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The impact of online display advertising and paid search advertising relative to offline advertising on firm performance and firm value

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This research examines the impact of online display advertising and paid search advertising relative to offline advertising on firm performance and firm value. Using proprietary data on annualized advertising expenditures for 1651 firms spanning seven years, we document that both display advertising and paid search advertising exhibit positive effects on firm performance (measured by sales) and firm value (measured by Tobin's q). Paid search advertising has a more positive effect on sales than offline advertising, consistent with paid search being closest to the actual purchase decision and having enhanced targeting abilities. Display advertising exhibits a relatively more positive effect on Tobin's q than offline advertising, consistent with its long-term effects. The findings suggest heterogeneous economic benefits across different types of advertising, with direct implications for managers in analyzing advertising effectiveness and external stakeholders in assessing firm performance.

1. Introduction

While the 2008 global financial crisis led many firms to reduce their marketing budgets, online advertising expenditures have grown significantly since then, exceeding $100 billion in 2018 in the United States (IAB, 2019) and surpassing television advertising spending already in 2016 (eMarketer, 2016). Practitioners remain divided on the impact of online advertising: some claim that it offers higher returns than offline advertising (Gregg, Kalaoui, Maynes, & Schuler, 2016), while others are skeptical of its long-term impact (Watson, 2016).

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Understanding the impact of online versus offline advertising on firm performance and firm value is therefore essential for both academics and practitioners (De Haan, Wiesel, & Pauwels, 2016). While prior research has examined the link between advertising and firm value, it does so primarily in the context of offline (i.e., traditional) advertising (e.g., Du & Osmonbekov, 2019; Joshi & Hanssens, 2009; Mian, Sharma, & Gul, 2018; Srinivasan & Hanssens, 2009). A notable exception is the work of Sridhar, Germann, Kang, and Grewal (2016), which provides initial insights into how online, regional, and national advertising affect firm value. However, the authors do not examine the differential effects of online advertising types—specifically, online display and paid search—relative to offline advertising on firm performance and firm value. With a sample restricted to manufacturing firms, they call for further research on other economic sectors. The current research addresses this call by assessing the relative impact of online display and paid search advertising on firm performance and firm value across different economic sectors.

Online *display advertising* is online advertising that includes banners, plain text, media-rich content, and video ads (Goldfarb, 2014); *paid search* is online advertising that appears along with organic results on search engines such as Google; and *offline advertising* is non-Internet-based advertising, including television, radio, and print ads. Display and paid search advertising share several key characteristics, including an ability to provide brand information (as is the case with offline advertising); a direct response component, which stimulates an immediate response from the consumer; and an ability for individual targeting that enables firms to approach consumers at the right stage of the purchase decision and direct them to purchase online, which significantly increases consumers' response to such advertising. The latter two characteristics result in better attribution of the response to the specific type of online advertising and allow the assessment of the individual impact on specific consumers.

By contrast, offline advertising (e.g., television, newspapers) typically cannot determine which customers were exposed to the advertisement or whether an immediate sale can be attributed directly to it. However, offline advertising can better differentiate a brand from its competitors in the minds of consumers by building brand awareness, consideration, and liking because of its better executional and placement opportunities. Within online advertising, display has an improved ability to build brands over paid search (e.g., Dinner, Van Heerde, & Neslin, 2014). Table 1 compares several features of online display, paid search, and offline advertising.

We exploit the characteristics that differentiate online display, online paid search, and offline (i.e., traditional) advertising to offer hypotheses on their effects on firm performance and firm value. To test the hypotheses, we use a proprietary panel dataset of annual observations of advertising expenditures of 1651 firms across 11 economic sectors spanning 2010–2016. Of note, our data allow decomposing advertising expenditures into display, paid search, and offline advertising. We assess the effectiveness of these different advertising types by comparing them in terms of two commonly employed outcome measures of firm performance: a short-term measure, with current period sales as our proxy, and firm value as a measure of long-term performance, with Tobin's q as our proxy. As firms may set advertising depending on unobserved factors, we use a control function approach (Petrin & Train, 2010) with exclusion restrictions to correct for potential endogeneity bias.

Our study provides four key contributions. First, it builds on prior research by partitioning online advertising into its two key types: display advertising and paid search advertising. Accordingly, our results provide insights into the heterogeneity that occurs *within* different types of online advertising. Second, we find that display and paid search advertising each exerts significantly positive effects on firm performance (measured by sales) and firm value (measured by Tobin's q). Third, we document that display advertising exhibits a relatively more positive effect on Tobin's q than offline advertising, consistent with its superior targeting ability, its direct response feature, and its significant cross-channel effects (Dinner et al., 2014). Relatedly, we show that paid search advertising has a more positive effect than offline advertising on sales, as it is closest to the actual purchase decision and has greater effectiveness in driving sales due to its enhanced targeting. Fourth, we show that paid search is more effective than online display advertising at generating sales.

We note that both types of online advertising have overlapping elements, including enhanced targeting, tracking, and placement. The differential impact of paid search on sales relative to online display reflects its customer-initiated feature and its occurrence closer to the purchase decision in consumers' purchase funnel. Furthermore, firms typically use paid search to generate a

Table 1
Comparison of paid search, display, and offline advertising.

Abilities	Paid search	Display advertising	Offline advertising	Supporting references
Brand building: building of the brand's value proposition in consumers' minds, leading (indirectly) to potential sales	Low	Medium	High	De Vries et al. (2017); Draganska, Hartmann, and Stanglein (2014)
Direct response: stimulation of an immediate response from the consumer in the same media, which can directly lead to sales	High	Medium	Low	Evans (2009); Ghose and Yang (2009); Rutz et al. (2012); Skiera and Abou Nabout (2013)
Targeting: reaching the right consumer at the right time with the right message	High	High	Low	Bleier and Eisenbeiss (2015); Chandra (2009); Evans (2009); Goldfarb and Tucker (2011); Lambrecht and Tucker (2013)
Placement: control over the placement context of the advertisement	High	Medium	High	Goldfarb and Tucker (2010); Fournier and Srinivasan (2018)
Attribution: attribution of sales of an individual consumer to a specific advertisement	High	High	Low	Danaher and Dagger (2013); Evans (2009); Goldfarb (2014)
Individual impact: assessing the impact of an advertisement on a specific consumer	High	Medium	Low	Lewis and Reiley (2014); Li and Kannan (2014)

sales response, while the goal of online display advertising is often brand building. Overall, our study contributes to the marketing–finance interface by quantifying the relationship between online display, paid search, and offline advertising and firm performance and firm value.

Our findings offer several implications for theory and practice. First, we add to the collective understanding of how display, paid search, and offline advertising work together in driving firm performance and firm value. By combining several datasets to derive the impact of both display and paid search advertising, our research goes beyond marketing expenditure data available in public financial statements. Second, our use of both short- and long-term firm performance metrics answers previous calls to consider multiple outcome measures (Katsikeas, Morgan, Leonidou, & Hult, 2016), and our use of a broad cross-sectional multi-year sample allows us to both generalize our findings (beyond one sector such as manufacturing) and provide stronger external validity. Third, our findings not only confirm variation in the effectiveness of online versus offline advertising but also highlight variation in the effectiveness *within* the two main types of online advertising. Our results suggest that display (paid search) advertising's differential advantage accrues primarily through its effects on longer-term value reflected in Tobin's q (shorter-term performance reflected in sales). Understanding these differential effects is a critical step toward the managerial goal of better allocating advertising expenditures across display, paid search, and offline advertising. While our results show that online advertising generates stronger economic effects than offline advertising, we caution that this is not *ipso facto* evidence justifying extreme shifts in advertising budgets (e.g., allocating all offline expenditures to paid search): most sample firms already invest in offline advertising, and they obtain stronger effects of display and paid search in this context.

2. Prior literature and hypotheses

Firms allocate advertising expenditures across online and offline advertising. Online advertising, or Internet-based advertising, is a technology-enabled, two-way form of dynamic communication (Goldfarb, 2014). Broadly, online advertising has stronger targeting and tracking abilities, while offline advertising is more effective at brand building (e.g., by controlling placement context). Prior research provides broad support for these general characteristics (e.g., Bleier & Eisenbeiss, 2015; Danaher & Dagger, 2013; De Vries, Gensler, & Leeflang, 2017; Evans, 2009; Goldfarb & Tucker, 2010; Li & Kannan, 2014), which we leverage to develop hypotheses on their relative effects on firm performance and firm value.

