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Relating Online, Regional, and National Advertising to Firm Value

Firms spend billions of dollars on advertising every year but remain uncertain about allocation across various advertising vehicles. Allocation decisions are even more complex as online advertising has proliferated and consumers' media usage patterns have become more fragmented. To determine advertising effectiveness, the authors group firms' advertising vehicle choices into three theoretically grounded and empirically verified smaller subsets: national, regional, and online advertising. Subsequently, they assess how the three advertising vehicles independently and jointly affect firm performance. Using 12 years of data covering 662 manufacturing firms, the authors find that while national, regional, and online advertising each have a positive and significant main effect on firm performance, each advertising vehicle weakens the effectiveness of the respective other two advertising vehicles (e.g., a 1% increase in online advertising increases firm performance by .32% but also decreases national [.15%] and regional [.03%] advertising effectiveness). A battery of robustness checks triangulates this result. Although all three media vehicles contribute to net increases in performance, the authors discuss the need to strategically integrate them to maximize combined effectiveness.

Keywords: advertising effectiveness, media mix, marketing resource allocation, national/regional/online advertising

Firms are good at estimating the aggregate impact of advertising spending (Joshi and Hanssens 2010), in part because it involves such sizable investments.[1] However, advertising budgets remain almost static, placing increasing burden on appropriate allocation of advertising budgets across media (Danaher and Dagger 2013; Gordon, Basu, and Klapdor 2015).[2] Indeed, firms allocate advertising across several media vehicles to increase reach, brand awareness, sales, and profitability. Moreover, firms strive to build a cohesive message across all media vehicles to increase the individual and joint impact of media spending. Yet firms are uncertain about the disaggregate allocation of their advertising spending—that is, how to effectively allocate dollars across media vehicles (e.g., national, regional, online). This issue represents the focus of our study.

Achieving individual medium and combined media effectiveness with multimedia advertising spending is nontrivial. First, the Internet has facilitated the growth of online advertising in the last decade, and online advertising has moved from a peripheral to a central advertising medium because of its unique targeting capabilities (Doctorow, Hoblit, and Sekhar 2009; Goldfarb 2014, p. 115; Moorman 2013). Yet firms struggle to integrate online advertising into their traditional advertising allocation strategy (Danaher and Dagger 2013). Second, media spending complexity is compounded by the emergence of "media multiplexing" (Lin, Venkataraman, and Jap 2013), the notion that consumers are now "snacking on short amounts of time with different types of media channels" (Steinberg 2012). Moreover, consumers use multiple media simultaneously between 24% and 65% of the time they are using media (Foehr 2006; Pilotta et al. 2004). For example, an average U.S. consumer watches more than five hours of video content per day across televisions, computers, and mobile devices (eMarketer 2015). Consumers' media repertoires also display considerable heterogeneity (Hasebrink and Popp 2006), making prediction of multiplexing uncertain and therefore increasing the complexity associated with building a cohesive narrative across media vehicles (Lin, Venkataraman, and Jap 2013). In short, the rapidly changing media advertising landscape and increasing media multiplexing behavior make it challenging for firms to keep track of the individual and joint effectiveness of their media advertising spending. Against this backdrop, we revisit the fundamental problem of advertising resource allocation and empirically study the individual and interactive effects of disaggregate media spending on firm performance.

We first group firms' media vehicle choices (18 in all) into theoretically grounded, smaller subsets for parsimony in conceptual development and analysis. We integrate several detailed descriptions of media vehicles (Katz 2014, p. 9;

[1]In 2014, IBM and Apple each spent more than US$1 billion on advertising, Johnson & Johnson spent approximately US$2.5 billion, and Procter & Gamble spent more than US$9 billion during that same time period.

[2]We thank the area editor for highlighting this point.

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Kelley, Jugenheimer, and Sheehan 2015, p. 25; Naples 1979; Warner and Buchman 2003, pp. 361–62) and offer convergent arguments that media vehicles' objectives differ along three dimensions: (1) quantity of the reach, (2) quality of the reach, and (3) type of product message. We subsequently classify media vehicles into national (not restricted to a particular geographic region of the United States), regional (restricted to a particular geographic region of the United States), and online (search and display) media advertising and discuss how they differ along quality of reach, quantity of reach, and product message.[3]

We then discuss the interactive effects among media vehicles on firm performance. Interactive effects (whether superadditive or subadditive) are possible because consumers use multiple media vehicles in bits and pieces (Lin, Venkataraman, and Jap 2013) and thus can be targeted by the same firms through multiple media channels. Notably, prior research has provided support for both super- and subadditive interactive effects. For example, empirical evidence for superadditive effects (Jagpal 1981; Naik and Raman 2003) has shown that in competitive product-market settings, advertising in multiple media induces memory reinforcement. Specifically, consumers could recall a firm's advertisement in the first medium as a result of an advertisement in the second; thus, the firm's advertising across two media creates a joint persuasive effect, which is more than any one medium can achieve by itself. In contrast, the literature has also produced evidence for subadditive effects (e.g., Naik, Raman, and Winer 2005; Sridhar and Sriram 2015; Voorveld, Neijens, and Smit 2011). For example, different media vehicles are used for inherently different purposes. Indeed, whereas national advertising is frequently used for brand-building purposes, regional and online advertising are often used for promotional purposes (e.g., Bolton 1989; Popkowski Leszczyc and Rao 1989). In turn, national advertising often prompts price premiums, whereas regional and online advertising frequently erode price premiums. Thus, when used jointly, national and regional/online advertising may result in subadditive effects.

Given the potential for either positive or negative interactive effects, we employ a descriptive empirical approach deliberately. We rely on advertising data from Kantar Media's Ad$pender database, which breaks down total firm advertising across 18 media vehicles, and financial performance data from Compustat. We focus on manufacturing firms in the 2000s and 3000s standard industrial classification (SIC) industries, for which advertising plays an important role (Chauvin and Hirschey 1993). We concatenate data on a large sample of 662 firms (6,970 observations), for which we have yearly advertising spending data across 18 advertising vehicles and financial performance data covering 2001–2012.

[3]For proof of relevance, we verify that our classification is used by media content providers selling advertising spots, advertising salespeople seeking buyers, and data infomediaries selling third-party information to advertising agencies. We also conducted an exploratory factor analysis using firms' actual spending decisions to triangulate the classification.

We use Tobin's q to measure firm performance because it captures variation in a firm's market value, as well as the effect of changes in unmeasured intangible assets that might result from the firm's advertising (e.g., Giroud and Mueller 2011; Parcharidis and Varsakelis 2010). In our model, we control flexibly for observed and unobserved heterogeneity in firm performance. Moreover, because firms may set advertising allocations in anticipation of actual performance or as a result of unobserved factors, advertising may be endogenous to firm performance. Therefore, we use a control function approach (Petrin and Train 2010) with exclusion restrictions to correct for potential endogeneity bias.

As expected, we find that national, regional, and online advertising all have a positive and significant main effects on firm performance. However, we also find all two-way interaction effects among the three media types to be negative and significant, indicating that although each media advertising vehicle exerts a positive effect on performance, it also weakens the force of the respective other two media vehicles. A battery of robustness checks related to model specification, identification assumptions, and subsample analysis provide triangulation.

Through our study, we intend to make three main contributions: First, embracing the disaggregate nature of media spending in the new media era, we show empirical evidence of *subadditive* joint effects of national-regional, national-online, and regional-online spending. Although this seems to be counterintuitive given some prior documentation of superadditive benefits with single-firm samples (e.g., Naik and Raman 2003), our findings do resonate with extant research that has documented negative interactive effects between brand building and promotion advertising (Naik, Raman, and Winer 2005; Voorveld, Neijens, and Smit 2011), possibly because of their conflicting overarching messages, and research on the substitute relationship between offline and online advertising (Goldfarb and Tucker 2011; Sheehan and Doherty 2001; Sridhar and Sriram 2015).

