel industry, our results are consistent with similar studies in other sectors. In particular, we believe that such externalities exist in all industries in which firms heavily advertise offline to consumers searching and/or buying online (e.g., apparel, electronics, events). However, the magnitude and direction of the effects may be different across industrial contexts.

The present paper is organized as follows. In Section 2, we review the past literature on advertising externalities, cross-media effects and their impact on the advertising industry. Section 3 sums up the research question and introduces the data used. Section 4 presents some descriptive evidence followed by the econometric methodology used to identify the presence of cross-media externalities. The results and mechanisms are discussed in detail in Section 5, while Section 6 addresses the implications for the advertising market.

Related works

Advertising externalities

Advertising is an important vector of externalities. Becker and Murphy (1993) model advertisement as a complementary good of the advertised product. Advertising increases or decreases the utility for the product depending on consumers' taste for the ad. The advertising effect is then internalized in the retail price of the good when consumers buy the product following an ad exposure. However, consumers often buy a product regardless of its advertisement. Conversely all individuals exposed to an ad do not purchase the good. In such cases, advertising effects do not result in transactions and are thus externalities. The literature reports many illustrations of advertising external effects for both firms and consumers.

For example, theoretical models investigate how advertising externally affects other firms on a competitive market vying for consumers' attention. Theoretical studies model how an advertiser's message represents a nuisance for other advertisers by potentially increasing consumers' incentive to filter messages (adblocking, zapping; Johnson, 2013; Wilbur et al., 2013). Online, the degree to which search ads impose externalities on each other by diverting consumers' attention from other slots has been found to be theoretically and empirically important (Ghosh & Mahdian, 2008; Jeziorski & Segal, 2015; Simonov et al., 2018).

Externalities on the consumer side have also been empirically documented. For example, television advertising campaigns may induce consumers to propagate word-of-mouth, which in turn increases consumer s' awareness and consideration for the product (Fossen & Schweidel, 2017). R. Lewis and Nguyen (2015) found that displaying an advertising banner on Yahoo!'s homepage increased search queries for the brand advertised and its competitors in the insurance and tablet markets. It also increased the number of clicks on complementary services such as online distributor or review sites.

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Cross-media effects

While advertising acts as a complementary commodity to the advertised product and produces externalities, it can be distributed offline as well as online. The relevant market definition of advertising is still in debate in the literature. While both offline and online advertising ensure the common economic function of providing infor- mation and narratives about products, they employ different targeting, pricing and measurement technologies (Evans, 2009; Goldfarb, 2014). On the one hand, a body of early research relied on theoretical (Bergemann & Bonatti, 2011) and experimental (Goldfarb & Tucker, 2011b,a) designs to demonstrate that offline and online ads were substitutes. On the other hand, many advertiser-level studies have tended to demonstrate the existence of cross-media effects in generating demand.

Naik and Peters (2009) provide a comprehensive review of cross-media effects. Furthermore, they show that, in the case of a car manufacturer, offline and online ads generated higher returns when they were released simultaneously.

Other studies have focused on the effect of television advertising on online search outcomes. By measuring consumers' interest for a product, online search is an interesting field for research on cross-media effects. Descriptive research based on Google queries found that television advertisements aired during notorious sports events generated immediate search picks for the brands and products advertised (R. A. Lewis & Reiley, 2013; Zigmond & Stipp, 2010). Going further in this Joo et al.

(2014), (2016)) empirically demonstrated that television advertising for financial services resulted in immediate queries for the brands advertised, while decreasing generic queries. Adding sales to the equation, other studies have quantified a positive effect of television advertisements on online searches, traffic and purchases, with strong heterogeneous effects depending on the advertising content (Guitart & Stremersch, 2021; Liaukonyte et al., 2015). More aggregated analysis has found that offline media generated online sales by increasing search ad impressions (i.e. more queries) and online purchases for a high-end clothing retailer (Dinner et al., 2014).

Fewer studies have investigated the effect of television advertising on the effectiveness of social media ads. Whereas TV advertising increases the effectiveness of unpaid social media posts, it does not foster the performance of paid ads (A. Kumar et al., 2016; V. Kumar et al., 2017).

All of these empirical studies suggest that online media outcomes are affected by offline advertising externalities.

Profit for advertisers and publishers

Cross-media externalities yield implications for both advertisers and publishers. On the advertiser-side, they impact advertising strategies. Media may produce external effects that ultimately benefit other media. This assumption has key implications for advertising media competition. Indeed, advertisers may end up allocating most of their budget to media that free-rides other media's external effects. This problem is exacerbated online, where advertisers are charged for each consumer's response to their ad (e.g., cost-per-click (CPC) or cost-per-acquisition (CPA) pricing).

A wide range of literature on attribution models advertisers' media investments as a function of their previous ad effectiveness measures. For example, Jordan et al. (2011) show that when an advertiser buys impressions from multiple publishers and does not consider externalities between ads, it ends up allocating most of its budget to publishers closer to the demand.[1] Similarly, Berman (2018) finds that when externalities exist between publishers, an advertiser's chosen attribution model constitutes a strategic choice that directly impacts both its own profit and that of the publishers. An empirical descriptive analysis has also proved that attribution modeling has an impact on advertising prices and in fine on consumer welfare (C. Tucker, 2013).

These attribution studies however only consider externalities between online ads. Moreover, they do not study the case of asymmetric pricing among ads generating externalities. For example, let us consider the case of an advertiser purchasing a television campaign priced on its expected audience and a search slot priced on a cost-per-click (CPC) basis. By generating search clicks, the television advertisement would simultaneously increase the effectiveness and the cost of the search engine advertisement and revenues. Meanwhile, by increasing advertisers' notoriety, television encourages competitors to poach the keywords used by the brands advertised (Sayedi et al., 2014). Eventually, the advertiser could end up either losing its search paid slot or keeping it for a higher advertising cost. In both cases, the search engine benefits from the higher competition in the auction. In this paper, we consider cross-media effects in a context where the media (offline and online) pricing model is asymmetric in two dimensions. Both the commodity sold (audience vs performance) and the allocation design (over-the-counter contract vs auctions) differ here.

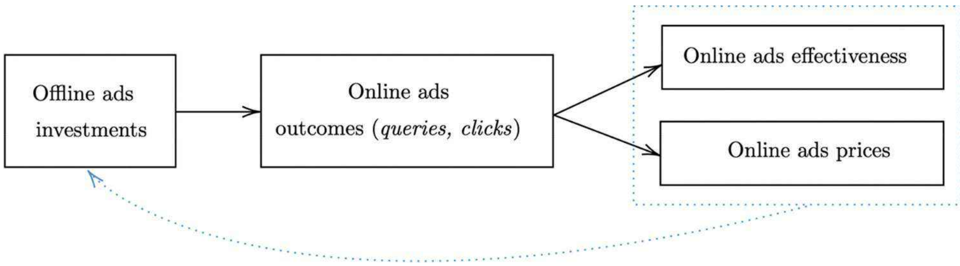
Research hypotheses & data

Conceptual framework

This paper fits in with the literature on cross-media effects by studying how advertisements on a given media impact the effectiveness of other media (see Table 1for a review). These effects are considered as externalities. Indeed, referring to cross- media effects as "synergies" supposes that the benefit is shared

[1]This phenomenon is known as last-touch attribution.

between the entities which generate the effect. As highlighted in the literature, a brand's television advertisement is likely to affect search queries and sponsored link clicks, increasing the search engine's revenues. However, this positive effect is not shared between the television ad network and the search engine. Similarly, when a brand's display ad fosters search queries for its competitors (R. Lewis & Nguyen, 2015), the effect is not internalized by any contract.



cross-media externalities, i.e. clicks. Indeed, the media synergy literature suggests that both online and offline media only generate externalities in favor of the advertisers. In doing so, it ignores the fact that while offline media are remunerated on an audience model (e.g., GRP), online media revenues directly depend on their outcomes (e.g., clicks). Hence, the effect of cross-media externalities on online advertising prices is rarely considered. In the next section, we present the data used to assess these effects.

Data sources

We use advertising data from three brand members in a global hotel group. Each of the three brands carries specific brand elements and their membership of the group is not signaled in their name or their logo. They differ in both price and quality: we distinguish between low-cost, mid-range^{-} and mid-range^{+} brands. The distinction between mid-range chains depends on the location and room prices. The mid-range^{+} brand offers more expensive rooms in locations closer to places of interest (e.g., downtown, airports).

The brands operate in two countries: the United Kingdom and Germany. However, the mid-rangee^{-} brand has a very low advertising activity in Germany[2] and is thus excluded from the analysis. We end up with 5 firms: 2 brands in both countries and 1 brand in the UK only. All variables are reported on a weekly basis from 18 January 2016 to 2 September 2019. Thus, the dataset is organized along three dimensions: brand (b) × country (c) × time (t) for a total of 950 observations.