With the recent rise of online advertising, research has become increasingly interested in examining its effects on sales. For example, Dinner et al. (2014) compare the independent and joint effects of online display, paid search, and offline advertising and find that cross-elasticities are similar to own-effect elasticities and that display and paid search are more effective than offline advertising, due to strong cross-effects on offline sales. Sridhar et al. (2016) compare the effects of online, regional, and national advertising on firm value and show that the joint effects are lower than all independent effects. Sridhar and Sriram (2015) examine the cannibalization of print advertising, documenting that as online newspaper advertising increases, print advertising decreases. Collectively, these studies provide evidence of the differential effects of online relative to offline advertising on certain aspects of firm performance.

We build on these studies in three ways. First, we partition total advertising into online display, paid search, and offline (i.e., traditional) advertising; by contrast, most studies do not distinguish between online display and paid search. Doing so is important, however, because these two online categories are not interchangeable: display advertising exhibits some characteristics of traditional advertising (e.g., brand building, "pushed" by the firm) that paid search advertising does not. Collectively, the differences suggest that heterogeneous effects exist across these two advertising categories. To our knowledge, only Dinner et al. (2014) partition online advertising into these two categories; however, they do not examine the long-term effects on firm value, and their sample is restricted to a single firm (a retailer) and a short time horizon (two-year sample), which inhibits generalizability. Furthermore, while the increasing coefficients across offline, display, and paid search advertising on sales in Dinner et al. (2014; see their Table 8) are consistent with our results, the authors neither predict nor statistically test for these differences.

Second, we concurrently examine both short-term (via sales) and long-term (via Tobin's q) effects of the three advertising types, whereas extant literature does not jointly examine both effects. Doing so enables us to compare the impact across the three advertising types and, thus, to provide evidence consistent with expectations of heterogeneous effects of the differing advertising types on firm performance, conditional on horizon.

Third, our sample covers all economic sectors and a long time series (2010–2016). This broad coverage allows us to generalize our findings. Most research is more narrowly focused, using a single firm (e.g., Dinner et al., 2014), a single industry (e.g., Sridhar et al., 2016), or a single publisher (one newspaper; Sridhar & Sriram, 2015). Our use of a cross-sectional sample enables insights that generalize to a wide population of firms and thus provides strong external validity for our findings. Table 2 shows the positioning of our research relative to extant literature.

2.1. Impact of display advertising on firm performance and firm value

Display advertising allows for behavioral targeting, as advertisers can track pre- and post-impression consumer response. Behavioral targeting technologies enable firms to tailor display advertisements to consumers on the basis of their past browsing history (Kannan & Li, 2017). As such, display advertising enables better matching between the firm's products and customers' tastes through targeting (Hoban & Bucklin, 2015). Display advertising also allows firms to attribute individual consumer sales to a specific advertisement.

Table 2
Assessment of prior literature and contribution.

	Dinner et al. (2014)	McAlister et al. (2016)	Sridhar et al. (2016)	Sridhar and Sriram (2015)	This research
Objective	Compare independent and joint effects of ODA, PSA, and offline advertising on online/offline sales	Examine LT effect of advertising for differentiators versus cost leaders	Compare independent and joint effects of online, regional, and national advertising on firm value	Examine online newspaper advertising cannibalization of print advertising	Compares ST and LT impact of ODA, PSA, and offline advertising
Primary finding(s)	Cross-elasticities ≈ own-effect elasticities; ODA/PSA more effective than offline advertising from strong cross-effects on offline sales	Advertising only has LT effect for differentiators	Joint effects weaken all independent (positive) effects	As online newspaper advertising increases, print advertising decreases	ODA and PSA have stronger ST/LT effects than offline advertising; PSA has stronger ST but weaker LT effect than ODA
Dependent variable					
Firm value	No	Yes	Yes	No	Yes
Sales	Yes	Yes	No	Yes	Yes
Sample					
# Observations	5150[a]	4471	6970	Varied[d]	8124
# Firms	1	1430	662	1	1651
# Years	2 (2008–2010)	4 (1990–1993[c])	12 (2001–2012)	7 (2005–2011)	7 (2010–2016)
Industries	1 Retailer[b]	Unknown	Manufacturing	1 Newspaper[e]	All sectors
Experimental variable					
Online advertising	Yes	No	Yes	Yes	Yes
Partition ODA/PSA	Yes	No	No	No	Yes
Controls					
Advertising carryover	Yes (AdStock)	No	No	No	Yes (AdStock)
Data sources					
COMPUSTAT/CRSP	No	Yes	Yes	No	Yes
Kantar Ad$pender	No	No	Yes	No	Yes
Kantar Stradegy	No	No	No	No	Yes

Notes: ODA = online display advertising. PSA = paid search advertising. ST (LT) = short-term (long-term).
[a] 1 firm × 25 markets × 103 weeks × 2 (online and offline).
[b] U.S. clothing retailer.
[c] Robustness tests: 15 (1996–2009).
[d] 7 years × 2253 advertisers.
[e] With 2253 customers from many industries.

Evidence suggests that online display campaigns can increase site visitation, brand search queries, and both online and offline sales (Fulgoni & Mörn, 2009). For example, Lewis and Reiley (2013) examine 1.6 million users and find persistent positive effects of display advertising on sales of a retailer. Furthermore, Manchanda, Dubé, Goh, and Chintagunta (2006) show that display advertising has a positive effect on customer retention and, thus, repeat purchases. Accordingly, we argue that display advertising increases short-term sales as well as investors' expectations of sales (i.e., firm value), leading to the following prediction[5]:

H1. Online display advertising has a positive impact on both (a) firm performance and (b) firm value.

2.2. Impact of display versus offline advertising on firm performance and firm value

As noted previously, online display advertising exhibits some characteristics of traditional advertising, including its brand building ability and "push" by the firm (e.g., Colicev, Malshe, Pauwels, & O'Connor, 2018). A key advantage of display advertising is its ability to target consumers (e.g., via behavioral targeting technologies). Specifically, offline advertising targets consumers coarsely on broad demographic or psychographic variables, whereas display advertising uses information about individual-level behavior to target consumers.

The marketing literature documents that targeting increases click-through rates of banner ads (Chandon, Chtourou, & Fortin, 2003; Chatterjee, Hoffman, & Novak, 2003; Sherman & Deighton, 2001). Matz, Kosinski, Nave, and Stillwell (2017) provide evidence for the effectiveness of psychological targeting in the context of online display advertising: persuasive appeals matched to the psychological profiles of large groups of people resulted in up to 40% more clicks and 50% more purchases than their mismatched or non-personalized counterparts. These arguments lead to the following expectations:

H2. Online display advertising has a greater impact on (a) firm performance and (b) firm value than offline advertising.

[5] As a tension in this expectation, privacy concerns due to targeting and obtrusiveness of display advertising, as well as less control on the placement context, can negatively affect its effectiveness (e.g., Bleier, Goldfarb, & Tucker, 2019; Goldfarb & Tucker, 2011).