Second, our analysis provides a basis for informed decisions on national, regional, and online adverting. For example, we find that a 1% increase in national advertising increases performance by .12%, but this performance increase is reduced by 4% with every 10% increase in regional advertising. Assessing such trade-offs could help firms allocate multimedia advertising to maximize individual and joint outcomes across all vehicles (Mantrala 2002) and execute them with strategic integration across vehicles (Sheehan and Doherty 2001).

Third, our findings indicate that firms continue to struggle to integrate online advertising into their traditional advertising allocation strategy (Danaher and Dagger 2013). Specifically, considering the subadditive interactive effects among the three advertising media types (national, regional, and online), our results suggest that online advertising's effectiveness is most negatively influenced by increases in national and regional advertising.

In the next section, we present the conceptual background. After we describe our data and methodology, we present our findings. Finally, we conclude by discussing the implications of our findings for marketing theory and practice.

Conceptual Background

In the following subsections, we first build a theoretical justification for our categorization of advertising as national, regional, and online. We then briefly discuss the expected main effects before arguing why the interactive effects among the types of advertising may be positive or negative.

Theory-Based Representation of Firms' Media Decisions

According to our comprehensive data (which we detail subsequently), firms use 18 media vehicles to target consumers.[4] It would be unreasonable to expect firms to measure advertising responses accurately across these 18 advertising vehicles and their combinations (there would be hundreds of combinations) and then set media budgets and allocations optimally for each period. However, classifying firms' media vehicle choices into smaller, manageable, and theory-based subsets of similar choices offers a pragmatic alternative. Accordingly, we grouped media vehicles using common denominators with respect to their goals.

From the classic work on media planning calculus by Little and Lodish (1969) to recent media advertising handbooks by Warner and Buchman (2003, pp. 361–62) and Katz (2014, p. 9), we learn that the broad goal of a media advertising portfolio is to reach (1) a sufficiently large and (2) high-quality audience, with (3) the appropriate type of advertising message. Thus, synthesizing foundational (e.g., Naples 1979) and recent summaries of advertising media types (e.g., Kelley, Jugenheimer, and Sheehan 2015, p. 25, Exhibit 4.2), we identify the following three criteria with which to categorize media advertising alternatives:

1. *Quantity of reach*, or the count of the captive audience (viewers, listeners, readers) that the firm obtains through an advertising spot, which is important for generating a threshold quantity of leads that eventually turn into purchases. The quantity of reach is of paramount importance to advertisers during multimedia advertising because it enlarges a firm's target group.
2. *Quality of reach*, or how well the media channel's reach is customized to fit the advertiser's specific target market in terms of future buying potential (e.g., demographics, psychographics), which is crucial for inducing purchase.
3. *Product message*, or how the advertiser aims to build in product differentiation by demonstrating a favorable comparison of key product attributes over a competitor. Broadly, advertisers are focused on product messages that either induce immediate effects (e.g., using promotional advertising to increase sales) or create or change consumer beliefs and attitudes (e.g., using advertising for brand building) (Vakratsas and Ambler 1999).

In line with the three criteria, we group the 18 media vehicles into national, regional, and online advertising. We next describe each kind of advertising and how it relates to the three criteria. We also synthesize this information in Table 1.

[4]Namely, cable, network, spot, syndicated, and Hispanic television; local, network, and national radio; local, national, Sunday, and Hispanic newspapers; consumer, business, local, and Hispanic magazines; outdoor advertising; and online advertising.

National advertising. We define media vehicles whose message and reach are not restricted to a particular geographic region of the United States as national media. We classify advertising through network television, Spanish language television, cable television, national spot radio, network radio, Hispanic magazines, Sunday magazines, national magazines, Hispanic newspapers, national newspapers, and business-to-business (B2B) magazines as national media advertising. National advertising is best suited for targeting a large mass audience (i.e., the quantity of reach dimension) because most national media are well-known and considered credible and familiar. However, targeting a mass audience means low specificity and high generality, which could limit the relevance of national advertising's reach. Achieving a high-quantity reach with low relevance enables national advertising to be useful to convey simple product concepts, making it suitable for brand-building purposes (e.g., Belch and Belch 2015, p. 20).

Regional advertising. We define media vehicles whose message and reach are restricted and customized to a particular geographic region of the United States as regional media. We classify advertising through local newspaper, local radio, local magazines, syndicated television, and spot television as regional media. Because regional advertising spots are viewed only by small but well-defined market segments, they are highly relevant to specific local demographics and lifestyle. However, because there is extreme fragmentation in regional media (e.g., up to 60 local radio stations), it could lead to a low-threshold quantity of reach for the medium (Warner and Buchman 2003). Finally, smaller reach lowers the price of a regional advertising slot, which in turn enables advertisers to provide more product/promotional information content in the message. Thus, the goal of regional advertising is usually to generate immediate sales and is thus more short-term focused (e.g., Bolton 1989; Popkowski Leszczyc and Rao 1989). For example, a local fast-food retailer might target a local radio advertising spot to announce a new promotion because it is most relevant to local residents.

Online advertising. We define Internet-based media advertising (i.e., search and display advertising) as online advertising. Unlike the other 17 vehicles, which are one-way forms of communication, online advertising is a technology-enabled, two-way form of dynamic communication (Goldfarb 2014). From a capabilities standpoint, online advertising's reach is ubiquitous (and can even include an international audience), but from a pragmatic perspective, online advertising's reach is limited by the volume of visits to the content-based website, or online search behavior. Moreover, because advertisers can track prior- and postimpression online behaviors of their consumers, the targetability and relevance of an online ad is superior to their offline counterparts. Finally, behavioral targeting technologies enable firms to tailor online display advertisements to consumers on the basis of their past browsing history, and therefore such advertisements are used to build brand awareness. By design, online advertising is thus better in targetability than traditional advertising media, and it often occurs closer to a user's

TABLE 1
Description of Media Types

Media Type	Categorization	Quantity of Reach	Quality of Reach	Product Message
National	Network television, Spanish-language television, cable television, national spot radio, network radio, Hispanic magazines, Sunday magazines, national magazines, Hispanic newspapers, national newspapers, and B2B magazines	National advertising is best suited for targeting a large mass audience (i.e., the quantity of reach dimension) because most national media are well-known and considered credible and familiar.	Targeting a mass audience means low specificity and high generality, which could limit the relevance of national advertising's reach.	National advertising is useful to convey simple product concepts, making it suitable for brand-building purposes.
Regional	Local newspaper, local radio, local magazines, syndicated television, and spot television	Because there is extreme fragmentation in regional media (e.g., up to 60 local radio stations), it could lead to a low-threshold quantity of reach for the medium.	Regional advertising is targeted only at small but well-defined market segments, and thus they are highly relevant to specific local demographics and lifestyles.	Smaller reach lowers the price of a regional advertising slot, which in turns enables advertisers to provide more product/promotional information content in the message.
Internet	Online search/display advertising	Quantity of reach is technically ubiquitous but limited by the volume of website visits.	Because advertisers can track prior- and postimpression online behaviors of their consumers, relevance could be superior to offline counterparts.	Online ads could be used for both brand-building and promotional information.

purchase decision (Hosanagar and Cherepanov 2008). Firms often use this immediate response feature to stimulate immediate sales through promotional advertising messages.

As proof of relevance, our classification of local, regional, and online advertising mirrors planning guides used by media advertising salespeople before they visit prospective media buyers (Warner and Buchman 2003, pp. 361–62). Moreover, our classification is mirrored by media content providers such as Comcast, which advertises its marketplace along regional, national, and online segments (https://business.comcast.com/spotlight). Finally, our classification of regional, national, and online advertising is also used by third-party data infomediaries, which sell reports of firms' advertising spending potential/forecasts to advertising agencies (https://www.borrellassociates.com/market-data/ad-spending-data). Thus, our classification is grounded in both theory and practice.