The hotel industry is particularly suited to the study of offline-to-online effects. Indeed, while large hotel chains significantly advertise offline, consumers mainly search and book rooms online. Approximately two-thirds of travel industry revenues are generated online (Statista, 2021a). Thus, advertising campaigns simultaneously take place on several media, and offline ads are very likely to generate externalities online. These characteristics of the hotel industry makes it easier to measure meaningful effects.

Media Spending The dataset provides ad expenditure in euro for several media – both offline (TV, radio, cinema, press, outdoor) and online (display and video advertisements). Google search and Facebook ad budgets are excluded from online investments. The aggregated media mix is generally balanced between offline and online media campaigns in the amount invested. However, both media exhibit different investment patterns: while offline campaigns often take place in specific periods, online campaigns are conducted throughout the year. Thus, the fact that offline investments are often null leads to a lower share of advertising budget in firms' media-mix.

[2]In addition to a low level of spending, the firm does not advertise offline in Germany at all. This reduced advertising activity is due to a low number of hotels supplied by the chain abroad.

Google and Facebook Data Using data collected from Google and Facebook's respective advertising tool, we retrieve the number of clicks and impressions recorded by consumers living in the firm's country. We will exploit this specificity further in the identification strategy. While Google data are available for all brands in both countries for most of the period (N = 890), Facebook data are only reported for the two German hotel brands (N = 269).

Competitors data Competitors' weekly spending by country and media are retrieved from a Nielsen database for each brand in each country.

Descriptive evidences

The main summary statistics are reported by brand in Table A2 and by country in Table A3. As we can see, demand and advertising variables exhibit strong standard deviations, suggesting significant seasonal effects. As depicted in Figures 1, the seasonality of clicks varies slightly across countries, however the trends differ strongly. We also observe significant differences in volatility and trend between Google and Facebook outcomes (Figure 2).[3]

Figure 3 is more directly related to our research question. It displays the evolution of offline spendings and Google+Facebook clicks. A slight correlation between both variables is perceptible: when offline ad investments decrease, the number of clicks takes a downward trend. However, this is not always the case (especially at the end of the period). In addition, the effect of traditional advertising on search and social clicks seems delayed and diffused, suggesting an adstock effect.

It is also worth noting that a number of confounding factors may affect the relationship between offline advertising and online demand behavior. Offline and online investments may be correlated since firms are more than likely to coordinate their advertising strategies simultaneously on several media. Moreover, ad spending and consumer behavior exhibit common seasonality, making it difficult to infer a causal relationship of the former on the latter. This classic endogeneity issue has been widely identified in the advertising literature. In the next subsection, we provide our estimation strategy to identify cross-media externalities.

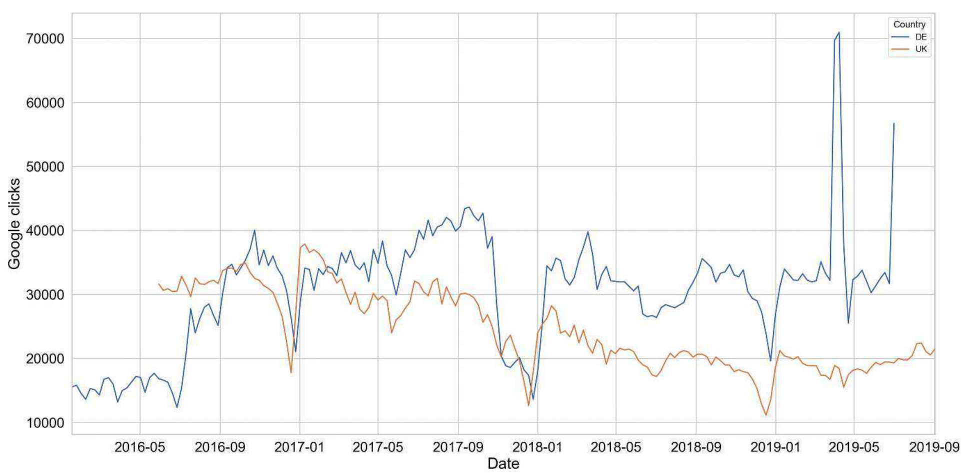


Figure 1. Google clicks variation by country.

[3]A similar plot by brand reveals some heterogenity between low-cost and middle range brands (Figure A1)

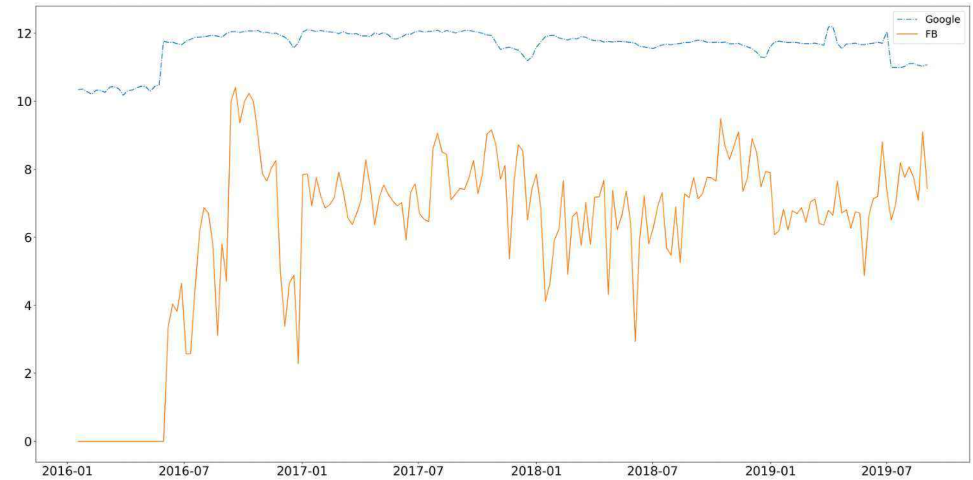


Figure 2. Logs of Google and Facebook clicks trend.

Identification strategy

We seek to estimate whether the effectiveness of Google and Facebook ads is impacted by externalities from other media campaigns, especially offline. We measure online effectiveness by the total number of clicks recorded on an ad Y_{bct}. Here, clicks approximate consumers' utility for the ad. Clicks are more related to sales than impressions and have been used in previous empirical researches to approximate advertising effectiveness (C. E. Tucker, 2014; Jeziorski & Segal, 2015; Shehu et al., 2021). In addition, click are one the main pricing instruments on which advertisers are charged (in CPC contracts). In order to identify the effect of the offline advertising activity on online ad effectiveness, we specify the following log-log fixed effects regression:

$$\log(Y_{bct}) = \alpha + \sum_{m} \beta_m \log(1 + A_{mbct}) + \gamma \mathbf{X}_{bct} + \mu_{bc} + \left[\delta_{z(t)} + \delta_{y(t)}\right] + \varepsilon_{bct} \tag{1}$$

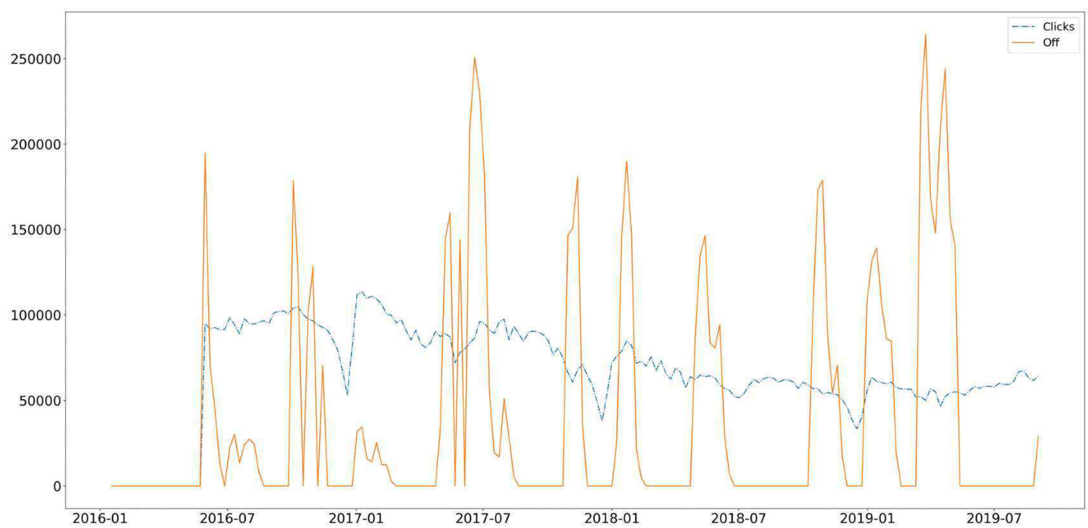


Figure 3. Evolution of Google+Facebook clicks and offline ad investments through time.