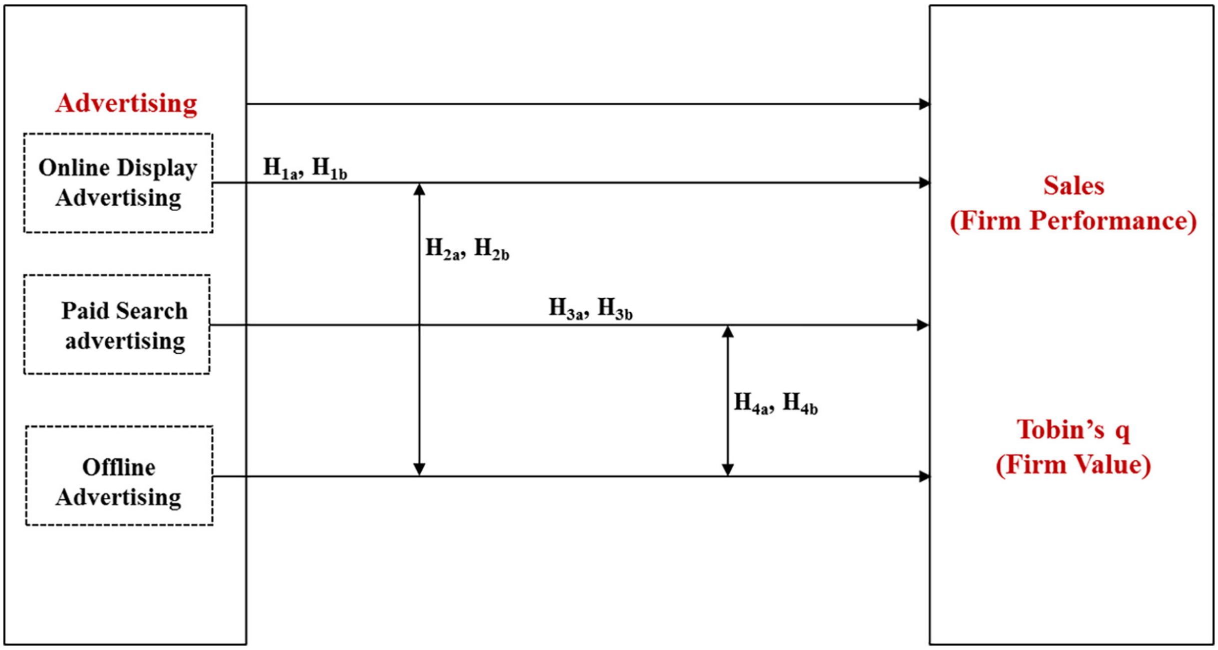

Fig. 1. Conceptual framework: impact of online display, paid search, and offline advertising on firm performance and firm value.

2.3. Impact of paid search advertising on firm performance and firm value

Paid search advertising targets consumers who have already shown interest in the product by searching for an associated keyword on a search engine (Abou Nabout, Skiera, Stepanchuk, & Gerstmeier, 2012; Sayedi, Jerath, & Srinivasan, 2014). As such, paid search has a high ability to create awareness and deliver a strong sales impact by targeting consumers who are already in the process of buying, translating more readily into sales (Dinner et al., 2014; Kireyev, Pauwels, & Gupta, 2016; Liaukonyte, Teixeira, & Wilbur, 2015; Srinivasan, Rutz, & Pauwels, 2016). Paid search can also result in increased click-through and conversion rates and higher customer lifetime value than other types of advertising (Berman & Katona, 2013; Chan, Wu, & Xie, 2011; Rutz & Bucklin, 2011).

Paid search advertisers match their ads to the content of search (Jerath, Ma, & Park, 2014). Consumers' search strings reveal information about the products they are interested in and their stage in the purchase process. Paid search's targeting results in relevant ads directed to consumers (Rutz, Bucklin, & Sonnier, 2012), an enhanced ability to control the placement context, and an improved assessment of its impact on specific consumers. Accordingly, we hypothesize the following[6]:

H3. Paid search advertising has a positive impact on both (a) firm performance and (b) firm value.

2.4. Impact of paid search versus offline advertising on firm performance and firm value

We next compare paid search advertising with offline advertising. As mentioned previously, offline advertising has an improved ability to differentiate a brand from its competitors from consumers' perspective, which eventually leads to purchases (e.g., Colicev et al., 2018). However, paid search outperforms offline advertising on virtually every other relevant characteristic (see Table 1)—from its direct response to targeting, to attribution, to its ability to assess the impact of an advertisement on a specific consumer. Specifically, paid search advertising affords superior targeting to offline advertising, which typically involves only loose targeting (e.g., based on demographics).

Paid search advertising, which tends to occur closer to the purchase decision, is more likely to elicit a final purchase decision by consumers (Goldfarb, 2014). In addition, paid search advertising often elicits a behavioral response from consumers (i.e., a click), which is uncommon and (if available) less convenient in offline advertising (e.g., toll-free numbers). Overall, these characteristics of paid search advertising lead to the following expectations:

H4. Paid search advertising has a greater impact on (a) firm performance and (b) firm value than offline advertising.

[6] Some research suggests that excessive targeting from paid search advertising can increase firms' costs because of search engines' ability to capitalize on delivering better performance to advertisers (Abou Nabout, Lilienthal, & Skiera, 2014; Chandra, 2009).

Fig. 1 summarizes the hypotheses.

3. Data and variables

3.1. Data description

We sourced the advertising data from Kantar Media's Ad$pender and Stradegy databases and the financial performance data from COMPUSTAT. Research in marketing (e.g., Sridhar et al., 2016) and accounting and finance (e.g., Cohen, Mashruwala, & Zach, 2010) has also used the Kantar Ad$pender data. The Stradegy database is the source of paid search data; all other advertising data is from Ad $pender. The Kantar advertising data are also more granular than the commonly used COMPUSTAT advertising data. In particular, for each firm-year, we obtain the total dollars spent for both online advertising (including disaggregated amounts within display advertising and paid search advertising) and offline advertising (including amounts within magazines; national and regional newspapers; cable, network, and spot television; national spot and network radio; and syndication and outdoor advertising).

Our initial Kantar dataset includes 641,312 firms for 2010–2016; most are smaller, private firms. We identify the 2589 firms that are publicly listed on U.S. stock exchanges and merge the Kantar advertising data with the related COMPUSTAT data on financial performance and control variables. Finally, we exclude non-December-31 fiscal year end firms, as Kantar's data corresponds to calendar years. This exclusion further ensures that all sample firms are subject to the same (temporal) industry conditions (e.g., Bayer, Tuli, & Skiera, 2017; Dao, Raghunandan, & Rama, 2012; Jones, 2007). Our final unbalanced panel dataset comprises 8124 firm-year observations for 1651 firms[7] over 2010–2016 and covers all 11 economic sectors. The percentage of non-manufacturing (manufacturing) firms in our sample is 66% (34%).[8] In this way, we offer generalizability of our findings to industry settings beyond the manufacturing firms studied in Sridhar et al. (2016).

3.2. Dependent variables

To measure firm performance, we use current-period sales (*Sales*), which assesses the immediate (short-term) effects of advertising expenditures (e.g., Lodish et al., 1995; Tellis, 2004). Following prior research, we use the natural logarithm of total sales (e.g., McAlister, Srinivasan, Jindal, & Cannella, 2016) to facilitate the interpretation of coefficients as elasticities.

To measure firm value, we follow prior research and use *Tobin's q*, defined as the ratio of the firm's market value to the replacement cost of its assets (e.g., Srinivasan & Hanssens, 2009). Tobin's q captures both a firm's market value and possible effects of changes in intangible assets from advertising expenditures (McAlister et al., 2016). Furthermore, it is a forward-looking, risk-adjusted, and cumulative measure reflecting short- and long-term effects of firms' advertising expenditures (e.g., Mittal, Anderson, Sayrak, & Tadikamalla, 2005). Finally (and relevant to our multi-industry study), it is unaffected by accounting conventions, industry specifics, or differences in firms' organizational goals (Wernerfelt & Montgomery, 1988). Similar to sales, we take the natural logarithm of Tobin's q. Table 3 provides the definitions of our dependent variables.

3.3. Advertising variables

Kantar collects annual advertising expenditures for a large array of firms; in particular, it obtains the Ad$pender and Stradegy data through a systematic monitoring of firms' advertising activities across different media. As a first step, we consider total Kantar advertising expenditures (*KantarAdv*), which comprise the total dollar amount across all advertising categories, including online display and paid search advertising and offline advertising (television, radio, magazines, newspapers, outdoor, and syndication). Our focus is on firm-level advertising (not brand-level advertising) across these advertising categories, given our study's emphasis on linking firm advertising to firm performance and firm value (i.e., at the same levels of aggregation).