National, Regional, and Online Advertising and Firm Performance

We now focus on how national, regional, and online advertising affect firm performance. All else being equal, higher advertising spending is expected to increase firm performance for a variety of reasons. For example, advertising can increase purchase quantities, result in the acquisition of previously unaware prospects, lead to brand switching, and also result in retaining a larger fraction of the existing customer base (e.g., Dekimpe and Hanssens 2007, p. 248). Not surprisingly, there is evidence in the literature that suggests that the main effect of national advertising is positive (e.g., Anderson and Simester 2004; Dekimpe and Hanssens 1999; Hirschey 1982). Likewise, although evidence is less rampant, extant literature has also indicated that regional advertising boosts firm performance (e.g., Nowak, Cameron, and Krugman 1993; Reid et al. 2005). Finally, there is also sufficient evidence that online advertising positively influences firm performance (e.g., Agarwal, Hosanagar, and Smith 2011; Agarwal, Athey, and Yang 2009). Thus, all three media are expected to have a positive impact on firm performance. However, because we aim to understand how firms should consider the joint impact of national, regional, and online advertising so as to maximize the effectiveness of their overall advertising budget, we next consider the interactive effects among the three types of advertising.

Interactive Effects Among National, Regional, and Online Advertising

Arguments can be made for both positive and negative interaction effects among the three media types. We elaborate on these in the following subsections.

Arguments for positive interaction effects among media. The underlying basis for predicting a positive interactive effect between any two types of media spending is that firms might accrue superadditive benefits by spending in two separate advertising media (e.g., Naik and Peters 2009). A positive interaction effect between two media (e.g., regional and online) means that, all else held equal, the marginal effect of spending in one of the media channels is enhanced by spending in the other medium.

The intuition for superadditive effects is that consumers view multiple media in bits and pieces (Lin, Venkataraman, and Jap 2013) and also that consumers frequently see advertising from the same firm across two media channels (Naik and Raman 2003). However, because of the temporal gap between the first media advertisement and the second media advertisement, the consumer might forget the exact nature of the advertisement or product by the time (s)he sees the advertisement in the second medium (Raman 2006). Indeed, the phenomenon of consumers forgetting advertisements because of excessive exposure to advertising within and across media channels and competitive interference is well-documented (Burke and Srull 1988). Thus, consumers might view advertising from a firm in one medium but forget the exact nature of the advertising or product. However, when a consumer sees an advertisement from the same firm in another medium, it can lead to memory reinforcement effects, whereby the consumer remembers the previous advertisement because of the second advertisement and thus purchases the firm's product as a result of the joint persuasiveness of both advertisements. Thus, the first advertising media's effectiveness is enhanced because of the presence of the second media, creating positive interactive effects. Extant research has documented positive interactive effects between radio and newspaper advertising (Jagpal 1981), television and radio ads (Edell and Keller 1989), television and print advertising (Naik and Raman 2003), and offline and online advertising (Naik and Peters 2009).

Arguments for negative interaction effects among media. The underlying basis for predicting a negative interactive effect between any two types of media spending is that firms might accrue subadditive benefits by spending in two separate advertising media (e.g., Sridhar and Sriram 2015). Specifically, a negative interaction effect between two media (e.g., regional and online) means that, all else held equal, the marginal effect of spending in one of the media channels is mitigated by spending in the other medium.

One intuition for subadditive effects is that the media vehicles are used for inherently different purposes. For example, national advertising is typically used for brand-building purposes, whereas regional as well as online advertising are often used for promotional purposes (e.g., Bolton 1989; Popkowski Leszczyc and Rao 1989). Because of its brand-building focus, national advertising often attempts to establish a brand's sustainable competitive advantage in the marketplace and thus create brand equity and price premium advantages in the long run. However, regional and online advertising often have a promotional focus and are frequently used to create short-term advantages (e.g., through sales bumps), even at the cost of brand equity and price premiums (e.g., Naik, Raman, and Winer 2005; Voorveld, Neijens, and Smit 2011). Thus, the focus of regional and national advertising may be inherently different from the focus of national advertising. Therefore, national and regional/online advertising may yield conflicting messages and confuse consumers when used jointly (i.e., the positive marginal effect of spending in one of the media channels is mitigated by spending in the other medium), thereby resulting in subadditive effects.

A second intuition for subadditive effects rests on the notion that strategic and tactical integration (e.g., Sheehan and Doherty 2001) among the various media firms likely becomes increasingly complex as the number of media firms increases. Strategic and tactical integration are the hallmarks of integrated marketing communication; strategic integration refers to maintaining an overarching communication theme among the various media employed, whereas tactical integration refers to having consistency with retrieval cues (e.g., key visuals, distinctive slogans) among the media (e.g., Deighton 1996; Keller 1996; Sheehan and Doherty 2001). Indeed, each medium has its own characteristics in terms of information richness and message delivery (e.g., Belch and Belch 2015, p. 367), rendering thematic integration among various media a complex task. Importantly, lack of thematic integration likely confuses consumers, resulting in subadditive effects. Moreover, thematic integration is likely even more complex in today's media landscape, in which consumers multiplex (Lin, Venkataraman, and Jap 2013). That is, as consumers pay increasingly less attention to the various media to which they are exposed, they are more likely to miss integrative elements of the various ads (e.g., the overarching communication theme), amplifying the confusion and thus the potential subadditive effects. Indeed, critics have pointed out that multiplexing inhibits consumer attention to firms' advertising across media and mitigates interaction effects (Jeong, Hwang, and Fishbein 2010).

Extant research in single-firm contexts has documented negative interaction effects between brand building and promotion advertising (Naik, Raman, and Winer 2005; Voorveld, Neijens, and Smit 2011). Moreover, the literature offers evidence that advertisers may perceive subadditive benefits from spending in online and offline media (Goldfarb and Tucker 2011; Sridhar and Sriram 2015).

In summary, it is unclear whether to expect positive or negative interactive effects among national, regional, and online advertising. Accordingly, our approach is deliberately descriptive. We take no stance on the nature of the interaction effects among local, national, and online media. Instead, we let the empirical analysis reveal whether, on average, interaction effects are negative or positive.

Method

Data Sources

We use Kantar Media's Ad$pender, an advertising database that tracks firm-level media advertising expenditures, as our data source. Ad$pender breaks down a firm's media advertising into 18 media vehicles, spanning television (cable, network, Hispanic, spot, and syndicated), radio (local, network, and national), magazines (business to customer, B2B, local, Hispanic, and Sunday), newspapers (local, national, and Hispanic), Internet, and outdoor. We focus on manufacturing firms in the 2000s and 3000s SIC code industries because of advertising's important role in these firms, compared with other industries such as agriculture, mining, or construction (e.g., Chauvin and Hirschey 1993; Mizik and Jacobson 2003). We concatenate the data on firm performance and other control variables obtained from the Compustat annual database with the advertising data from Ad$pender.[5] After manual data collection and concatenation, and after removing firms with fewer than three years of data (performance, advertising spending, or control variables), our sample consisted of 662 firms and 6,970 observations over a 12-year period (2001–2012).