Table 1. Relationship with related empirical studies. The "Pricing" column indicates whether the study investigated the impact of media synergies on the online advertising cost. The last column "Mechanism" refers to whether the paper explained the mechanism by which cross-media effects appear: e.g., do offline ads increase search volumes or the propensity to click? Does it increase the volume of online sales or the average purchase value?.

	Media of interest		Effect modeled		Features		
Authors	Search	Social	Offline	Competitors	Adstock	Pricing	Mechanism
Naik and Peters (2009)	No	No	Yes	No	No	No	No
Dinner et al. (2014)	Yes	No	Yes	Yes	Yes	No	No
Liaukonyte et al. (2015)	Yes	No	TV only	No	No	No	No
Joo et al. (2016)	Yes	No	TV only	No	Yes	No	Effect on TV on search, keyword choice and click
A. Kumar et al. (2016)	No	Yes	TV only	No	Yes	No	Effect on TV × social media on con- sumer spending, buying behavior and profit
Kireyev et al. (2016)	Yes	No	No	No	No	Yes	Effect of offline ads on Google click propensity, queries and budget
This study	Yes	Yes	Yes	Yes	Yes	Yes	Effect of offline ads on Google click propensity, queries and budget

Our feature of interest, A_{mbct}, is media m's (offline, online, competitors) advertising stock for brand b in country c on week t. The vector $\mathbf{X}_{bct}$ contains the log of impressions delivered by Google (or Facebook) ads and a country-specific time trend. The latter variable takes into account the specific click trends observed across both countries as depicted earlier in Figure 1. The model also relies on a set of fixed effects to account for unobserved heterogeneity. The brand-country fixed effects μ_{bc} capture time-invariant brand characteristics at the local level (e.g., national market characteristics, brand positioning, specific advertising strategies). Seasonality is captured by month FEs $\delta_{z(t)}$ while general long-term effects are accounted by implementing year FEs $\delta_{y(t)}$. Although relatively straightforward, this model requires additional estimation challenges.

Adstock Parameter First, the adstock function is to be specified. We implement a linear decay stock specification: $A_{mbt} = a_{mbct} + \lambda_m A_{mbc,t-1}$ where the media-specific carryover parameter $\lambda_m \in (0,1)$ is to be set. We follow the literature and estimate carryover rates by conducting a grid search. We run model (1) with different $\lambda_m, m \in$ {offline, online} and choose the pair of rates under which the sum of squared residuals (SSR) is minimized (as in Dinner et al. (2014)). A full description of the method is given in appendix A.3. Parameters returned by the procedure are reported in Appendix 2.

Endogeneity Endogeneity between demand and advertising is a common issue in marketing models (Rutz & Watson, 2019). Indeed, advertising investments are neither random nor independent from clicks: an omitted variable could affect both the decision of firms to advertise and the propensity of consumers to click on hotel ads (e.g., firms anticipating their demand). To attenuate this bias, we use an instrumental variable approach.

In a given country, c we look for an instrument that affects a firm's advertising expenditure without being directly correlated to the endogeneity source or demand. It is tempting to consider using competitors' ad spending as a valid instrument. However, competitors are also very likely to advertise according to the anticipation of their demand. This is a problem since, by definition, competitors target the same demand as the brands we study here (hereafter, *focal* brands). Our idea is to instrument the spending of our focal brands by advertising from competitors in a foreign country c'. Practically, the advertising stock of competing hotel brands in the UK will be used to instrument German hotels' advertising and viceversa. Indeed, advertising investments in the domestic and foreign markets should be correlated: firms in the European hotel industry share common cost and demand characteristics which may underlie common advertising strategies. As they do not target the same demand, we believe that foreign competitors' spending attenuates the endogeneity between advertising and demand in the domestic market. Especially since we only consider clicks by consumers located in the domestic market. The exploitation of marketing variables in foreign regions or close non-competing markets has proven to provide effective instruments (Chintagunta et al., 2006; Nevo, 2001; Van Heerde et al., 2013). We implement the instrument using a 2SLS approach. The first-stage equation and results are detailed in Appendix A.4.

Standard Errors Finally, we estimate the model using heteroskedasticity-robust standard errors clustered at the week-of-the-year level (52 groups). Our intuition behind this choice is twofold. First, our standard errors may be correlated across weeks for each year and brand due to the seasonality of an unobserved component. Second, the treatment (i.e. advertising expenditure) may be correlated with the period of the year: firms allocate their advertising investments for each week of the year. Because the five firms observed here belong to the same hotel group, their advertising strategies may be correlated through time. Especially because they are likely to work with a common advertising agency. In other words, focal brands may share the same media planning strategy.

Table 2. Carryover estimated and reported in the literature.

Paper	Media studied	λOffline	λOnline
Dubé et al. (2005); Shapiro et al. (2021)	TV	.90	–
He et al. (2018)	TV & Online	.69	.70
Dinner et al. (2014)	Offline & Online	.89	.84
This study	**Offline & Online**	**.85**	**.90**

Table 3. Regression results with offline and online adstocks. Robust standard errors clustered by week-of-the-year. Facebook data were only available for UK firms: country-level FEs and trends dropped.

	IV results	
	Google clicks	Facebook clicks
$\log(A_{\text{offline}})$	0.0495***	0.147
	(0.0118)	(0.170)
$\log(A_{\text{online}})$	−0.0321***	−0.492
	(0.00862)	(0.436)
$\log(A_{\text{competitors}})$	0.0008	0.175
	(0.0130)	(0.242)
log(Impressions)	X	X
Month FEs	X	X
Year FEs	X	X
Brand × Country FEs	X	
Brand FEs		X
Time trend	Country-specific	General
Observations	875	269
Adjusted R-squared	.950	.408
F-statistic	4653.9	16.24
KP LM-stats	19.45	23.11
KP Wald F-Stats	14.29	14.63

Note: *p < 0.1; **p < 0.05; ***p < 0.01

Results and discussion

Adstock carryover rates

Parameters λ^*_m estimated from the grid search procedures are reported in Table 2. As we can see, these rates are globally consistent with those previously estimated in the literature. Although having $\lambda_{\text{online}} > \lambda_{\text{offline}}$ can seem counter-intuitive, He et al. (2018) also found a greater advertising carry-over effect online. This can be related to brands' high online share of budget, highlighted before. This also coincides with the fact the hotel industry is a sector where sales mainly take place online.

Offline-online average effects

Table 3 provides the results of model (1) for the coefficients of interest. The effect of control features and the first stage of the model are reported in Appendix A.6 (Table A3, A5, A6 and A7). The KP Wald F-Stats and first stage F-Stat both indicate a good validity of the instrument. Google and Facebook models display a good adjusted R^2.

Our results demonstrate that the existence of statistically significant externalities generated by offline ads impact on the effectiveness of Google ads. A 10% increase in the offline adstock generates a 0.5% increase in Google ad clicks. This finding is consistent with previous studies on offline-search behaviors (R. A. Lewis & Reiley, 2013; Dinner et al., 2014; Joo et al., 2014, 2016; Liaukonyte et al., 2015; Reiley et al., 2010).[4]

[4]Dinner et al. (2014) found a negative non-significant effect of a luxury clothing retailer's display ads on the click rate for search ads. In contrast, Kireyev et al. (2016)'s study on a bank showed that display impressions often increased search effectiveness while search ads decreased display performance. The study by R. Lewis and Nguyen (2015) also showed that display advertising could trigger consumers' search for competing brands, explaining these ambiguous findings.

More surprisingly, the effect of online ads (display, video) on search clicks is negative. This echoes contradictory findings in the literature. Thus, negative externalities between online ads do exist – confirming the theoretical literature previously described – but they seem heterogeneous among industries. In our case, we have established several reasons for this result. First, negative externalities between online ads may be a consequence of a competition for clicks and attention among online media. Second, display ads generally come later in the purchase decision process: a consumer targeted by a banner ad may have already shown interest in the advertised brand or product category and thus be less willing to search.

Equally interesting is that competitors do not affect search clicks. While previous studies have reported the presence of brand poaching in many markets, this is not likely to be the case here. Finally, we do not find any significant effect of advertising expenditure on Facebook clicks. We can point out two hypotheses to explain this surprising result. A practical reason may be found in the data: we have few Facebook observations and their standard deviations are very high. This may harm the estimation, as shown by the relatively lower R2 of the Facebook model. In addition, the mechanism whereby offline ads externally affect Facebook ads is not clear. As seen before, V. Kumar et al. (2017) found no effect of television × social media ads on sales. Thus, the offline-to-social media externality mechanism is not straightforward.

Our results show the existence of strong externalities from offline advertising impacting online search ads. This effect of mass-media advertisements is reflected in the increase in clicks on sponsored links. These findings raise a new question: who do these effects benefit (or harm)? In the next subsection, we investigate the effect of offline advertising on several Google outcomes to further document the offline-to search externality mechanism.