For our primary analyses, we consider the following key advertising variables: (1) online advertising, (2) the decomposition of online advertising into display advertising (*DisplayAdv*) and paid search advertising (*SearchAdv*), and (3) offline advertising (*OfflineAdv*). We define the last variable as the difference between total Kantar advertising expenditures (*KantarAdv*) and online advertising (i.e., display and paid search advertising). Our hypotheses focus on the effects of these advertising variables on firm performance (i.e., sales) and firm value (i.e., Tobin's q). Following previous research (e.g., Cohen et al., 2010; Sridhar et al., 2016), we use the published advertising expenditures from Kantar; to assess the mapping of the Kantar advertising expenditures to sales and Tobin's q, we benchmark against a model with the measure of COMPUSTAT advertising.[9]

To control for advertising carryover effects of each advertising category, we use *AdStock* (i.e., smoothed advertising expenditures). We scale it by total assets to normalize across firms, as our sample has substantial size-based heterogeneity (Datta, Ailawadi, & van Heerde, 2017). Thus, *AdStock* is the cumulative value of a firm's advertising in each advertising category at a given point in time. The inclusion of *AdStock* stems from the notion that advertising builds a stock of consumer goodwill, which then decays over time.

[7] Our sample includes both single- and multi-brand firms. For the latter, the respective advertising expenditures represent the sum over all the firm's brands.

[8] Of the 1651 firms in our sample, 1089 do not belong to the manufacturing industry sector as measured by North American Industry Classification System codes 31–33.

[9] The results from using aggregate Kantar expenditures and COMPUSTAT advertising expenditures on sales and Tobin's q are similar and are available from the authors on request.

Table 3
Measures of key variables.

Variable	Measure
Tobin's q	Share price (PRCC_F) times common shares outstanding (CSHO) plus preferred stock (PSTK) plus short-term liabilities (LCT) minus short-term assets (ACT) plus long-term debt (DLTT), divided by total assets (AT) (in logarithms)
Sales revenues	Total revenues (REVT) (in logarithms)
Kantar advertising	Log of ((Stock of advertising expenditures on online display; paid search; magazines incl. Sunday magazines; national and regional newspapers; outdoor; cable, network, and spot TV; syndication; national spot and network radio)/total assets (AT) + 1); 1 added to obtain uniformly positive values
Offline advertising	Log of (Stock of (Kantar's Advertising Expenditures − online display − paid search)/total assets (AT) +1); 1 added to obtain uniformly positive values
Online display advertising	Log of (Stock of online display advertising/total assets (AT) + 1); 1 added to obtain uniformly positive values
Paid search advertising	Log of (Stock of paid search advertising/total assets (AT) + 1); 1 added to obtain uniformly positive values
Financial leverage	Ratio of total long-term debt (DLTT) to total assets (AT)
Profit	Earnings before interest and taxes (EBIT) with advertising expenditures (XAD) added back, scaled by total assets (AT)
Firm size	Number of employees (EMP) (in logarithms)
Industry growth	Total revenues (REVT) in year *t* minus log of total revenues (REVT) in year *t* − 1, defined by four-digit Standard Industrial Classification (SIC) code (in logarithms)
Industry concentration	Herfindahl–Hirschman industry index, defined by 4-digit SIC code
Industry turbulence	Standard error of τ's estimated regression coefficient divided by industry sales average for years t − 5 to t − 1, in a regression covering years *t* through τ (with τ = 1, 2, …, 5) that has year t − τ sales for the industry indicated by a firms four-digit SIC code as the dependent variable and τ as a predictor variable

Notes: In line with Eqs. (5)–(8), AdStock of firm *i* in year *t* is $\lambda \times \text{AdStock}_{i,\ t\text{-}1} + (1 - \lambda) \times \text{Advertising}_{it}$. We estimate λ by using a grid search on the interval [0, 0.9] in increments of 0.1 and choose the model with the best likelihood; in the first year of the time series, AdStock equals the advertising expenditures in the first year; advertising is in logs as shown.

3.4. Control variables

We include control variables previously shown to influence firm sales and firm value. First, we include financial leverage (*Lev*) to control for the capital required for sales growth and its potential effects on cost of capital (Harris & Raviv, 1991) and firm size (*Size*) to control for economies of scale or scope (e.g., McAlister et al., 2016; Rao, Agarwal, & Dahlhoff, 2004). Second, to control for industry effects, we include industry growth (*IndGrow*) (McAlister et al., 2016; McDougall, Covin, Robinson Jr, & Herron, 1994), industry concentration (*IndConc*) (Hirschey & Weygandt, 1985), and industry turbulence (*IndTurb*). Finally, we include current profit (*Profit*) when Tobin's q (i.e., firm value) is the dependent variable, as it is a key input to shareholder value; however, we exclude profit when using sales as the dependent variable, as it is not a predictor of current sales (McAlister et al., 2016). All control variables come from COMPUSTAT data.

4. Research methodology

4.1. Primary regressions

To test the proposed hypotheses, we estimate two models for each of our two dependent variables of sales and Tobin's q: (1) the effect of total Kantar advertising (*KantarAdv*) and (2) the effects of display advertising (*DisplayAdv*), paid search advertising (*SearchAdv*), and offline advertising (*OfflineAdv*). We use model (1) to assess the effect of total Kantar advertising on our two dependent variables; it provides validation of the Kantar advertising data because it enables comparisons with results of prior studies that use COMPUSTAT data. We use model (2) as our primary regressions, which assess the absolute and relative effects of display and paid search advertising relative to those of offline advertising (and thus serve as tests of our hypotheses).

Several research design choices warrant further discussion. First, to isolate the effect of advertising expenditures on the dependent variables beyond variables previously shown to influence sales and firm value, the models include not only the control variables established in prior research but also year-specific indicator variables, to account for time trends. Second, we estimate models with random intercepts and random error terms, which is a parsimonious way to parameterize unobserved heterogeneity around firm performance, as the random intercept captures mean unobserved firm performance.[10] Third, the choice of advertising expenditures can depend on both observable factors, such as current performance (i.e., profit), and unobservable factors potentially correlated with the error term; that is, firms' decisions about advertising expenditures may be endogenous to firm performance and value (Sridhar et al., 2016). Accordingly, we employ a control function approach with exclusion restrictions to correct for potential endogeneity bias. In particular, we include the predicted residuals from auxiliary regressions as controls in

[10] We alternatively used a likelihood ratio test to examine whether a random slope model is more appropriate than a random intercept model, but we failed to reject this null hypothesis. We also conducted a pooling test, which confirmed that we can pool our response parameters across the 11 economic sectors included in our sample.

the main models. Finally, we use robust standard errors to make our estimates robust to cross-sectional heteroskedasticity and within-panel (serial) correlation.

The two models with sales as dependent variable are (key variables bolded)

$$\begin{aligned} Sales_{i,t} = {} & \alpha_{0i} + \beta_1 \boldsymbol{KantarAdStock}_{i,t} + \beta_2 Lev_{i,t} + \beta_3 Size_{i,t} + \beta_4 IndGrow_{i,t} + \beta_5 IndConc_{i,t} + \beta_6 IndTurb_{i,t} \\ & + \beta_7 KantarAdv\_Resid_{i,t} + \beta_8 Year_t + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

and

$$\begin{aligned} Sales_{i,t} = {} & \alpha_{0i} + \beta_1 \boldsymbol{OfflineAdStock}_{i,t} + \beta_2 \boldsymbol{DisplayAdStock}_{i,t} + \beta_3 \boldsymbol{SearchAdStock}_{i,t} + \beta_4 Lev_{i,t} + \beta_5 Size_{i,t} + \beta_6 IndGrow_{i,t} \\ & + \beta_7 IndConc_{i,t} + \beta_8 IndTurb_{i,t} + \beta_9 OfflineAdv\_Resid_{i,t} + \beta_{10} DisplayAdv\_Resid_{i,t} + \beta_{11} SearchAdv\_Resid_{i,t} + \beta_{12} Year_t \\ & + \varepsilon_{i,t}. \end{aligned} \tag{2}$$