Dependent Variable

We sought a dependent variable that could capture not only variation in a firm's market value but also the effects of variations on unmeasured, intangible assets (Bharadwaj, Bharadwaj, and Knosynski 1999) resulting from advertising, such as enhanced goodwill, brand equity, or loyalty. Therefore, we used Tobin's q as our performance measure. This capital market–based measure is appropriate for our study for several reasons. First, advertising investments have short- and longer-term performance impacts (Sethuraman, Tellis, and Briesch 2011). Short-term measures, such as return on assets or sales growth, fail to capture the longer-term effects, whereas Tobin's q reflects the firm's expected long-term profitability (Smirlock, Gilligan, and Marshall 1984). It incorporates all information about the firm's expected future earnings and is thus a performance measure that is forward looking, risk adjusted, and cumulative (Mittal et al. 2005). Second, because it is a capital market–based measure, Tobin's q is not affected by accounting conventions but instead adjusts for industry-specific performance idiosyncrasies. Third, Tobin's q is agnostic about organizational goals, so it allows for performance comparisons across firms that pursue different performance goals (e.g., growth vs. profits). By using Tobin's q, we can compare firms' performance across the various organizations and industries in our sample (Montgomery and Wernerfelt 1988). Fourth, as a market-based measure, Tobin's q is not vulnerable to distortions from tax laws or latitude in interpreting regulations (Montgomery and Wernerfelt 1988). Unsurprisingly, Tobin's q has gained wide acceptance as a measure of economic performance (e.g., Giroud and Mueller 2011; Parcharidis and Varsakelis 2010). Consistent with Chung and Pruitt's (1994) method, we operationalize Tobin's q as

$$\text{(1)} \qquad \text{Tobin's q} = \frac{\text{MVE} + \text{PS} + \text{DEBT}}{\text{TA}},$$

where MVE is the closing prices of shares at the end of the fiscal year × number of common shares outstanding, PS refers to the liquidation value of outstanding preferred stock, DEBT is the value of the firm's debt, and TA is the book value of total assets.

Media Advertising Variables

We rely on advertising data from Kantar Media's Ad$pender database to collect our media advertising variables. Specifically, we directly measured online advertising spending from the Ad $pender database. Moreover, we classify advertising through local newspaper, local radio, local magazines, syndicated television, spot television, and outdoor (billboards) as regional media, and we classify advertising through network television, Spanish-language television, cable television, national spot radio, network radio, Hispanic magazines, Sunday magazines, national magazines, Hispanic newspapers, national newspapers, and B2B magazines as national media advertising.

As discussed previously, national and regional advertising differ conceptually on the quantity of reach, quality of reach, and product message. Moreover, we also conducted an exploratory factor analysis of the 17 offline media vehicles to determine whether clusters of firms' spending behavior matched our conceptual classifications. Because two factors explained 96% of the variation in spending, we inferred that a two-factor solution was best. We present the dominant factor loading, as well as the uniqueness in the factor loading associated with each media vehicle, in Table 2. We note that 14 of the 17 factor loadings map on the conceptual classification, triangulating our classification.

We divided each advertising dollar measure by the firm's total sales. This advertising-to-sales ratio mirrors how firms approach advertising budgeting in practice, and marketing literature is replete with evidence of this usage (e.g., Lilien and Little 1976). Because advertising decisions are complex and involve multiple trade-offs in dynamic and turbulent business environments (Mantrala 2002), firms rely on this rule of thumb to simplify their advertising decisions (Doctorow, Hoblit, and Sekhar 2009). The advertising-to-sales ratio also is costless to replicate, and dividing dollars of advertising spending by sales enables normalization across firms while still empirically documenting spending effectiveness. This feature is necessary for our sample, which contains many firms that vary greatly in size. Finally, we log-transformed the advertising-to-sales ratios (after adding 1 to obtain uniformly positive values), as is common in studies of the advertising–performance relationship (e.g., Doyle and Saunders 1990) to allow for diminishing returns to spending.[6]

Media Advertising Patterns

On average, in any given firm-year, national media spending received 70% of the advertising budget ($22.6 million), regional media spending accounted for 27% ($8.0 million), and online media received 5% ($1.6 million). Thus, national media received the largest share of the media budget, on average. In the plots in Figure 1, Panels A–D, we present temporal spending patterns. Online advertising grew the fastest, with an average year-over-year growth rate of 14.4%, more than four times that of national media advertising (3.0%) and significantly higher than regional advertising (−1.1%). Moreover, online advertising showed positive annual growth in 11 of the 12 years in the sample, while national advertising and regional showed positive annual growth in 6 of the 12 years each. We verified the general trend of fast-rising online advertising, slow-rising national advertising, and steady regional advertising with advertising-to-sales ratios (which we used to calibrate the model).

[5]In the manual data collection from Ad$pender, a researcher entered a query (firm name, as represented in Compustat), and Ad $pender returned disaggregate advertising spending results, if available. Concatenation required an exact match of firm names between both databases.

[6]Results about the main and interactive effect hold when we use raw spending figures as well, which we assessed as robustness.

TABLE 2
Exploratory Factor Analysis of Individual Media

Media Type	Conceptual Classification	Factor 1 Loading	Factor 2 Loading	Uniqueness
Network TV	National	**.91**		.08
Spanish-language TV	National	**.90**		.09
Cable TV	National	**.92**		.05
National spot radio	National	**.63**		.22
Network radio	National	**.82**		.25
Hispanic magazines	National	**.63**		.55
Sunday magazines	National	**.51**		.70
National magazines	National	**.80**		.18
Hispanic newspapers	National	**.71**		.17
National newspapers	National		**.58**	.61
B2B magazines	National	.07	.21	.95
Local outdoor (billboard)	Regional		**.73**	.12
Local newspaper	Regional		**.46**	.60
Local radio	Regional		**.46**	.20
Local magazines	Regional		**.76**	.43
Syndicated TV	Regional	**.93**		.12
Spot TV	Regional	**.87**		.22

Notes: Factors 1 and 2 combine to explain 96% of the variation. Numbers in boldface represent dominant loadings.

We present evidence of cross-sectional heterogeneity in advertising spending in Figure 2, Panels A–C. In Panel A, we plot the distribution of total spending by SIC on national media advertising, while in Panels B and C, we plot the distribution of spending by SIC on regional and online advertising, respectively. We observe that across all types of advertising, there is a good representation of small, medium, and large levels of spending.

Overall, these data suggest that media spending vehicles are well represented across industries in our sample. National media advertising always commands the largest share of advertising spending; online advertising is the fastest-growing media.

Control Variables

To the extent that a firm's performance might be driven by size effects, such as economies of scale or scope, we follow extant research and control for a firm's total assets, financial leverage, and total debt (Fama and French 1988; Rao, Agarwal, and Dahlhoff 2004) before assessing the effects of advertising on performance. Moreover, the performance effects of media spending might be influenced by market- and competition-related factors in the industry (e.g., McAlister et al. 2016; Sethuraman, Tellis, and Briesch 2011), and we therefore include industry competitive intensity and industry munificence as additional control variables. We note that we measured industry competitive intensity using the reciprocal of the Herfindahl index (we use the reciprocal so that higher values reflect greater competitive intensity [e.g., Anderson, Fornell, and Mazvancheryl 2004]). Furthermore, following Dess and Beard (1984), we measured industry munificence by regressing time (t) against industry sales for the five years preceding t. Subsequently, we divided the regression slope coefficient by the mean sales value to obtain the value of munificence per industry and year. In Table 3, we provide the descriptive statistics, which indicate a low correlation among the predictor variables and thus a low multicollinearity threat.