Mechanism

Two mechanisms may explain the positive effect of offline ads on Google clicks. On the one hand, traditional mass-media ads may increase the volume of searches, and thus clicks, (extensive margin) by informing consumers about the existence of the brand. On the other hand, offline ads may increase consumers' utility for the brand and thus induce more consumers to click for a constant number of impressions (intensive margin). Thus, if offline ads affect the volume of searches and/or users' propensity to click, how does this translate into advertising prices?

Table 4. Effect of advertising stocks on brands' Google queries, advertising click rate and costs. Robust standard errors clustered by week-of-the-year.

		Google		
	logit(Trends)	logit(CTR)	log(Budget)	log(CPM)
$\log(A_{\text{offline}})$	0.157*	0.0538***	0.172***	0.0258
	(0.0926)	(0.0127)	(0.0664)	(0.0302)
$\log(A_{\text{online}})$	−0.138*	−0.0334***	−0.199***	−0.102***
	(0.0750)	(0.00894)	(0.0477)	(0.0189)
$\log(A_{\text{competitors}})$	0.0399	−0.0118	0.259***	0.142***
	(0.0592)	(0.0152)	(0.0778)	(0.0384)
Month FEs	X	X	X	X
Year FEs	X	X	X	X
Brand × Country FEs	X	X	X	X
Country-specific trend	X	X	X	X
log(Investment)		X		
Observations	950	875	875	875
Adjusted R-squared	.215	.380	.0144	.0884
F-statistic	36.02	259.3	388.0	124.5
KP LM-stats	14.38	18.70	18.50	18.50
KP Wald F-Stats	3.118	14.84	11.68	11.68

Note: *p < 0.1; **p < 0.05; ***p < 0.01

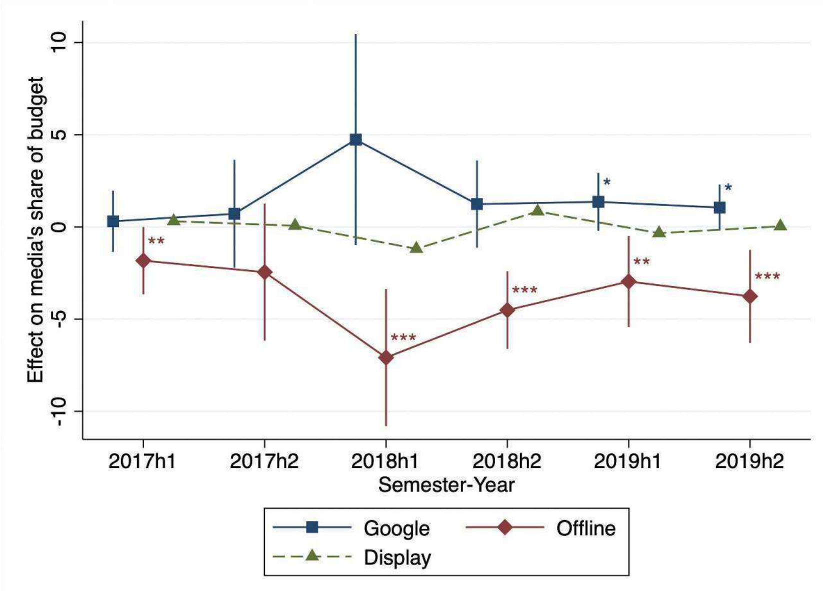


Figure 4. Effect of past year's Google clicks on media investment by semester. Marginal effects of log($Y_{bc,t-2}$) estimated from equation (2). 95% confidence intervals displayed. Standard errors robust to heteroskedasticity and auto-correlation used. N = 30. Note: *p < .1; **p < .05; ***p < .01

We answer these questions by running model (1) on four new alternative Google dependent variables:

(i) the brand's query index,[5] (ii) advertising click through-rate (CTR), total campaign cost and cost-per 100-impressions.

Results reported in Table 4 confirm our two hypotheses: offline advertising increases both the brands' query volume and the advertising click rate on Google. The first effect seems relatively higher than the second. This is confirmed by the externality offline adstock generated on Google costs. Traditional media campaigns increase the overall Google budget rather than cost-per-1000-impressions. Consistently with the previous results, we find that online ads tend to decrease search queries, clicks, and thus costs.

effect may denote a brand poaching strategy which may be twofold. First, competitors may invest in focal firms' branded keywords and, even if they do not win the auction, their bids will increase the second price paid by the focal firm. This is likely to happen here, since we found that competitors' spending does not affect clicks or CTR significantly, suggesting that these firms do not steal Google slots from focal brands. Conversely, focal brands may bid on competitors' keywords whenever their adstock is high to free-ride on their notoriety. We carried out a similar analysis on Facebook ads data (Table A11) and found no significant effects.

In the long-run, the increased effectiveness of search ads (partly due to offline investments) may augment the budget allocated to Google ads at the expense of other media. To test for this effect, we aggregate our data at the semester-year level and analyze the effect of past clicks on Google and the offline budget share in our data by running the following model:

$$\text{logit}(\text{S}_{\text{bct}}) = \alpha + \delta_t + \beta \times \log\left(Y_{b,c,t-2}\right) + \sum_t \phi_t \times \log\left(Y_{b,c,t-2}\right) \times \delta_t + \mu_{cb} + \varepsilon_{bct} \qquad (2)$$

[5]The query index, retrieved from the Google Trends service is normalized between 0 and 1 on the study period.

The share of budget S is estimated as a function of the clicks Y obtained two semesters before.[6] Results in Figure 4 suggest that a high Google performance in the past year increases Google's share of the budget at the expense of traditional media. This effect tends to get stronger with time. The effect of Google clicks on the online display budget share is not significant and does not exhibit any trend.

Robustness checks

Several checks are performed to ensure the robustness of our findings. First, the assumption that competitors' ad investments should be instrumented is debatable. Table A9 in the appendix shows that instrumenting competitors' adstock has no effect on our coefficient of interest $\log(A_{\text{offline}})$ and marginally impacts other coefficients. It also shows the importance of accounting for trends and seasonal effects. Second, we test for different standard error specifications (robustness to heteroskedasticity and/or auto-correlation, clustering units). Table A10 shows that such changes have no impact on the significance of the coefficients.

Implications

In the previous sections, we found that both offline and competitors' ad campaigns affect search ads. Google free-rides on these externalities because it can charge the brand advertised for more clicks and a higher CPM. For their part, advertisers end up paying an extra cost to Google and giving up offline media. Also, some brands may decide to under-invest offline and poach their competitors' online branded keywords. In this section, we present the implications of such findings for the advertising industry.

Managerial implications for advertisers

The presence of externalities between advertising media yields implications for firms' advertising strategies. Indeed, our results suggest that when an advertiser invests offline, this not only increases the effectiveness of its online campaigns but also its cost. We provide an estimation of such effects in Appendix A.5. We find that doubling the offline ad stock results, in average, in 1,252 additional clicks on Google sponsored links, which ultimately cost the advertiser around €357 to the advertiser.[7] As discussed earlier, offline-online effects have already been highlighted in the marketing literature, but their effects on the price of online campaigns and media substitution have not been investigated.

Our results suggest that the computation of media ROIs may be biased in the presence of externalities. Online ROIs may be overestimated because search ads may be addressed to consumers already exposed to firms' promotional efforts (including offline campaigns). However, firms may continue to advertise with their branded keyword because of the opportunity cost of leaving such a strategic place to competitors, as suggested by our results.

[6]The reason for choosing $t-2$ instead of $t-1$ is that firms are likely to adjust their advertising budget on a year-on-year basis. This is especially true for offline ads which are typically bought far in advance (6 months to a year), before advertisers have observed search ads' performance. Thus, the full effect of Google's performance on the media budget share may be observed at least two semesters after the performance has been reported. A model run with $\log(Y_{bc,t-1})$ shows similar but less significant results (Figure A2), suggesting that a semester is not the appropriate time span to observe a substitution effect.

[7]The amount of the marginal offline adstock increases is comprised between e978 and e1148 but is hardly determinable because of a very high standard deviation.

Free-riding and market power

Our results suggest that Google free-rides on advertising externalities generated by other media campaigns. As the only gateway to consumer searches online, Google benefits from brands' promotional efforts. This set-up is similar to vertical relationships in which a manufacturer's advertising generates vertical externalities for the retailer of the product (Murry, 2017).