The two models for which Tobin's q is the dependent variable are

$$\begin{aligned} Tobin's\ q_{i,t} = {} & \alpha_{0i} + \beta_1 \boldsymbol{KantarAdStock}_{i,t} + \beta_2 Lev_{i,t} + \beta_3 Profit_{i,t} + \beta_4 Size_{i,t} + \beta_5 IndGrow_{i,t} + \beta_6 IndConc_{i,t} + \beta_7 IndTurb_{i,t} \\ & + \beta_8 KantarAdv\_Resid_{i,t} + \beta_9 Year_t + \varepsilon_{i,t}, \end{aligned} \tag{3}$$

and

$$\begin{aligned} Tobin's\ q_{i,t} = {} & \alpha_{0i} + \beta_1 \boldsymbol{OfflineAdStock}_{i,t} + \beta_2 \boldsymbol{DisplayAdStock}_{i,t} + \beta_3 \boldsymbol{SearchAdStock}_{i,t} + \beta_4 Lev_{i,t} + \beta_5 Profit_{i,t} + \beta_6 Size_{i,t} \\ & + \beta_7 IndGrow_{i,t} + \beta_8 IndConc_{i,t} + \beta_9 IndTurb_{i,t} + \beta_{10} OfflineAdv\_Resid_{i,t} + \beta_{11} DisplayAdv\_Resid_{i,t} \\ & + \beta_{12} SearchAdv\_Resid_{i,t} + \beta_{13} Year_t + \varepsilon_{i,t}, \end{aligned} \tag{4}$$

where (see also Table 3):

$Sales_{i,t}$	= total revenues of firm *i* in year *t* (in logs),
$Tobin's\ q_{i,t}$	= Tobin's q of firm *i* in year *t* (in logs),
$KantarAdStock_{i,t}$	= stock of Kantar advertising expenditures of firm *i* in year *t* (in logs),
$OfflineAdStock_{i,t}$	= stock of offline advertising expenditures of firm *i* in year *t* (in logs),
$DisplayAdStock_{i,t}$	= stock of display advertising expenditures of firm *i* in year *t* (in logs),
$SearchAdStock_{i,t}$	= stock of paid search advertising expenditures of firm *i* in year *t* (in logs),
$Lev_{i,t}$	= financial leverage of firm *i* in year *t*,
$Profit_{i\ t}$	= profit of firm *i* in year *t*,
$Size_{i,t}$	= size of firm *i* in year *t*,
$IndGrow_{i,t}$	= growth of the industry of firm *i* in year *t*,
$IndConc_{i,t}$	= concentration in the industry of firm *i* in year *t*,
$IndTurb_{i,t}$	= turbulence in the industry of firm *i* in year *t*,
$KantarAdv\_Resid_{i,t}$	= residual from auxiliary regression for Kantar advertising expenditures of firm *i* in year *t*,
$DisplayAdv\_Resid_{i,t}$	= residual from auxiliary regression for online display advertising expenditures of firm *i* in year *t*,
$SearchAdv\_Resid_{i,t}$	= residual from auxiliary regression for paid search advertising expenditures of firm *i* in year *t*,
$OfflineAdv\_Resid_{i,t}$	= residual from auxiliary regression for offline advertising expenditures of firm *i* in year *t*,
$Year_t$	= binary indicator variable that denotes year *t*,
α_{0i}	= random intercept of firm *i*, and
$\varepsilon_{i,t}$	= random error term of firm *i* in year *t*.

We define the stock variables in Eqs. (1)–(4) as follows (e.g., Dinner et al., 2014), where parameters λ represent carryover effects:

$$KantarAdStock_{i,t} = \lambda_{Kantar}\ KantarAdStock_{i,t-1} + (1-\lambda_{Kantar})\ KantarAdv_{i,t}. \tag{5}$$

$$OfflineAdStock_{i,t} = \lambda_{Offline}\ OfflineAdStock_{i,t-1} + \left(1-\lambda_{Offline}\right)\ OfflineAdv_{i,t}. \tag{6}$$

$$DisplayAdStock_{i,t} = \lambda_{Display}\ DisplayAdStock_{i,t-1} + \left(1-\lambda_{Display}\right)\ DisplayAdv_{i,t}. \tag{7}$$

$$SearchAdStock_{i,t} = \lambda_{Search}\ SearchAdStock_{i,t-1} + (1-\lambda_{Search})\ SearchAdv_{i,t}. \tag{8}$$

Following Dinner et al. (2014), we use a grid search to determine the carryover parameters. In addition, we take the natural logarithm of all advertising variables, to allow the coefficients to be interpreted as elasticities.

Table 4
Distribution of observations across economic sectors and descriptive statistics.

Panel A. Distribution of firm-year observations across economic sectors

	Total sample	% of sample
Financials	1709	21.0
Information technology	1449	17.8
Consumer discretionary	1264	15.6
Industrials	1131	13.9
Health care	906	11.2
Energy	478	5.9
Materials	374	4.6
Utilities	305	3.8
Consumer staples	258	3.2
Telecommunication services	156	1.9
Real estate	94	1.2
Number of firm-year observations	8124	100.0%

Panel B. Descriptive statistics ($N = 8124$)

		Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12
1	*Tobin's q*	1.340	1.402	1.00											
2	*Sales*	0.763	0.685	0.34	1.00										
3	*KantarAdStock*	0.095	0.535	0.14	0.15	1.00									
4	*OfflineAdStock*	0.062	0.443	0.11	0.13	0.88	1.00								
5	*DisplayAdStock*	0.010	0.081	0.10	0.09	0.43	0.30	1.00							
6	*SearchAdStock*	0.025	0.238	0.08	0.08	0.55	0.10	0.17	1.00						
7	*Lev*	0.217	0.205	0.22	0.03	−0.07	−0.04	−0.07	−0.06	1.00					
8	*Profit*	0.058	0.133	0.21	0.41	0.12	0.14	0.08	−0.02	0.04	1.00				
9	*Size*	1.309	1.880	0.01	0.30	−0.12	−0.07	−0.09	−0.13	0.20	0.30	1.00			
10	*IndGrow*	0.084	0.270	0.14	0.10	0.02	0.01	0.01	0.02	0.04	0.00	−0.02	1.00		
11	*IndConc*	0.368	0.287	0.12	0.26	0.01	0.03	−0.02	−0.04	0.07	0.18	0.19	0.03	1.00	
12	*IndTurb*	1.314	0.782	0.01	−0.03	0.00	0.00	−0.01	−0.01	−0.08	−0.04	−0.16	0.04	0.07	1.00

An alternative to our modeling approach is a vector autoregressive model (VAR), which is well-suited to capture long-term effects when granular weekly data are available for a long time span (e.g., Kireyev et al., 2016). The data requirements to estimate a VAR model in our context are substantial: in particular, it would require the availability of weekly sales revenue data.[11] However, such granular data are unavailable for the large set of firms we study. Accordingly, our proposed approach aligns with our goal to assess the effects of online display, paid search, and offline advertising on firm performance and value in a broad cross-sectional/time-series setting.

4.2. Auxiliary regressions

Eqs. (1)–(4) include the predicted residuals as control variables from auxiliary regressions, which we use to correct for potential endogeneity bias (Petrin & Train, 2010). The four predicted residuals are *KantarAdv_Resid*, *DisplayAdv_Resid*, *SearchAdv_Resid*, and *OfflineAdv_Resid*. The auxiliary regressions use the respective advertising variables as dependent variables and require a new variable that correlates with each of our four advertising variables but does not directly correlate with unobserved determinants of *Sales* and *Tobin's q*.

Following Sridhar et al. (2016), we use the average advertising expenditures by firms, excluding the focal firm, in the same four-digit SIC code (see also Lev & Sougiannis, 1996). We expect the instrument to positively relate to our advertising expenditure variables. The identifying assumption is that the industry's overall average advertising expenditures do not correlate with firm-specific performance shocks but are highly correlated with our variables.[12] Adding the predicted residuals from the auxiliary regressions mitigates potential endogeneity, as the retained independent variables should no longer correlate with the error terms in Eqs. (1)–(4). Eqs. (9)–(12) show the auxiliary regressions; the suffix *_IndAvg* indicates the industry's average of the respective advertising stock variable (for related results, see Web Appendix A):

$$\begin{aligned} KantarAdStock_{i,t} = {} & \alpha_{0i} + \beta_1 KantarAdStock\_IndAvg_{i,t} + \beta_2 Lev_{i,t} + \beta_3 Profit_{i,t} + \beta_4 Size_{i,t} + \beta_5 IndGrow_{i,t} + \beta_6 IndConc_{i,t} \\ & + \beta_7 IndTurb_{i,t} + \beta_8 Year_t + \varepsilon_{i,t}. \end{aligned} \tag{9}$$

[11] Regarding our main equations (models 2 and 4), the *Sales* (*Tobin's q*) equation has 10 (11) parameters (including the intercept and excluding the auxiliary regression residuals). Including the five equations in the VAR with exogenous variables (one each for display, paid, and offline advertising as well as for sales and Tobin's q) leads to the large number of parameters to estimate, in addition to the 15 parameters required for the variance–covariance matrix.