Empirical Strategy

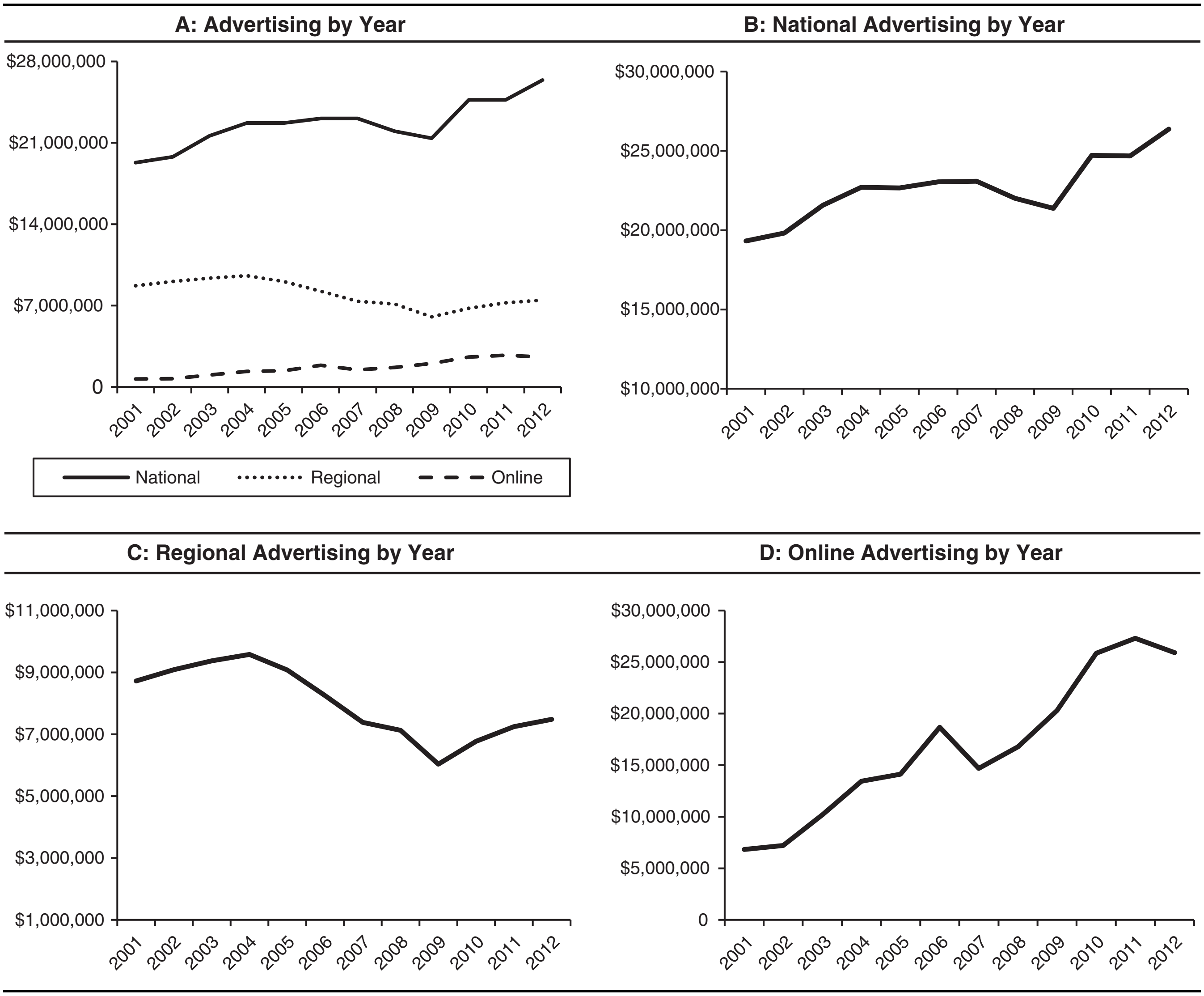
In our panel data setting, we observe firms' performance and media advertising decisions over multiple years. We seek a robust, conservative assessment of the effects of their media advertising decisions on performance and therefore test the main and interaction effects of national, regional, and online advertising. Thus, for a firm i in year t, we estimate the following model:

$$\text{(2)} \quad \begin{aligned} PERF_{it} = {} & \alpha_0 + \alpha_1 NATIONAL_{it} + \alpha_2 REGIONAL_{it} \\ & + \alpha_3 ONLINE_{it} + \alpha_4 NATIONAL_{it} \\ & \times REGIONAL_{it} + \alpha_5 NATIONAL_{it} \\ & \times ONLINE_{it} + \alpha_6 REGIONAL_{it} \\ & \times ONLINE_{it} + \varepsilon_{it}, \end{aligned}$$

where α_0 captures the intercept term; α_1–α_3 represent the main effects of national, regional, and online advertising, respectively; α_4–α_6 represent the interactions between national and regional advertising, national and online advertising, and regional and online advertising, respectively; and ε_{it} is a random error term.

This simple model suffers from two challenges. First, firm performance depends on myriad factors, including idiosyncratic firm characteristics and temporal variation in environmental factors (e.g., recessions; Gordon, Basu, and Klapdor 2015). Second, firms might make advertising decisions strategically, in anticipation of actual performance or other unobserved factors (e.g., how much competitors spend). To the extent that some of the unobserved factors that drive media advertising decisions are also correlated with the error term (e.g., competitors' advertising decisions could lower the focal firm's performance), they render advertising decisions endogenous to performance. In the presence of such potential endogeneity, the coefficients pertaining to advertising effectiveness could be biased and

FIGURE 1
Temporal Plots of Media Spending



inconsistent. Moreover, the presence of omitted variables that drive strategic marketing decisions are a source of first-order endogeneity (Rossi 2014) in empirical marketing models. Thus, to mitigate this problem, we specify a richer model:

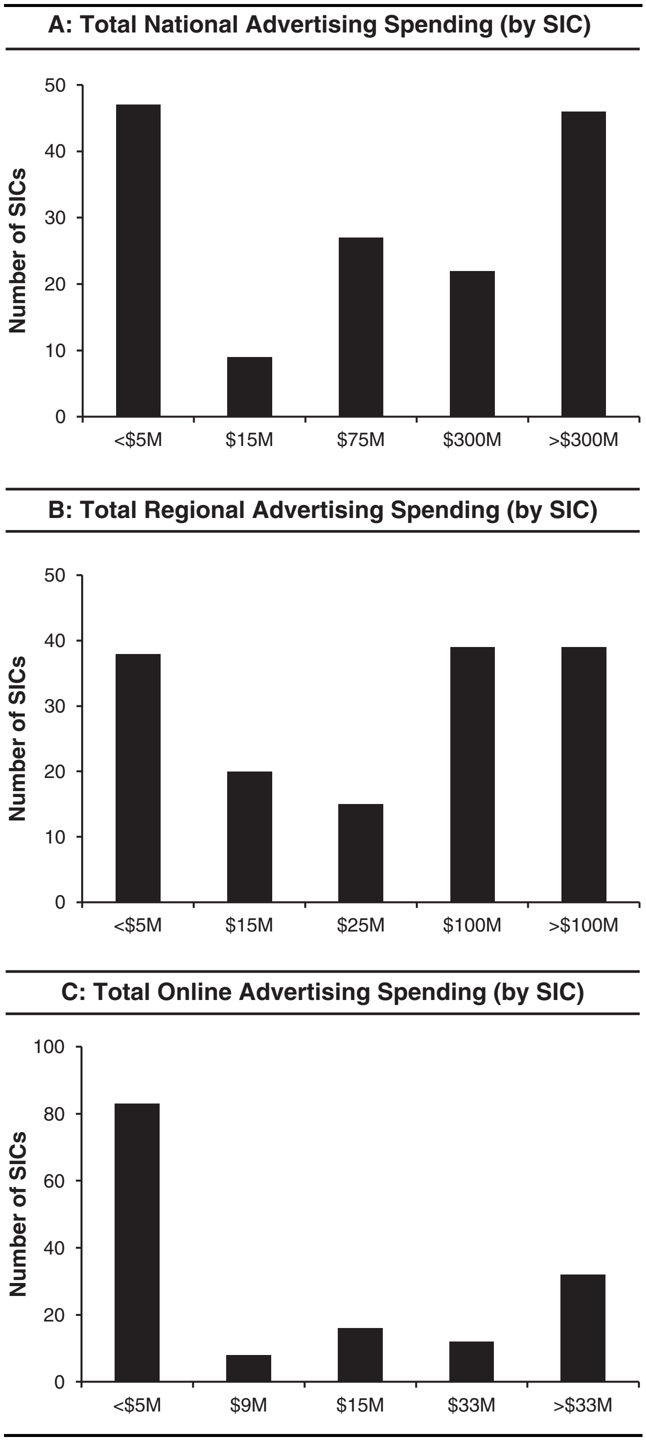
$$
\begin{aligned}
(3)\quad \mathrm{PERF}_{it} = {} & \alpha_{0i} + \alpha_1 \mathrm{NATIONAL}_{it} \\
& + \alpha_2 \mathrm{REGIONAL}_{it} + \alpha_3 \mathrm{ONLINE}_{it} \\
& + \alpha_4 \mathrm{NATIONAL}_{it} \times \mathrm{REGIONAL}_{it} \\
& + \alpha_5 \mathrm{NATIONAL}_{it} \times \mathrm{ONLINE}_{it} \\
& + \alpha_6 \mathrm{REGIONAL}_{it} \times \mathrm{ONLINE}_{it} + \boldsymbol{\alpha_7 Z_{it}} + u_{it}.
\end{aligned}
$$

Equation 3 improves on the previous specification along two dimensions. First, we include the set of control variables captured in $\mathbf{Z_{it}}$ (total assets, total debt, financial leverage, industry competitive intensity, and industry munificence, all of which could drive firm performance) as well as year fixed effects through the coefficient vector $\boldsymbol{\alpha_7}$. Second, we rewrite ε_{it} from Equation 2 as $\varepsilon_{it} = \alpha_{0i} + u_{it}$, where α_{0i} represents a firm random intercept and u_{it} is a random error term. The random intercept α_{0i} captures mean unobserved firm performance and is a parsimonious way to parameterize unobserved heterogeneity around firm performance.