One can think of Google as a monopolist retailer, or gatekeeper, located between firms and consumers, that free-rides on brands' notoriety investments. Prat and Valletti (2022) showed that a monopolist attention broker – a platform selling consumer's attention to businesses though advertising – could use its monopoly power to increase advertising prices. By contrast, Facebook may not be able to free-ride on advertising externalities because the platform does not have a monopoly power over display advertisements.[8]

Moreover, the unique ability of Google to auction branded keywords allows competing firms to freeride on each other's renown. As shown in Table 4, Google prices increased due to competitors' advertising activity. Similarly, R. Lewis and Nguyen (2015) found that display advertising increased search queries for the advertised brand and its competitors, especially on markets where firms heavily advertised offline. The ability of Google to auction trademark keywords has also been discussed, both in courts and papers (Bomsel, 2013; DLAPiper, 2015). Our results empirically confirm that poaching creates a prisoner dilemma for brands, which ultimately benefits the search engine (Desai et al., 2014). Although it may increase competition among firms, we suggest that brand poaching should be at least regulated, perhaps prohibited. A study on the effect of poaching on market concentration, retail prices, and media revenues would be welcome to enlighten the welfare effect of this practice.

Advertising media market

Empirical studies have shown that outdoor and mail advertising restriction increases online ad spending, concluding that both markets are substitutes (Goldfarb & Tucker, 2011b). However, more recent papers on television and print have provided evidence that offline and online ads are likely to be complementary (Chandra & Kaiser, 2014; He et al., 2018). We supplement this empirical literature by showing that online advertising performance and revenues also depend on the activity in the offline advertising market. In particular, we argue that offline and online advertising are vertical markets. Offline ads massively provide information and narratives about products, which then tend to initiate consumer searches and clicks online.

However, the results depicted in Figure 4 go against this hypothesis: the offline advertising activity decreases with Google clicks. Based on our results, we can give three reasons for brands to advertise on Google at the expense of traditional media. First, as explained, brands may be poached and over-invest in search ads to defend their branded keywords. Second, investing offline increases both search ad costs and competitors' willingness to poach (Table 4). This can encourage advertisers to avoid traditional media campaigns. Third, they can poach keywords from notorious advertisers instead of advertising in mass-media.

In all cases, advertisers under-invest offline.

Conclusion

In this study, we consider advertising as a commodity that impacts consumers' preferences for products. When a firm invests in offline advertisements, it produces a complementary good that tends to increase consumers' utility for its product.[9] Google benefits from this incremental utility

[8]In 2019, the entire Facebook group controlled less than half of display ad spendings (Statista, 2021b).
[9]As our results suggest, online advertisement generates a distinct complement that has different effects on online searches.

because it induces consumers to look for brands online and click more on sponsored links. Moreover, the search ad auction design creates incentives for competitors to poach notorious brands advertised offline. Such externalities turn into additional revenues for the search engine.

We found no similar effects on Facebook ads. The reason may be that, as a monopolist retailer, gatekeeper or attention broker, Google is able to charge firms to access online consumers (Prat & Valletti, 2022). The search engine benefits from firms' promotional efforts which attract consumers online. This effect is particularly strong in the travel industry, where most sales take place online.

This study suffers from both technical and theoretical limitations. First, Facebook data are limited in the number of observations and quality, which complicated identification. Second, using clicks to measure externalities can lead to over- or underestimating advertising effects. On the one hand, it is unclear whether clicks eventually lead to sales for advertisers (Blake et al., 2015). On the other hand, externalities between advertisements may produce effects beyond clicks (Zenetti et al., 2014).

More broadly, our study is based on a particular industry. In short, the present paper only focuses on the measure of a certain type of advertising externalities in a given industrial context. The difficulty to generalize advertising effects is the curse of advertising research.

The technical and theoretical limitations of this study open the path to further modeling and policy topics. In particular, the study may be replicated on a more diverse set of periods and industries. Indeed, offline-to-online effects, poaching and media substitution are all likely to vary across industries. Conversions and online purchase data could also be used in order to observe whether cross-media effects effectively lead to sales.

Further analyses could tackle how under-investment in offline advertising induces collateral effects on the quality of copyrighted works outside traditional media such as news, movies or documentaries. Similarly, the effect of poaching firms' competition, retail prices, and media revenues needs to be studied to gauge whether poaching is favorable.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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References

Becker, G. S., & Murphy, K. M. (1993). A simple theory of advertising as a good or bad. *The Quarterly Journal of Economics*, *108*(4), 941–964. https://doi.org/10.2307/2118455

Bergemann, D., & Bonatti, A. (2011). Targeting in advertising markets: Implications for offline versus online media. *The RAND Journal of Economics*, *42*(3), 417–443. https://doi.org/10.1111/j.1756-2171.2011.00143.x

Berman, R. (2018). Beyond the Last Touch: Attribution in online advertising. *Marketing Science*, *37*(5), 771–792. https://doi.org/10.1287/mksc.2018.1104

Blake, T., Nosko, C., & Tadelis, S. (2015). Consumer heterogeneity and paid search effectiveness: A large-scale field experiment: paid search effectiveness. *Econometrica*, *83*(1), 155–174. https://doi.org/10.3982/ECTA12423

Bomsel, O. P. (2013). Copyright and brands in the digital age: Internalizing the externalities of meaning. *Contemporary Economic Policy*, *31*(1), 126–134. https://doi.org/10.1111/j.1465-7287.2011.00288.x

Chandra, A., & Kaiser, U. (2014). Targeted advertising in magazine markets and the advent of the internet. *Management Science*, *60*(7), 1829–1843. https://doi.org/10.1287/mnsc.2013.1830
Chintagunta, P. K., Kadiyali, V., & Vilcassim, N. J. (2006). Endogeneity and simultaneity in competitive pricing and advertising: A logit demand analysis. *The Journal of Business*, *79*(6), 2761–2787. https://doi.org/10.1086/507998
Desai, P. S., Shin, W., & Staelin, R. (2014). The company that you keep: When to buy a competitor's keyword. *Marketing Science*, *33*(4), 24. https://doi.org/10.1287/mksc.2013.0834
Dinner, I. M., Heerde Van, H. J., & Neslin, S. A. (2014). Driving online and offline sales: The cross channel effects of traditional, online display, and paid search advertising. *Journal of Marketing Research*, *51*(5), 527–545. https://doi.org/10.1509/jmr.11.0466
DLAPiper. (2015). "Say it with flowers" . . . But beware of keywords!
Dub´e, J.-P., Hitsch, G. J., & Manchanda, P. (2005). An empirical model of advertising dynamics. *Quantitative Marketing and Economics*, *3*(2), 107–144. https://doi.org/10.1007/s11129-005-0334-2
eMarketer. (2021). *Worldwide digital ad spending year-end update*. Technical report, eMarketer.
Evans, D. S. (2009). The online advertising industry: Economics, evolution, and privacy. *Journal of Economic Perspectives*, *23*(3), 37–60. https://doi.org/10.1257/jep.23.3.37
Fossen, B. L., & Schweidel, D. A. (2017). Television advertising and online word-of-mouth: An empirical investigation of social TV activity. *Marketing Science*, *36*(1), 105–123. https://doi.org/10.1287/mksc.2016.1002
Ghosh, A., & Mahdian, M. (2008). Externalities in online advertising. *Proceeding of the 17th international conference on World Wide Web - WWW '08* (pp.161). ACM Press.
Goldfarb, A., & Tucker, C. (2011b). Substitution between offline and online advertising markets. *Journal of Competition Law and Economics*, *7*(1), 37–44. https://doi.org/10.1093/joclec/nhq034
Goldfarb, A. (2014). What is different about online advertising? *Review of Industrial Organization*, *44*(2), 115–129. https://doi.org/10.1007/s11151-013-9399-3
Guitart, I. A., & Stremersch, S. (2021). The impact of informational and emotional television ad content on online search and sales. *Journal of Marketing Research*, *58*(2), 299–320. https://doi.org/10.1177/0022243720962505
He, X., Lopez, R., & Liu, Y. (2018). Are online and offline advertising substitutes or complements? Evidence from U.S. Food Industries. *Journal of Agricultural & Food Industrial Organization*, *15*(2). https://doi.org/10.1515/jafio-2017-0031
Jeziorski, P., & Segal, I. (2015). What makes them click: Empirical analysis of consumer demand for search advertising. *American Economic Journal: Microeconomics*, *7*(3), 24–53. https://doi.org/10.1257/mic.20100119
Johnson, J. P. (2013). Targeted advertising and advertising avoidance. *The RAND Journal of Economics*, *44*(1), 128–144. https://doi.org/10.1111/1756-2171.12014
Joo, M., Wilbur, K. C., Cowgill, B., & Zhu, Y. (2014). Television advertising and online search. *Management Science*, *60*(1), 56–73. https://doi.org/10.1287/mnsc.2013.1741
Joo, M., Wilbur, K. C., & Zhu, Y. (2016). Effects of TV advertising on keyword search. *International Journal of Research in Marketing*, *33*(3), 508–523. https://doi.org/10.1016/j.ijresmar.2014.12.005
Jordan, P., Mahdian, M., Vassilvitskii, S., & Vee, E. (2011). The multiple attribution problem in pay-perconversion advertising. In *International symposium on algorithmic game theory*, Springer. (pp. 31–43). https://doi.org/10.1007/978-3-642-24829-0_5
Kireyev, P., Pauwels, K., & Gupta, S. (2016). Do display ads influence search? Attribution and dynamics in online advertising. *International Journal of Research in Marketing*, *33*(3), 475–490. https://doi.org/10.1016/j.ijresmar.2015.09.007
Kumar, A., Bezawada, R., Rishika, R., Janakiraman, R., & Kannan, P. (2016). From social to sale: The effects of firm-generated content in social media on customer behavior. *Journal of Marketing*, *80*(1), 7–25. https://doi.org/10.1509/jm.14.0249
Kumar, V., Choi, J. B., & Greene, M. (2017). Synergistic effects of social media and traditional marketing on brand sales: Capturing the time-varying effects. *Journal of the Academy of Marketing Science*, *45*(2), 268–288. https://doi.org/10.1007/s11747-016-0484-7
Lewis, R. A., & Reiley, D. H. (2013). Down-to-the-minute effects of super bowl advertising on online search behavior. In *Proceedings of the fourteenth ACM conference on electronic commerce, EC '13* (pp. 639–656). Association for Computing Machinery.
Lewis, R., & Nguyen, D. (2015). Display advertising's competitive spillovers to consumer search. *Quantitative Marketing and Economics*, *13*(2), 93–115. https://doi.org/10.1007/s11129-015-9155-0
Liaukonyte, J., Teixeira, T., & Wilbur, K. C. (2015). Television advertising and online shopping. *Marketing Science*, *34*(3), 311–330. https://doi.org/10.1287/mksc.2014.0899
Murry, C. (2017). Advertising in vertical relationships: An equilibrium model of the automobile industry. *Available at SSRN 2549247*.
Naik, P. A., & Peters, K. (2009). A hierarchical marketing communications model of online and offline media synergies. *Journal of Interactive Marketing*, *23*(4), 288–299. https://doi.org/10.1016/j.intmar.2009.07.005
Nevo, A. (2001). Measuring market power in the ready-to-eat cereal industry. *Econometrica*, *69*(2), 307–342. https://doi.org/10.1111/1468-0262.00194