[12] Sridhar et al. (2016) provide an extensive discussion of the use of the industry's overall average advertising expenditures as an excluded variable.

$$DisplayAdStock_{i,t} = \alpha_{0i} + \beta_1 DisplayAdStock\_IndAvg_{i,t} + \beta_2 Lev_{i,t} + \beta_3 Profit_{i,t} + \beta_4 Size_{i,t} + \beta_5 IndGrow_{i,t} + \beta_6 IndConc_{i,t} + \beta_7 IndTurb_{i,t} + \beta_8 Year_t + \varepsilon_{i,t}. \tag{10}$$

$$SearchAdStock_{i,t} = \alpha_{0i} + \beta_1 SearchAdStock\_IndAvg_{i,t} + \beta_2 Lev_{i,t} + \beta_3 Profit_{i,t} + \beta_4 Size_{i,t} + \beta_5 IndGrow_{i,t} + \beta_6 IndConc_{i,t} + \beta_7 IndTurb_{i,t} + \beta_8 Year_t + \varepsilon_{i,t}. \tag{11}$$

$$OfflineAdStock_{i,t} = \alpha_{0i} + \beta_1 OfflineAdStock\_IndAvg_{i,t} + \beta_2 Lev_{i,t} + \beta_3 Profit_{i,t} + \beta_4 Size_{i,t} + \beta_5 IndGrow_{i,t} + \beta_6 IndConc_{i,t} + \beta_7 IndTurb_{i,t} + \beta_8 Year_t + \varepsilon_{i,t}. \tag{12}$$

5. Results

5.1. Descriptive statistics

Panel A of Table 4 presents the number of observations in each economic sector, revealing broad representation, and panel B presents the descriptive statistics and correlation matrix. On average, the firms exhibit moderate leverage (*Lev* = 0.217), are profitable (*Profit* = 0.058), and are moderate in size (*Size* = 1.309). The share of Kantar's online advertising expenditures (i.e., display and paid search advertising) as a percentage of total Kantar advertising expenditures varies from 17% to 19% for our sample of 8124 firm-year-specific observations. All four advertising variables (*KantarAdStock*, *OfflineAdStock*, *DisplayAdStock*, and *SearchAdStock*) correlate positively with *Sales* and *Tobin's q*.

To assess the reliability of the Kantar advertising data, we estimate the intra-class correlation coefficient (ICC) between total Kantar advertising expenditures (*KantarAdStock*) and the total advertising expenditures disclosed by the firms and available on COMPUSTAT. The ICC and its 95% confidence interval measures (1) absolute agreement or (2) consistency of agreement by using a two-way random-effects model in each case. The ICC (0.766 [0.745; 0.786]) for absolute agreement and the ICC (0.773 [0.763; 0.783]) for consistency of agreement are within the range indicating reliability of the Kantar data (Cicchetti, 1994).

Table 5
Impact of online display and paid search advertising on firm performance and firm value.

Dependent variable:	*Sales* (*N* = 8124)						*Tobin's q* (*N* = 8124)					
	Coeff.	S.E.		Coeff.	S.E.		Coeff.	S.E.		Coeff.	S.E.	
	(1)			(2)			(3)			(4)		
Advertising variables												
KantarAdStock	0.242	0.060	***				0.239	0.088	***			
OfflineAdStock				0.097	0.019	***				0.270	0.132	**
DisplayAdStock (H1)				0.231	0.108	**				0.880	0.295	***
SearchAdStock (H3)				0.583	0.107	***				0.562	0.319	*
Control variables												
Lev	−0.011	0.016		−0.015	0.016		0.557	0.095	***	0.564	0.062	***
Profit							1.109	0.154	***	1.064	0.092	***
Size	0.030	0.004	***	0.030	0.004	***	−0.055	0.016	***	−0.054	0.012	***
IndGrow	0.006	0.003	***	0.007	0.002	***	0.131	0.022	***	0.132	0.022	***
IndConc	0.044	0.008	***	0.040	0.007	***	0.135	0.062	**	0.148	0.058	**
IndTurb	−0.001	0.006		−0.001	0.006		−0.010	0.038		−0.011	0.029	
KantarAdStock_Resid	−0.078	0.017	***				−0.072	0.093				
OfflineAdStock_Resid				−0.084	0.020	***				0.048	0.045	
DisplayAdStock_Resid				−0.017	0.123					−0.786	0.311	***
SearchAdStock_Resid				−0.002	0.020					0.102	0.043	***
Constant	0.842	0.009	***	0.846	0.008	***	−0.515	0.068	***	−0.530	0.044	***
Fixed effects	Year			Year			Year			Year		
R^2	0.32			0.30			0.06			0.06		
Overall test of significance (Wald)	232.49	***		214.70	***		741.50	***		890.17	***	
DisplayAdStock = *OfflineAdStock*, Chi^2 (1)			(H2a)	1.44					(H2b)	3.28	*	
SearchAdStock = *OfflineAdStock*, Chi^2 (1)			(H4a)	19.47	***				(H4b)	0.66		
SearchAdStock = *DisplayAdStock*, Chi^2 (1)				6.75	***					0.56		

Notes: See Table 3 for variable definitions. The residuals are obtained from the auxiliary regressions. All variables are winsorized (1%). Coeff = coefficient; SE = robust standard error.

* $p < 0.10$.

** $p < 0.05$.

*** $p < 0.01$.

Table 6
Robustness checks.

Dependent variable:	*Sales* ($N = 8124$)						*Tobin's q* ($N = 8124$)					
	Coeff.	S.E.		Coeff.	S.E.		Coeff.	S.E.		Coeff.	S.E.	
	(1)			(2)			(3)			(4)		
	Fixed Effects			Interactions			Fixed Effects			Interactions		
Advertising variables												
OfflineAdStock	0.092	0.010	***	0.091	0.018	***	0.216	0.082	***	0.409	0.121	***
DisplayAdStock	0.180	0.057	***	0.344	0.139	***	1.244	0.423	***	0.682	0.298	**
SearchAdStock	0.291	0.035	***	0.607	0.110	***	0.955	0.189	***	0.328	0.121	***
DisplayAdStock × *OfflineAdStock*				0.038	0.050					−0.017	0.033	
SearchAdStock × *OfflineAdStock*				0.013	0.012					−0.046	0.046	
DisplayAdStock × *SearchAdStock*				−0.740	0.109	***				0.253	0.156	
Control variables												
Lev	−0.052	0.009	***	−0.015	0.016		1.048	0.053	***	0.581	0.062	***
Profit							1.227	0.114	***	0.988	0.095	***
Size	0.025	0.001	***	0.030	0.004	***	−0.066	0.007	***	−0.049	0.012	***
IndGrow	0.010	0.007		0.007	0.002	***	0.255	0.034	***	0.133	0.022	***
IndConc	0.054	0.007	***	0.040	0.007	***	−0.116	0.038	***	0.138	0.058	**
IndTurb	0.000	0.005		−0.001	0.006		−0.064	0.028	**	−0.002	0.029	
KantarAdStock_Resid	−0.080	0.011	***	−0.085	0.020	***	0.039	0.038		−0.147	0.046	***
OfflineAdStock_Resid	−0.189	0.061	***	−0.014	0.124		−1.059	0.463		−0.545	0.310	*
DisplayAdStock_Resid	0.006	0.009		−0.001	0.020		−0.887	0.198	**	−0.183	0.121	
Constant	0.833	0.016	***	0.845	0.008	***	−0.961	0.082	***	−0.547	0.045	***
Fixed effects	Year			Year			Year			Year		
R^2	0.35			0.30			0.45			0.07		
Overall test of significance	164.37	*** (F-test)		308.48	*** (Wald)		196.12	*** (F-test)		909.76	*** (Wald)	
DisplayAdStock = *OfflineAdStock*, F (1)/Chi^2 (1)	2.01			3.28	*		5.40	**		0.67		
SearchAdStock = *OfflineAdStock*, F (1)/Chi^2 (1)	26.76	***		21.64	***		12.95	***		0.23		

Notes: See Table 3 for variable definitions. The residuals are obtained from the auxiliary regressions. All variables are winsorized (1%). Coeff = coefficient; SE = robust standard error.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

The advertising carryover parameters from Eqs. (5)–(8) are similar to the carryover estimates of Dinner et al. (2014) for the high-end apparel retailer they analyze. The values of the carryover parameters are as follows: $\lambda_{Traditional} = 0.6$, $\lambda_{OnlineDisplay} = 0.8$, and $\lambda_{PaidSearch} = 0.2$.