Control Function Approach

Even with extensive control variables that reflect observed heterogeneity in firm performance, we cannot capture all omitted variables that influence media advertising decisions. Instead, it would be ideal to include the institutional details of the setting to generate exclusion restrictions to mitigate endogeneity caused by omitted variables bias. We thus use the control function approach, as recommended by Petrin and Train (2010). We introduce a new variable, corresponding to each of the three endogenous independent variables (control function correction) in Equation 3 (i.e., national, regional, and online adverting). After accounting for the influence of

FIGURE 2
Histograms (Highest- and Lowest-Spending SIC Codes)



the control function correction on firm performance, the endogenous independent variable should no longer correlate with the error term in Equation 3. When the control function correction enjoins Equation 3, the independence assumption pertaining to the potentially endogenous variable becomes established, and endogeneity is mitigated.

Obtaining the control function corrected estimates requires two steps. First, we perform an auxiliary estimation with the potentially endogenous variable as the dependent variable and find variables that could satisfy the exclusion restriction, such that they correlate with media advertising decisions but do not *directly* correlate with unobserved determinants of firm performance. The predicted residuals from the auxiliary estimation provide a control function correction in the main estimation.

We estimate three auxiliary estimations (national, regional, and online adverting), using the average spending on that media by other firms in the same four-digit SIC code as the excluded variable. Spending by other firms in the same industry is commonly used as an excluded variable (Lev and Sougiannis 1996). The identifying assumption is that industry advertising levels remain unaffected by firm-level idiosyncratic shocks and cannot correlate strongly with the residuals in Equation 3 (Lev and Sougiannis 1996). Although a firm's focal competitor's advertising might directly affect the focal firm's performance (and thus affect its performance shock), it is highly unreasonable that the industry's overall average directly correlates with a firm's demand shock because the industry average spending represents the collective sentiment of the industry's wisdom with respect to whether advertising needs to be increased or decreased. Industry spending could be a function of myriad factors, including past sales growth, future sales growth, anticipated competitor attacks from other industries, recessions, and product demand in the industry, among others (for a study of advertising budgeting, see Piercy [1987]). We instead expect high correlations across a firm's national, regional, and online adverting and the respective industry averages because they are guided by similar norms. For example, firms know that they should invest their advertising dollars into the media that offer the highest growth potential rather than the media that have traditionally performed well (Gordon, Basu, and Klapdor 2015). Because this construct is difficult to assess, firms are known to look to their peers to guide their marketing actions, as they assume that their peers' decisions might reflect important economic information (Banerjee 1992; Bikhchandani, Hirshleifer, and Welch 1992).[7] Our auxiliary estimations are given by the following:

[7]We also used a second set of excluded variables based on growth in audience for each media advertising outlet. Data from 2001 to 2012 revealed that the (1) average viewership of national newspapers, cable television, and average weekly radio audience as drivers of national advertising; (2) average readership of local newspapers and local television as drivers of regional media spending; and (3) average Internet penetration are drivers of online advertising. All data came from Pew Research Center's "State of the News Media" annual survey (Mitchell 2015), a prominent and credible source of U.S. media usage. Firms need to internalize audience growth in individual media, which should directly influence their individual media budgets but should relate only indirectly to firm performance shocks. Audience growth metrics drive firms' media advertising decisions, which in turn drive firm performance. Our results remain robust even when we include these additional variables.

TABLE 3
Descriptive Statistics and Correlation

Variable	Mean	SD	Correlations								
Tobin's q	1.53	1.14	1.00								
National advertising	.14	.24	.11	1.00							
Regional advertising	.10	.17	.13	.40	1.00						
Online advertising	.02	.07	.09	.34	.21	1.00					
Total assets	8,066.14	26,196.79	–.10	.10	.00	.02	1.00				
Total debt	2,303.97	11,654.09	–.09	.09	.03	.02	.92	1.00			
Financial leverage	.55	10.66	.00	–.01	.00	.00	.02	.02	1.00		
Industry competitive intensity	.90	.92	.09	.22	.11	.07	–.02	.00	.00	1.00	
Industry munificence	.01	.09	.09	–.03	–.01	–0.02	.03	.02	.00	.03	1.00

Notes: Advertising is measured by ln(1 + x/s), where x is the actual dollars spent in that medium (e.g., national advertising), and s is the sales in dollars.

$$\text{(4a)} \qquad \text{NATIONAL}_{it} = \beta_{01i} + \beta_{11}\text{IND\_NATIONAL}_{it} + \boldsymbol{\beta_{21}}\mathbf{Z_{1it}} + \mu_{1it},$$

$$\text{(4b)} \qquad \text{REGIONAL}_{it} = \beta_{02i} + \beta_{12}\text{IND\_REGIONAL}_{it} + \boldsymbol{\beta_{22}}\mathbf{Z_{2it}} + \mu_{2it},$$

$$\text{(4c)} \qquad \text{ONLINE}_{it} = \beta_{03i} + \beta_{13}\text{IND\_ONLINE}_{it} + \boldsymbol{\beta_{23}}\mathbf{Z_{3it}} + \mu_{3it}.$$

In Equation 4a, the fixed effect β_{01i} captures firm-specific heterogeneity in national advertising, β_{11} represents the effect of industry national advertising (IND_NATIONAL), the coefficient vector $\boldsymbol{\beta_{21}}$ captures the impact of the set of control variables $\mathbf{Z_{1it}}$ (total assets, total debt, financial leverage, industry competitive intensity, and industry munificence, year fixed effects), and μ_{1it} is a random error term. The same intuition applies to Equations 4b and 4c, which capture the auxiliary regressions pertaining to regional and online advertising, respectively. We then estimate the model in Equation 3 with the three predicted residuals from Equations 4a–c. Thus, our final model is

$$\text{(5)} \qquad \text{PERF}_{it} = \alpha_{0i} + \alpha_1\text{NATIONAL}_{it} + \alpha_2\text{REGIONAL}_{it} + \alpha_3\text{ONLINE}_{it} + \alpha_4\text{NATIONAL}_{it} \times \text{REGIONAL}_{it} + \alpha_5\text{NATIONAL}_{it} \times \text{ONLINE}_{it} + \alpha_6\text{REGIONAL}_{it} \times \text{ONLINE}_{it} + \boldsymbol{\alpha_7}\mathbf{Z_{it}} + \boldsymbol{\delta}\widehat{\boldsymbol{\mu}_{it}} + u_{it},$$

where the vector $\boldsymbol{\delta}$ captures the effect of the three predicted residuals in the vector $\widehat{\boldsymbol{\mu}_{it}}$ from the auxiliary regressions pertaining to national, regional, and online advertising.

Results

We provide the results of the auxiliary media advertising regressions in Table 4. Industry average spending is a significant driver of national, regional, and online spending, respectively, which is important for ensuring the legitimacy of the control function approach.