Onishi, H., & Manchanda, P. (2012). Marketing activity, blogging and sales. *International Journal of Research in Marketing*, *29*(3), 221–234. https://doi.org/10.1016/j.ijresmar.2011.11.003

Prat, A., & Valletti, T. M. (2022). Attention oligopoly. *American Economic Journal: Microeconomics*, *14*(3), 530–557. https://dio.org/10.1257/mic.20200134

Reiley, D. H., Li, S.-M., & Lewis, R. A. (2010). Northern exposure: A field experiment measuring externalities between search advertisements. *Proceedings of the 11th ACM conference on electronic commerce* (pp.297–304).

Rutz, O. J., & Watson, G. F. (2019). Endogeneity and marketing strategy research: An overview. *Journal of the Academy of Marketing Science*, *47*(3), 479–498. https://doi.org/10.1007/s11747-019-00630-4

Sayedi, A., Jerath, K., & Srinivasan, K. (2014). Competitive poaching in sponsored search advertising and its strategic impact on traditional advertising. *Marketing Science*, *33*(4), 586–608. https://doi.org/10.1287/mksc.2013.0838

Shapiro, B. T., Hitsch, G. J., & Tuchman, A. E. (2021). TV advertising effectiveness and profitability: Generalizable results from 288 brands. *Econometrica*, *89*(4), 1855–1879. https://doi.org/10.3982/ECTA17674

Shehu, E., Abou Nabout, N., & Clement, M. (2021). The risk of programmatic advertising: Effects of website quality on advertising effectiveness. *International Journal of Research in Marketing*, *38*(3), 663–677. https://doi.org/10.1016/j.ijresmar.2020.10.004

Simonov, A., Nosko, C., & Rao, J. M. (2018). Competition and crowd-out for brand keywords in sponsored search. *Marketing Science*, *37*(2), 200–215. https://doi.org/10.1287/mksc.2017.1065

Statista. (2021a). Global: Travel & tourism sales channel share.

Statista. (2021b). Net digital display ad revenues of facebook as percentage of total digital display ad revenues in the United States from 2016 to 2019.

Tucker, C. (2013). The implications of improved attribution and measurability for antitrust and privacy in online advertising markets. *Georges Mason Law Rev*, *203*, 1025–1054.

Tucker, C. E. (2014). Social networks, personalized advertising, and privacy controls. *Journal of Marketing Research*, *51*(5), 546–562. https://doi.org/10.1509/jmr.10.0355

Van Heerde, H. J., Gijsenberg, M. J., Dekimpe, M. G., & Steenkamp, J.-B. E. (2013). Price and advertising effectiveness over the business cycle. *Journal of Marketing Research*, *50*(2), 177–193. https://doi.org/10.1509/jmr.10.0414

VideoWeek. (2022). Friends and opponents lay out arguments for tf1/m6 merger. *Video Week*.

Wilbur, K. C., Xu, L., & Kempe, D. (2013). Correcting audience externalities in television advertising. *Marketing Science*, *32*(6), 892–912. https://doi.org/10.1287/mksc.2013.0807

Zenetti, G., Bijmolt, T. H., Leeflang, P. S., & Klapper, D. (2014). Search engine advertising effectiveness in a multimedia campaign. *International Journal of Electronic Commerce*, *18*(3), 7–38. https://doi.org/10.2753/JEC1086-4415180301

Zigmond, D., & Stipp, H. (2010). Assessing a new advertising effect: Measurement of the impact of television commercials on internet search queries. *Journal of Advertising Research*, *50*(2), 162–168. https://doi.org/10.2501/S0021849910091324

A Appendix

A.1 Additional descriptive statistics

Figure A1. Trends in Google+Facebook clicks by brand.

Table A1. Correlation matrix

	Google clicks	Google imp	Fb clicks s	Fb imp	Online	Offline	Competitors	F comp on	F comp off	Off share
Google clicks	1									
Google imp	0.970***	1								
Fb clicks	0.187***	0.156***	1							
Fb imp	0.187***	0.152***	0.705***	1						
Online	0.195***	0.186***	0.250***	0.274***	1					
Offline	0.0764*	0.0829*	0.0243	0.0141	0.177***	1				
Competitors	−0.296***	−0.291***	−0.0835*	−0.0735*	−0.0605	−0.00672	1			
F comp on	−0.0966**	−0.118***	0.0854**	0.0238	0.0385	0.00752	0.220***	1		
F comp off	−0.177***	−0.190***	0.0694*	0.0413	−0.0453	−0.0440	0.0385	−0.0149	1	
Off share	0.0760*	0.0739*	0.0827*	0.0508	0.146***	0.709***	−0.0140	0.0587	−0.0173	1

Note: *p < 0.1; **p < 0.05; ***p < 0.01

A.2 Facebook weekly data computation

The heterogeneous lengths of social ad campaigns is an issue we have to deal with since all our explanatory features are reported on calendar weeks. Let ${Y_{bp}}^F$, be the clicks recorded on Facebook ad campaigns for brand b in a period $p \in \mathcal{P}$ associated to a length of $d(p)$ days. We convert data from heterogeneous period length into calendar weeks as following:

$$Y^F_{bt} = \sum_{p \in \mathcal{P}} \{ \left[\frac{Y^F_{bt}}{d(p)} \right] \times d(p \cap^t) \} \tag{3}$$

The terms inside the brackets correspond to the daily-average Facebook features. We then multiply it by the number of days for which period p overlaps week t, i.e. $0 \le d(p \cap t) \le 7$. The same calculation is used for Facebook impressions and costs.

Table A2. Statistics averaged by brand and week.

	Low cost		Mid range^{+}		Mid range^{-}		Total	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Google clicks	40619	16098	14199	7406	14619	6293	24851	17298
Google impressions	156382	60513	74633	40370	75600	30780	107526	62410
Facebook clicks	840	3156	330	1012	0	0	468	2120
Facebook impressions	103924	383807	22600	52901	0	0	50609	248822
Online	11313	24920	5785	7071	8896	8553	8618	16991
Offline	10899	40625	7014	26115	14338	40928	10032	35676
Competitors	59900	118989	159158	209294	263601	314754	140343	220575
Offline adstock	72316	113552	46306	71464	94446	121929	66338	102387
Online adstock	110883	125318	55606	37101	85157	42448	83627	88277
Competitors off adstock	278421	421336	898169	774589	1604164	1015113	791469	870590
Competitors on adstock	178663	202144	201313	163636	201803	425590	192351	251417
IV on adstock	178663	202144	201313	163636	222375	190230	196465	185716
Competitors off adstock	278421	421336	898169	774589	180214	102375	506679	645114
Offline share of budget	.13	.28	.11	.27	.14	.31	.12	.28
Observations	380		380		190		950	
Period covered	01/2016 to 09/2019							

A.3 Grid search algorithm

A grid search algorithm is used to estimate the carryover parameter of our adstock function. Two parameters are to be estimated: $\lambda^{*}_{\text{offline}}$ and $\lambda^{*}_{\text{online}}$. The grid search procedure consists in running the regression model with different carryover-rate and then selecting the optimal λ^{*}s which minimize the error of the model.