5.2. Empirical results

Table 5 presents the results for the effects of online display and paid search advertising on firm performance and value. Columns (1) and (2) present the results with firm performance (*Sales*) as the dependent variable, and Columns (3) and (4) present those with firm value (*Tobin's q*) as the dependent variable. In line with the findings of previous research (e.g., Srinivasan & Hanssens, 2009), we document that total Kantar advertising has positive effects on both sales (0.242, $p < 0.01$) and firm value (0.239, $p < 0.01$). In addition, offline advertising shows positive effects on both sales (0.097, $p < 0.01$) and Tobin's q (0.270, $p < 0.05$).[13]

We now turn to testing our hypotheses. First, assessing the absolute effects of online display advertising (*DisplayAdStock*), we find significantly positive coefficients on both *Sales* (0.231, $p < 0.05$) and *Tobin's q* (0.880, $p < 0.01$); this result provides support for H1a and H1b. Second, we assess the relative effects when *Sales* is the dependent variable in Column (2) of Table 5. As expected, the coefficient for display advertising (0.231) is directionally more positive than that for offline advertising (0.097), but this difference is insignificant ($\chi^2 = 1.44$); thus, we fail to find support for H2a. However, when *Tobin's q* is the dependent variable (Column (4)), the coefficient for display advertising (0.880) is significantly more positive than that for offline advertising (0.270) ($\chi^2 = 3.28$), in support of H2b.

Note that these estimates for advertising's impact on Tobin's q (which capture the effects of advertising intensity) are similar in magnitude to previous research. For example, McAlister et al. (2016) report a firm value impact of 0.53 for advertising of differentiators, and Sridhar et al. (2016) report estimates of 0.12 for national advertising, 0.32 for online advertising, and 0.76 for regional advertising. Edeling and Fischer (2016) note that the optimality of advertising expenditure implies a firm value

[13] As further validation of the Kantar advertising data (i.e., the Kantar data are broadly representative of advertising investment by the sample firms), untabulated results using advertising from COMPUSTAT (as well as our sample observations and control variables) reveal the expected significantly positive coefficients between this latter variable and both *Sales* and *Tobin's q*. In addition, our results are unaffected by the choice of *AdStock* as operationalization of advertising variables versus unsmoothed advertising expenditures.

elasticity of zero, assuming that firms want to maximize shareholder value. An implication therefore is that firms do not set optimal advertising budgets, given that the (average) firm value elasticity estimates are higher than zero.[14]

Next, we examine the effects of paid search advertising. Focusing on the absolute effects, we find significantly positive coefficients for paid search advertising (*SearchAdStock*) both when *Sales* is the dependent variable (0.583, $p < 0.01$) and when *Tobin's q* is the dependent variable (0.562, $p < 0.10$); thus, we find support for H3a and H3b. For the relative effects, when *Sales* is the dependent variable, we find a significantly more positive coefficient for paid search advertising (0.583) than offline advertising (0.097) ($\chi^2 = 19.47$), in support of H4a. As Ailawadi (2018) notes, paid search elasticities, which are higher in magnitude than typical advertising elasticities, should be compared with distribution elasticities because paid search is more about finding products online rather than advertising; empirical generalizations in marketing indicate that distribution elasticities should be at least an order of magnitude higher than advertising elasticities (Hanssens, 2015). As expected, when *Tobin's q* is the dependent variable, the coefficient for paid search advertising (0.562) is directionally more positive than that for offline advertising (0.270), but this difference is insignificant ($\chi^2 = 0.66$); thus, we fail to find support for H4b.

Finally, we also assess the relative effects of paid search versus online display advertising. For the relative effects, when *Sales* is the dependent variable, we find a significantly more positive coefficient for paid search advertising (0.583) than online display advertising (0.231) ($\chi^2 = 6.75$). This result (see Table 5) indicates that paid search has a stronger impact than online display advertising on short-term firm performance. When *Tobin's q* is the dependent variable, the coefficient for online display advertising (0.880) is directionally more positive than that for paid search advertising (0.562), but this difference is insignificant ($\chi^2 = 0.56$).

5.3. Control variables

We next confirm that the control variables operate as expected. When *Sales* is the dependent variable, consistent with economies of scope and scale, we find that size (*Size*) consistently exhibits a significantly positive effect on sales. In addition, we find a similar positive effect for industry growth (*IndGrow*) (Haleblian & Finkelstein, 1993; McDougall et al., 1994). Although financial leverage (*Lev*) and industry turbulence (*IndTurb*) are insignificant (as in McAlister et al., 2016), we find a significantly positive coefficient on industry concentration (*IndConc*), consistent with the notion that concentrated industries have high market power.

When *Tobin's q* is the dependent variable, we find a significantly positive association with leverage (*Lev*), which increases firm value through either signaling or lower cost of capital. We also find a consistently positive association between profit (*Profit*) and firm value (Srinivasan, Pauwels, Silva-Risso, & Hanssens, 2009). In addition, size (*Size*) has a negative impact on firm value, consistent with “size” effects documented in both finance (Schwert, 1983) and marketing (McAlister et al., 2016). Industry concentration (*IndConc*) is positively associated with firm value, as concentrated industries offer improved opportunities to the firm (McDougall et al., 1994). Industry growth (*IndGrow*) is also positively associated with firm value, while industry turbulence (*IndTurb*) is insignificant (McAlister et al., 2016). Overall, the results for the control variables are consistent with prior research.

5.4. Robustness checks

We perform several robustness checks; in general, the results from these analyses are consistent with our primary results. First, we re-estimate the primary Eqs. (2) and (4), now using fixed effects instead of the random effects used in the primary analyses. Use of industry-fixed effects controls for industry-specific factors that may drive our outcome variables. Table 6 presents the results, with *Sales* as the dependent variable in Column (1) and *Tobin's q* as the dependent variable in Column (3). The estimates (and related inferences) are similar to those of our main models in Table 5.

Second, we supplement Eqs. (2) and (4) by including interactions between our three advertising variables: display, paid search, and offline advertising. These interactions account for different kinds of advertising varying in their ability to target consumers. In addition, this specification provides insights into the joint impact of the three advertising types to maximize the effectiveness of overall advertising expenditures. Columns (2) and (4) of Table 6 present the results. We again find similar coefficients to those of our main models (Table 5).

Regarding potential synergies across the advertising types, we find that the interactions of online display and paid search advertising with offline advertising are insignificant for both *Sales* and *Tobin's q*. Thus, we fail to find evidence of sub- or super-additive joint effects of display and paid search advertising with offline advertising. However, the interaction between online display and paid search advertising is significantly negative for *Sales* in Column (2) of Table 6 (−0.740, $p < 0.01$); this finding suggests that paid search advertising mitigates the marginal effect of display advertising (and vice versa) (Sridhar et al., 2016). When *Tobin's q* is the dependent variable (Column (4)), we fail to find a significant interaction between online display and paid search advertising.