Main Effects

In Table 5, we present Model 1, which employs a firm random-effects specification along with year fixed effects. The overall model is significant (the Wald test for the model is significant at $p < .001$), and the variance inflation factors range from 1 to 4.66, indicating a low threat of multicollinearity. The results suggest that two control variables—the firm's total assets (b = –.000001, $p < .05$) and industry munificence (b = .208, $p < .10$)—explain variation in firm performance. Turning to the focal variables of interest, we find a strong positive main effect for regional advertising (b = 1.285, $p < .01$) and online advertising (b = .867, $p < .05$) and a weaker positive main effect for national advertising (b = .278, $p < .10$).

Interaction Effects

As discussed previously, the signs of the interaction effects among national, regional, and online media advertising are unclear a priori. However, the estimates in Model 1 suggest a negative and significant interaction between national and regional advertising (b = −.638, $p < .05$), national and online advertising (b = −1.548, $p < .05$), and regional and online advertising (b = −1.701, $p < .05$). These results suggest an interesting trade-off: each of the three types of media advertising exerts positive effects on firm financial performance of its own accord but weakens the force of the other two media. We verify the result with several robustness tests.

Robustness Analyses

Model 2: firm fixed effects. We first estimated a model with firm fixed effects instead of firm random effects. The identifying assumption for this model is that firm fixed effects pick up time-invariant sources of unobserved heterogeneity, which might induce an endogeneity bias, and that such a specification again places less burden on the control function approach because it serves only to condition out the time-varying sources of unobserved variation that correlate with the error term. The results of Model 2 in Table 5 are similar to those of the retained Model 1, in support of the stability of the results.

Model 3: firm random effects, no year fixed effects. We estimated a model with firm random effects and without year fixed effects. Our rationale was that the year fixed effects might soak up most of the variation in the data and the resulting variation might be too sparse to identify the effects.

TABLE 4
Excluded Variables Regression

	National Advertising Auxiliary Regression	Regional Advertising Auxiliary Regression	Online Advertising Auxiliary Regression
Industry average spending	.710***	.733***	.773***
	(85.00)	(60.57)	(58.04)
Total assets	.00000113***	−.000000347**	.000000147**
	(6.19)	(−2.22)	(2.37)
Total debt	−.00000153***	.000000769**	−.000000243
	(−3.73)	(2.19)	(−1.74)
Financial leverage	−.0000558	.0000438	−.0000208
	(−.31)	(.28)	(−.34)
Competitive intensity	.00102	.000735	.000638
	(.47)	(.41)	(.89)
Munificence	−.0136	.00242	−.00210
	(−.64)	(.13)	(−.29)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Intercept	.000217	.0101***	.000640
	(.07)	(3.70)	(.65)

*$p < .05$.
**$p < .01$.
***$p < .001$.
Notes: t-statistics in parentheses. N = 6,914.

By allowing no year fixed effects, we free up more temporal variation in the data. The identifying assumption for this model is that firm random effects pick up time-invariant sources of unobserved heterogeneity. The results of Model 3 in Table 5 are similar to those of the retained Model 1.

Model 4: firm fixed effects, no year fixed effects. We also estimated a model with firm fixed effects, but no year fixed effects, following a rationale similar to Model 3. The identifying assumption for this model is that firm fixed effects pick up time-invariant sources of unobserved heterogeneity. Again, the results of Model 4 are consistent with Model 1.

Models 5, 6, 7, and 8: other robustness checks. As for further robustness checks, in Table 6 we present the results of a model without endogeneity corrections (Model 5), a model that dropped a random subset of 10% of the firms (Model 6), a model that dropped years 2001 and 2002 from the analysis (Model 7), and a model that dropped years 2011 and 2012 from the analysis (Model 8). Across all models, our substantive results are unchanged: each of the three types of media advertising exert positive effects on firm financial performance of their own accord but weaken the effects of the other two media.

Discussion

Firms spend massively on advertising but remain uncertain about how best to allocate their advertising dollars among the various media vehicles available to them. This uncertainty has grown with the proliferation of online advertising, which requires firms to investigate how online advertising affects their performance as well as the potential synergies across online and other media vehicles. Although researchers have devoted substantial effort to understand the performance implications of advertising (e.g., Joshi and Hanssens 2010; Sethuraman, Tellis, and Briesch 2011), no study that we are aware of has systematically explored the joint (interactive) effects among online advertising and other types of traditional media vehicles.

We use a theory-based classification of media advertising channels to group extant media vehicles into national, regional, and online media. Moreover, we use a descriptive approach deliberately to investigate the interaction effects among media spending, and we use data on firms' disaggregate media advertising decisions to show how the various forms of advertising influence firms' performance both individually and jointly. Our findings have implications for both theory and practice, which we discuss in the following subsections.

Theoretical Implications

Our study contributes to marketing theory in several ways. First, extant literature has shown that advertising budgets have remained fairly static in recent years (Danaher and Dagger 2013), placing an increased burden on getting media allocations right. However, media allocation is nontrivial, and it has become even more complex in recent years as a result of the emergence of online advertising. Moreover, although extant studies have extensively examined the aggregate impact of advertising spending (e.g., Joshi and Hanssens 2010; Sethuraman, Tellis, and Briesch 2011), they do not provide any guidance in terms of optimal advertising allocation across various media. Thus, by embracing the disaggregate nature of the media spending decision, we document the relative performance effects of different classes of media vehicles, as well as their interactive effects. Furthermore, our theory-based classification of media vehicles as national, regional, and online, which we triangulate through popular press evidence as well as exploratory factor analysis, offers a useful template for studying media allocation in the new media era.

TABLE 5
Estimation Results

	Model 1: Random Effects, Year Fixed Effects	Model 2: Firm Fixed Effects, Year Fixed Effects	Model 3: Random Effects, No Year Fixed Effects	Model 4: Firm Effects, No Year Fixed Effects
Total assets	−.00000506**	−.00000468*	−.00000552**	−.00000582***
	(−2.99)	(−2.31)	(−2.66)	(−3.38)
Total debt	.00000361	.00000368	.00000460	.00000430
	(1.17)	(1.10)	(1.33)	(1.36)
Financial leverage	.0000498	.00000137	.0000150	.0000628
	(.06)	(.00)	(.02)	(.07)
Industry competitive intensity	.0179	−.151*	.111	.0712*
	(.56)	(−2.32)	(1.79)	(2.21)
Industry munificence	.208	.0760	.342**	.445***
	(1.74)	(.63)	(2.85)	(3.75)
National advertising	.278	.254	.458*	.299
	(1.77)	(1.25)	(2.17)	(1.86)
Regional advertising	1.285***	1.187***	2.124***	2.046***
	(6.84)	(5.81)	(12.07)	(12.38)
Online advertising	.867*	.590	.823	.985*
	(2.02)	(1.34)	(1.80)	(2.23)
National advertising × Regional advertising	−.638*	−.358	−.602	−.864**
	(−2.23)	(−1.18)	(−1.93)	(−2.93)
National advertising × Online advertising	−1.548*	−1.379*	−1.867**	−2.012**
	(−2.37)	(−2.06)	(−2.69)	(−2.98)
Regional advertising × Online advertising	−1.701*	−1.860*	−2.050*	−1.831*
	(−2.11)	(−2.28)	(−2.42)	(−2.19)
National advertising residuals[a]	.123	−.0323	−.0677	.193
	(.99)	(−.21)	(−.43)	(1.51)
Regional advertising residuals[a]	−.700***	−.767***	−1.363***	−1.183***
	(−4.93)	(−5.02)	(−9.75)	(−8.99)
Online advertising residuals[a]	.0748	.0929	.0801	.129
	(.25)	(.30)	(.25)	(.41)
Year fixed effects	Yes	Yes	No	No
Intercept	1.522***	1.710***	1.211***	1.281***
	(24.76)	(19.79)	(18.65)	(26.84)
R-square	.0663	.029	.0413	.028
Overall test of significance	785.27 (Wald)	31.45 (F-test)	254.33 (Wald)	16.59 (F-test)
Wald test of significance	<.001	<.001	<.001	<.001

*p < .05.
**p < .01.
***p < .001.
[a]The residuals are obtained from the auxiliary regressions in Table 4.
Notes: t-statistics are in parentheses. N = 6,914.