Formally, we run the following simple model:

$$\log(Y_{bct}) = \underbrace{\alpha + \sum_{m} \eta_m \log[1 + A_{mbct}(\lambda_m)] + \gamma \mathbf{X}_{bct} + \mu_{\{bc\}} + \left[\delta_{z(t)} + \delta_{y(t)}\right]}_{\widehat{Y_{cbt}}(\lambda_m)} + \varepsilon_{bct}$$

Table A3. Statistics averaged by country and week.

	DE		UK		Total	
Variable	MeanSD		Mean	SD	MeanSD	
Google clicks	28990	18888	22091	15568	24851	17298
Google impressions	118226	67228	100393	57952	107526	62410
Facebook clicks	1171	3229	0	0	468	2120
Facebook impressions	126524	381309	0	0	50609	248822
Online	8814	24821	8488	8430	8618	16991
Offline	5607	31817	12983	37771	10032	35676
Competitors	75875	121360	183322	258282	140343	220575
Offline adstock	37355	71645	85660	114586	66338	102387
Online adstock	87732	130357	80891	40742	83627	88277
Competitors off adstock	333805	435549	1096578	951106	791469	870590
Competitors on adstock	246286	195903	156394	276811	192351	251417
IV on adstock	133690	152193	238315	194191	196465	185716
Competitors off adstock	842785	806528	282608	367547	506679	645114
Offline share of budget	.08	.24	.15	.31	.12	.28
Observations	570		380		950	
Period covered	01/2016 to 09/2019					

In the equation above, Y_{cbt} is the sum of Google and Facebook clicks while $\mathbf{X}_{bct}$ contains the log of Google+Facebook impressions and a linear time trend. $A_{mbct}(\lambda_m)$ is the adstock variable of media m given a carryover rate λ_m. The algorithm then chooses the best pair of $\lambda^*_m, m \in$ (offline, online) which minimizes the sum of squared residuals (SSR):

$$\lambda^*_m = \arg\min_{\lambda_m} \sum_{b,c,t} \left[Y_{bct} - \widehat{Y_{bct}}(\lambda^*_m) \right]^2$$

The algorithm searches for $\lambda_m \in (0.05{,}0.95)$ with a pas of 0.05. Once the adstock rate obtained, we compute the respective adstocks $A_{mbc,t} = \lambda^*_m A_{mbc,t-1} + a_{mbct}$ and proceed to the instrumentation strategy.

A.4 Instrumental variable approach

In regression (1), the adstock of media m is instrumented by the adstock of competitors in the foreign market on that same media. Formally, adstocks of firms located in the UK will be instrumented by competitors in the German market and vice-versa. The first-stage is the following one:

$$\log\left(A^m_{bct}\right) = \phi^m + \eta^m \log\left(C^m_{bc't}\right) + \zeta \mathbf{X}_{bc't} + \theta^m_{bc} + \rho^m_{z(t)} + \rho^m_{y(t)} + \nu^m_{bct}$$

Where $C_{bc't}$ is the stock of b's competitors in the foreign market c'; $\mathbf{X}_{bc't}$ is the same vector of controls as in equation (1); and are fixed effects. The results of the first stage are given in the following table.

Table A4. First stage results from equation (1).

	Google model			Facebook model		
	*A*offline	*A*online	*A*competitors	*A*offline	*A*online	*A*competitors
*C*offline	−0.202*	−0.0371	0.0771**	0.243***	0.242***	−0.0782**
	(0.110)	(0.0988)	(0.0332)	(0.0726)	(0.0226)	(0.0386)
*C*online	0.942***	0.334***	0.446***	0.0429	−0.0204	0.571***
	(0.102)	(0.0873)	(0.0382)	(0.167)	(0.0529)	(0.0831)
*C*competitors	0.234***	0.325***	0.0133***	0.620***	0.157***	−0.0134
	(0.0483)	(0.0338)	(0.00484)	(0.0664)	(0.0153)	(0.0130)
log(Impressions)	−0.355	1.070***	−0.743***	0.00286	0.119***	−0.0817***
	(0.289)	(0.281)	(0.0667)	(0.0742)	(0.0176)	(0.0210)
Constant	−13.52	−27.58	16.32	198.1	116.7**	−44.14
	(98.09)	(89.41)	(30.44)	(162.2)	(56.22)	(37.05)
log(Impressions)	X	X	X	X	X	X
Month FEs	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X
Brand × Country FEs	X	X	X			
Brand FEs				X	X	X
Time trend	Country	Country	Country	General	General	General
Observations	875	875	875	269	269	269
Adjusted Partial R^2	.01	.05	.09	.07	.10	.33
F-statistic	63.89	44.11	135.84	30.53	165.77	43.94

Note: *p < 0.1; **p < 0.05; ***p < 0.01
Robust standard errors in parenthesis

A.5 Clicks and cost elasticities in value

Our results suggest offline advertising increases the effectiveness of its online campaign and thus its cost. To have an approximation of such effects, we convert our elasticities β_m in values with the following back-of-the-envelope equation:

$$\frac{d\text{Cost}}{dA_m} = \underbrace{\left(\beta_m \times \bar{Y}\right)} \times \text{Cost} - \text{per} - \text{click} \equiv \xi_m,$$

where $\bar{Y}$ is the clicks mean. Results with confidence intervals are reported in Table A4.

Table A5. Confidence interval for Google's clicks and cost elasticities to offline adstock.

	η	ξ	dA
Mean	1252	€357	€71 990
Std. Dev	(641)	(203)	(3542)
95% CI	[1210 – 1294]	[344 – 370]	[71755–72224]
Obs	875	875	875

Confidence intervals for mean μ and standard deviations σ and observations N are computed by

$$\mu \pm 1.96\frac{\sigma}{\sqrt{N}}$$

A.6 Additional regression results

Table A6. Controls, brand-country FEs and trends.

	Facebook	Google				
	Clicks	Clicks	Trends	Google CTR	Budget	CPM
Constant	116.7	0.0315	73.92	1.504	−24.80	−27.36**
	(200.0)	(5.446)	(66.92)	(6.201)	(30.22)	(12.72)
Low-cost UK		3.724***	2.084	2.717**	36.81***	11.00***
		(1.004)	(5.040)	(1.104)	(5.280)	(2.304)
Mid range* DE		−0.340***	0.234**	−0.363**	−1.237**	−0.186***
		(0.0194)	(0.111)	(0.0237)	(0.0706)	(0.0247)
Mid range* UK		3.469***	2.874	2.456**	35.85***	10.85***
		(1.041)	(5.281)	(1.127)	(5.542)	(2.437)
Mid range UK		3.498***	2.798	2.490**	35.78***	10.74***
		(1.034)	(5.231)	(1.123)	(5.491)	(2.410)
DE x Date		−0.0000491	−0.00355	−0.000127	0.00148	0.00146**
		(0.000265)	(0.00326)	(0.000303)	(0.00146)	(0.000617)
UK x Date		−0.000233	−0.00367	−0.000265	−0.000267	0.000944
		(0.000275)	(0.00327)	(0.000308)	(0.00157)	(0.000665)
log(Impressions)	0.685*	0.971***				
	(0.0642)	(0.0163)				
log(budget)				0.0330* (0.0169)		
Mercure	−24.03					
	(29.15)					
Date	−0.00517					
	(0.00958)					

Note: *p < 0.1; **p < 0.05; ***p < 0.01
Robust standard errors in parenthesis

Table A7. Month fixed effect.

	Facebook	Google				
	Facebook clicks	Clicks	Trends	CTR	Budget	CPM
Month = 2	0.513	−0.0368**	0.0432	−0.0426**	−0.0804	−0.0566*
	(0.358)	(0.0148)	(0.153)	(0.0197)	(0.0639)	(0.0314)
Month = 3	0.509	−0.0301	0.101	−0.0338	−0.0999	−0.133**
	(0.609)	(0.0235)	(0.251)	(0.0297)	(0.122)	(0.0572)
Month = 4	0.649	−0.0116	0.0580	−0.00905	−0.157	−0.206***
	(0.889)	(0.0318)	(0.304)	(0.0397)	(0.167)	(0.0704)
Month = 5	0.653	−0.0307	0.169	−0.0316	−0.166	−0.132
	(1.156)	(0.0366)	(0.390)	(0.0439)	(0.192)	(0.0838)
Month = 6	−0.340	−0.0129	0.383	−0.0152	−0.0337	−0.0638
	(1.469)	(0.0444)	(0.500)	(0.0527)	(0.238)	(0.102)
Month = 7	0.0750	0.0214	0.706	0.0108	0.284	−0.000843
	(1.776)	(0.0545)	(0.596)	(0.0619)	(0.317)	(0.136)
Month = 8	0.412	0.0515	0.936	0.0351	0.562	0.116
	(2.059)	(0.0599)	(0.691)	(0.0679)	(0.346)	(0.149)
Month = 9	0.643	0.0238	1.359*	−0.0000310	0.516	0.0663
	(2.317)	(0.0666)	(0.786)	(0.0759)	(0.365)	(0.157)
Month = 10	1.084	−0.0645	0.949	−0.0916	0.148	−0.0372
	(2.631)	(0.0749)	(0.834)	(0.0853)	(0.373)	(0.167)
Month = 11	1.981	−0.0825	0.514	−0.0926	−0.284	−0.248
	(2.844)	(0.0852)	(0.975)	(0.0966)	(0.434)	(0.191)
Month = 12	2.038	−0.0867	0.0270	−0.0898	−0.372	−0.236
	(2.984)	(0.0858)	(1.054)	(0.0968)	(0.480)	(0.209)

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Table A8. Year fixed effects.