There are several potential explanations for the sub-additive effect of online display and paid search advertising. Display and paid search serve inherently different purposes. For example, firms use display advertising to build awareness at the top of the purchase funnel, while they frequently use paid search advertising to create short-term sales conversions at the bottom of the purchase funnel (e.g., Dinner et al., 2014). Thus, display and paid search advertising may have sub-additive effects when used jointly from the potentially conflicting messages that can lead to consumer confusion. In addition, consumers' serial consumption of online content within a short period (multiplexing) makes it difficult for media planners to understand potential substitutions and

[14] That is, the model-recommended allocation of advertising expenditures across the different types based on the relative elasticities of online and offline advertising versus the actual allocation in the sample of firms differs.

complementarities (e.g., Jeong & Fishbein, 2007; Lin, Venkataraman, & Jap, 2013). This difficulty is exacerbated in the online channel, as browsing on the Internet consists of reiterated (1) typing of keywords into a search engine, yielding paid (and non-paid) search results, and (2) consuming website content, including display advertisements. Finally, Sridhar et al. (2016) suggest that the sub-additive effects within their setting likely capture opportunity costs of poor tactical and strategic integration across media. For example, different digital advertising personnel typically manage display and paid search advertising for a firm, often resulting in a lack of coordination and, thus, synergy. Furthermore, recent empirical studies present mixed evidence of the presence of synergy between display and paid search: Kireyev et al. (2016) document positive synergy for a commercial bank, whereas Pauwels, Demirci, Yildirim, and Srinivasan (2016) do not find a positive synergy between display and paid search advertising in the four industries analyzed (retail, travel services, furniture supplier, and scholastic preparation services).

As a third robustness check, we examine alternative measures of our key dependent variables *Sales* and *Tobin's q*. Specifically, for short-term performance, we replace *Sales*, a measure of top-line performance, with *Return on Assets*, a measure of bottom-line performance. The results, presented in Column (1) of Web Appendix B, are unchanged from our primary results. For long-term performance, we similarly replace *Tobin's q* with *Unlogged Tobin's q*. Recall that our primary analyses use logged *Tobin's q* so that we can interpret the coefficients as elasticities. Nonetheless, use of *Unlogged Tobin's q* provides similar results, as revealed in Column (2).

Fourth, we investigate longitudinal trends in the aforementioned associations. In particular, the absolute magnitude of online (offline) advertising has been increasing (decreasing) over time, suggesting potential temporal changes in the associations we documented. Accordingly, we define an indicator variable *LaterPeriod* as equal to 1 for sample years 2014–2016 and 0 otherwise (i.e., for sample years 2010–2013). For both analyses of short-term firm performance (i.e., dependent variable of *Sales*) and long-term performance (i.e., dependent variable of *Tobin's q*), we interact *LaterPeriod* with each of the advertising variables. Column (3) in Web Appendix B presents the results for *Sales* and Column (4) the results for *Tobin's q*. In general, we fail to find evidence of temporal changes in the previously documented associations; only online display advertising appears stronger in the later part of our sample period ($DisplayAdv \times LaterPeriod = 0.150$, $p < 0.10$). This result corresponds to our expectation that online display advertising better targets consumers than offline advertising (e.g., via behavioral targeting technologies), as targeting abilities have improved over time (e.g., due to real-time advertising).

6. Discussion

Advertising expenditures worldwide for 2018 are $628 billion, with substantial growth driven by online advertising (eMarketer, 2018). However, little is known about the impact of the key types of online advertising (display and paid search) on firm performance and firm value. Using a proprietary panel dataset of annual observations of display, paid search, and offline advertising expenditures for a broad cross-section of firms spanning 2010–2016, we fill this void by testing hypotheses on the absolute effects of online display and paid search advertising on firm performance and value, as well as their effects relative to offline advertising.

This research advances the advertising literature by documenting that display and paid search advertising exhibit positive effects on short-term firm performance (measured by current period sales) and long-term firm value (measured by Tobin's q). These insights complement prior research (e.g., Sridhar et al., 2016) documenting a positive association between sales and firm performance, with online advertising broadly defined, by revealing that these effects manifest across both types of online advertising, with each exhibiting both short- and long-term effects. Of note, this study also documents *relatively* greater positive effects of paid search and display advertising than that of offline advertising: paid search (online display) advertising exhibits more positive effects on firm sales (firm value) than offline advertising. Furthermore, the stronger effect for online display is accentuated in the latter half of our sample period, consistent with improving targeting abilities over time that enhance online display's superiority to offline advertising. Finally, while online display and paid search advertising share characteristics such as enhanced targeting, tracking, and placement, we show that paid search exhibits more positive effects on firm sales than online display. This latter effect likely arises because paid search is consumer-initiated and occurs close to the purchase decision. Furthermore, firms typically use paid search for performance marketing, aiming to generate a direct sales response.

Combined, these results are consistent with online display (paid search) advertising's differential advantage accruing from a long-term (short-term) perspective and superior targeting. Paid search's differential advantage on sales is likely to accrue because of its ability to control the placement context of the advertisement; this ability is confirmed through its significantly more positive effect than online display on sales. Additional tests verify the robustness of these associations. Collectively, our results add to marketing theory and contribute to the literature on the marketing–finance interface by shedding more light on both the absolute and relative economic effects of display and paid search advertising.

6.1. Practical implications

Our findings offer several implications for managers and financial statement users. First, when allocating advertising budgets, marketing managers should be aware that online display, paid search, and offline advertising differ in their effects on firm performance and firm value. Our evidence reveals a differential advantage of paid search (online display) over offline advertising with respect to short-term sales (long-term firm value). We find that a 1% increase in online display (paid search) advertising intensity increases sales by 0.23% (0.58%) and firm value by 0.88% (0.56%). Similarly, we find that a 1% increase in offline advertising intensity increases sales by 0.10% and firm value by 0.27%. These results reflect the stronger economic effects of display and paid search advertising than offline advertising. However, we caution that our analyses do not allow us to conclude about advertising budgets' extreme shifts (e.g., allocating all offline advertising expenditures to online paid search), given that we obtain the effects of online display and paid search advertising from a sample of firms that have already invested in offline advertising.

Second, we show that the emphasis of advertising in the firm accentuates the effectiveness of paid search advertising, at least in the short run. In addition, our finding on the sub-additive effects of display advertising and paid search advertising suggests that managers should strive to better integrate, both strategically and tactically, their online display and paid search advertising to build a cohesive message across advertising types to increase their individual and joint impact.

Third, our findings also are relevant to financial statement users. In particular, the results show considerable variation in how the different types of advertising map onto firm performance and firm value. Given the dearth of information on the types of advertising expenditures—particularly from firm-sourced disclosures such as financial statements—our findings suggest potential benefits to financial statement users from efforts to obtain and analyze firms' investments across the various advertising categories (display, paid search, and offline advertising).

6.2. Limitations and future research directions

We note that our findings are subject to several limitations, which provide avenues for future research. Of primary consideration, the Kantar advertising data come from advertising outlets rather than firm-sourced disclosures. Future research could validate the Kantar data and better map the disaggregated advertising expenditures onto different aspects of firm performance.[15] In addition, our findings assume that our designations of the Kantar fields as display, paid search, and offline advertising reasonably capture the economic distinction of these three broad categories of advertising expenditures. Future research could consider alternative methods to partition the data into these groupings as well as other types of online advertising, such as mobile or social media advertising. Research also could examine firm-level (and industry-level) characteristics that may lead to variation in our documented effects, such as by comparing multi-channel firms with both physical and online stores with only physical or only online stores. Finally, going beyond firm value as a key performance metric, future research could examine how balancing advertising expenditures across display, paid search, and offline advertising affects firms' risk exposure.

Overall, our findings confirm heterogeneous effects of online display, paid search, and offline advertising on both short- and long-term firm performance in the context of a wide cross-section of firms over a multi-year period. These findings should be useful to managers in their resource allocation decisions regarding advertising expenditures, to investors in their evaluation of firms, and to regulators in their ongoing assessment of appropriate disclosure requirements for firms for this critical outlay.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijresmar.2020.02.002.

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[15] Our results may reflect an aggregation bias given that we estimate regressions using annualized data, while managerial allocations to the three advertising types we investigate may occur on a more granular (e.g., weekly, monthly) level. However, firms typically work with annual or quarterly advertising budgets; managers may have flexibility to alter spending patterns on a daily/weekly basis, but our operationalization of advertising as annual expenditures from Kantar is aggregate in nature and therefore aligned with annual advertising budgets. Furthermore, we believe these constraints have direct effects on all types of advertising.

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