	Facebook	Google				
	Clicks	Clicks	Trends	CTR	Budget	CPM
2017	Ref	−0.00729	1.222	−0.0414	0.518	−0.0294
		(0.0985)	(1.189)	(0.109)	(0.526)	(0.230)
2018	0.543	−0.0433	1.983	−0.0572	−0.0575	−0.421
	(3.557)	(0.197)	(2.383)	(0.219)	(1.047)	(0.455)
2019	2.682	−0.0302	3.031	−0.0521	0.0759	−0.632
	(7.009)	(0.293)	(3.558)	(0.327)	(1.572)	(0.682)

Note:*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Table A9. Robustness regression results. Robust standard errors clustered by week-of-the-year in parenthesis. Facebook data were only available for UK firms: country-level FEs and trends dropped.

	Google clicks				Facebook clicks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\log(A_{\text{offline}})$	11.50	0.318	0.0495***	0.0495***	0.0512	1.403	0.0587	0.274
	(1549.9)	(0.775)	(0.0125)	(0.0118)	(0.244)	(2.760)	(0.177)	(0.292)
$\log(A_{\text{online}})$	−31.35	−0.510	−0.0312	−0.0321***	0.119	−2.830	0.176	−0.677
	(4179.5)	(1.434)	(0.0225)	(0.00862)	(0.197)	(5.275)	(0.280)	(0.723)
$\log(A_{\text{competitors}})$			0.000106	0.000823			−0.0622	−0.135
			(0.00311)	(0.0130)			(0.153)	(0.325)
log(Impressions)	X	X	X	X	X	X	X	X
Brand × Country FEs	X	X	X	X	X	X	X	X
Month & Year FEs			X	X			X	X
Competitors IV				X				X
Time trend	No	No	Country	Country	No	No	General	General
Observations	875	875	875	875	269	269	269	250
Adjusted R-squared	−5208.6	−0.632	0.949	0.950	0.371	−1.323	0.398	0.325
F-statistic	0.0368	260.8	5409.3	4652.2	28.56	7.701	14.34	16.47
KP LM-stats	0.0000567	0.108	2.290	19.45	9.302	0.394	13.37	7.656
KP-Wald F-Stats	0.0000276	0.0548	1.863	14.29	4.949	0.187	13.06	2.857

Note: *p < 0,1; **p < 0,05; ***p < 0,01

Table A10. Robustness of the results to standard errors specification. Five models have been tested: (1) and (5) no robust SEs, (2) and (6) heteroskedasticity-robust SEs, (3) and (7) heteroskedasticity and autocorrelation robust SEs, (4) and (8) robust SEs clustered at the date level and (5) and (10) robust SEs clustered at the week-of-the-year level.

	Google clicks					Facebook clicks				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\log(A_{\text{offline}})$	0.0495	0.0495	0.0495	0.0495	0.0495	0.145	0.145	0.145	0.145	0.145
	(0.0185)	(0.0131)	(0.0177)	(0.0118)	(0.0118)	(0.182)	(0.159)	(0.145)	(0.156)	(0.160)
$\log(A_{\text{online}})$	−0.0321*	−0.0321*	−0.0321**	−0.0321**	−0.0321**	−0.520	−0.520	−0.520	−0.520	−0.520
	(0.0141)	(0.0119)	(0.0162)	(0.00938)	(0.00862)	(0.414)	(0.398)	(0.370)	(0.384)	(0.367)
$\log(A_{\text{competitors}})$	0.000823	0.000823	0.000823	0.000823	0.000823	−0.386	−0.386	−0.386	−0.386	−0.386
	(0.0222)	(0.0140)	(0.0188)	(0.0126)	(0.0130)	(0.446)	(0.438)	(0.425)	(0.429)	(0.394)
log(Impressions)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Robust SEs	No	Yes	HAC	Date	Week	No	Yes	HAC	Date	Week
Obs	875	875	875	875	875	230	230	230	230	230
Adj R^2	0.950	0.950	0.950	0.950	0.950	0.335	0.335	0.335	0.335	0.335
F-stat	711.9	1341.4	754.2	1725.2	4652.2	7.009	8.059	7.862	7.998	11.67
KP LM	10.89	18.37	10.29	15.30	19.45	26.48	19.58	13.38	17.63	17.90
KP-Wald	3.571	6.697	3.654	6.145	14.29	9.066	9.189	6.159	11.28	22.70

Note: **p < 0.1; **p < 0.05; ***p < 0.01*

Table A11. Results from the mechanism analysis for Google and Facebook advertising outcomes. Robust standard errors clustered by week-of-the-year.

		IV Results					
		Google				Facebook	
	logit(Trends)	logit(CTR)	log(Budget)	log(CPM)	logit(CTR)	log(Budge)	log(CPM)
log($A_{offline}$)	0.157*	0.0538***	0.172***	0.0258	0.235	−0.160	0.118
	(0.0926)	(0.0127)	(0.0664)	(0.0302)	(0.178)	(0.114)	(0.0790)
log(A_{online})	−0.138*	−0.0334***	−0.199***	−0.102***	−0.700	0.607*	−0.0715
	(0.0750)	(0.00894)	(0.0477)	(0.0189)	(0.473)	(0.315)	(0.218)
log($A_{competitors}$)	0.0399	−0.0118	0.259***	0.142***	0.127	0.0283	−0.177
	(0.0592)	(0.0152)	(0.0778)	(0.0384)	(0.274)	(0.171)	(0.136)
Month FEs	X	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X	X
Brand × Country FEs	X	X	X	X			
Country-specific trend	X	X	X	X			
Brand FEs					X	X	X
Trend					X	X	X
log(Investment)		X			X		
Observations	950	875	875	875	269	269	269
Adjusted R-squared	0.215	0.380	0.014	0.088	0.066	0.309	0.169
F-statistic	36.02	259.3	388.0	124.5	5.082	32.00	7.725
KP LM-stats	14.38	18.70	18.50	18.50	24.20	27.23	27.23
KP-Wald F-Stat	3.118	14.84	11.68	11.68	16.32	18.07	18.07

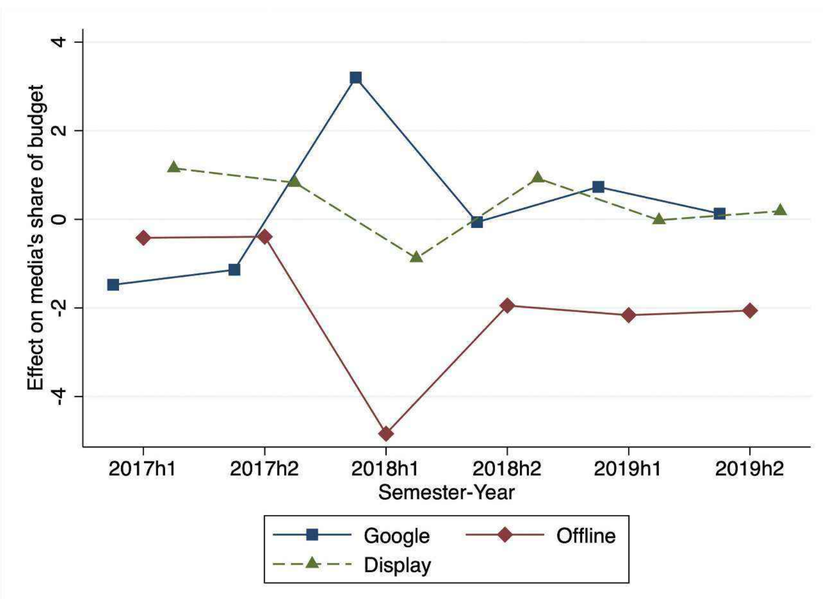

Figure A2. Effect on past year's google clicks on media's shares of budget. Note: *p < .1.; **p < .05; ***p < .01