Moreover, extant theory on how multiplexing (fragmented use of media by consumers) influences the creation of positive interaction effects among advertising vehicles is mixed. On the one hand, proponents argue that consumer multiplexing is beneficial to interactive effects across media because it makes consumers expect and appreciate joint narratives (Pilotta and Schultz 2005). On the other hand, critics point out that multiplexing inhibits consumer attention to firms' advertising across media and mitigates interaction effects (Jeong, Hwang, and Fishbein 2010).

We empirically test these assertions using a sample that spans 12 years and 662 firms and find that whereas main effects are consistently positive, interaction effects are consistently negative. Thus, while each of the three media types exerts a positive effect on firm performance on its own, they each weaken the performance impact of the respective other two media types. This finding provides potential evidence that consumers' multiplexing might make it more difficult for firms to build a cohesive superadditive narrative across media (e.g., Jeong and Fishbein 2007; Lin, Venkataraman, and Jap 2013).

Beyond multiplexing behavior, there are other potential explanations of the identified negative interaction effects among the three media types. For example, national advertising is typically used for brand-building purposes, whereas regional and online advertising are often used for promotional purposes (e.g., Bolton 1989; Popkowski Leszczyc and Rao 1989). In turn, national advertising often prompts price premiums, whereas regional and online advertising frequently erode price premiums (e.g., Naik, Raman, and Winer 2005). Thus, when used jointly, they may beget the risks of subadditive effects. Furthermore, decisions on which media to select should be linked to the objective of the ad (e.g., Danaher 2007, p. 308). For example, if the message is intended to elicit an emotional response, national advertising

TABLE 6
Additional Robustness Checks

	Model 1	Model 5: Without Endogeneity Correction	Model 6: Without Random Subset of Firms	Model 7: Without Years 2001 and 2002	Model 8: Without Years 2011 and 2012
Total assets	–.00000506**	–.00000529**	–.00000501**	–.00000601**	–.00000634**
	(–2.99)	(–3.13)	(–2.96)	(–3.17)	(–3.01)
Total debt	.00000361	.00000413	.0000035	.00000543	.00000612
	(1.17)	(1.34)	(1.13)	(1.59)	(1.62)
Financial leverage	.0000498	.0000648	.00000564	–.000388	–.000571
	(.06)	(.08)	(.01)	(–.40)	(–.54)
Industry competitive intensity	.0179	.0111	.0176	.0138	.0111
	(.56)	(.35)	(.55)	(.42)	(.33)
Industry munificence	.208	.19	.201	.177	.148
	(1.74)	(1.59)	(1.68)	(1.4)	(1.13)
National advertising	.278	.417***	.477***	.480***	.546***
	(1.77)	(3.86)	(3.82)	(3.65)	(3.89)
Regional advertising	1.285***	.577***	.335*	.326*	.330*
	(6.84)	(4.78)	(2.55)	(2.39)	(2.32)
Online advertising	.867*	.951**	.979**	1.017**	1.029**
	(2.02)	(3.15)	(3.07)	(3.11)	(3.04)
National advertising × Regional advertising	–.638*	–.672*	–.696*	–.820**	–1.036***
	(–2.23)	(–2.35)	(–2.43)	(–2.75)	(–3.30)
National advertising × Online advertising	–1.548*	–1.454*	–1.517*	–1.474*	–1.299
	(–2.37)	(–2.23)	(–2.32)	(–2.17)	(–1.82)
Regional advertising × Online advertising	–1.701*	–1.733*	–1.755*	–1.758*	–1.893*
	(–2.11)	(–2.14)	(–2.17)	(–2.10)	(–2.10)
National advertising residuals[a]	.123		–.125	–.0786	–.0373
	(.99)		(–.98)	(–.58)	(–.26)
Regional advertising residuals[a]	–.700***		.656***	.642***	.568***
	(–4.93)		(4.44)	(4.16)	(3.48)
Online advertising residuals[a]	.0748		–.0585	–.258	–.432
	(.25)		(–.19)	(–.80)	(–1.29)
Intercept	1.522***	1.619***	1.544***	1.548***	1.561***
	(24.76)	(28.13)	(25.3)	(24.8)	(24.39)

*$p < .05$.
**$p < .01$.
***$p < .001$.
[a]The residuals are obtained from the auxiliary regressions in Table 4.
Notes: t-statistics are in parentheses.

might be the best medium. By employing both national and regional advertising to convey the message, the firm might again incur subadditive effects owing to inadequate usage of some media vehicles.

Finally, the complexity of strategic and tactical integration among the various media vehicles (e.g., Sheehan and Doherty 2001), which increases as the number of media vehicles increases, may be another source of subadditive effects. Specifically, the task of maintaining an overarching communication theme among the various media and consistent retrieval cues among the media becomes complex as media vehicles increase. We hope that future studies will further explore these and other potential explanations for the identified negative interaction effects.

Managerial Implications

To understand the magnitude of the negative interaction terms relative to the positive main effects, we first use the parameter estimates of Model 1 (Table 5) and the descriptive statistics on mean media advertising spending and mean performance to calculate the elasticity (calculated at the mean values of spending) of a firm's media advertising spending, or the percentage change in performance for a 1% change in advertising.[8] The elasticity represents the total impact of advertising on performance, taking into account the positive main effects and the negative interaction effects.

For the average firm in our sample, we observe in Panel A of Table 7 that a 1% increase in national advertising increases performance by .12%, whereas a 1% increase in regional advertising increases performance by .76%, and a

[8]Note that our elasticity estimates are those of spending intensity (i.e., an increase in performance resulting from an increase in advertising-to-sales ratios). Yet we verified that our results hold even when we use raw advertising figures, which we note are not ideal to use when we possess large heterogeneity in spending caps across firms.

TABLE 7
Elasticity Analysis

A: Average Elasticity

Advertising Type	Mean Elasticity
National	.12
Regional	.76
Online	.32

B: Illustration of Negative Interactions

Advertising Type	Change in Effectiveness from 1% Increase in National Advertising	Change in Effectiveness from 1% Increase in Regional Advertising	Change in Effectiveness from 1% Increase in Online Advertising
National		−.35%	−.15%
Regional	−.08%		−.03%
Online	−.43%	−.36%	

1% increase in online advertising increases performance by .32%. Again, these findings suggest that the total impact of each form of advertising on performance is positive and significant.

The finding of relatively high effectiveness of online advertising might not come as a surprise to some managers. Indeed, consistent with our own findings (see Figure 1), the CMO Council (2015) reports that online advertising was and will continue to be the fastest-growing media vehicle. These shifts indicate that many firms' view online advertising as an attractive media vehicle.

Online advertising vehicles certainly offer several unique features. For example, firms can elect to pay search engines such as Google only if their target customers actually click on their banner ads (i.e., cost per click). Moreover, social media websites such as Facebook and Twitter enable companies to advertise to highly specific customer segments on the basis of demographic, psychographic, geographic, and behavioral information that the website collects about its users. Furthermore, advertisers on Facebook can track how consumers behave on the firm's own website (e.g., whether they made a purchase) after Facebook directs them there.

Despite the seemingly appealing features of online advertising, our findings indicate that regional advertising's performance effects are also surprisingly attractive, even though regional advertising is the only media vehicle that has been on a downward trajectory, especially in the latter half of our study period (see Figure 1). We also estimated our model using only data from 2007 to 2012 to assess whether the effectiveness of the activities has changed over time. The elasticities from this model indicate that, for the period from 2007 to 2012, a 1% increase in national advertising statistically increases performance by .24%, regional advertising effectiveness was not significant, and a 1% increase in online advertising statistically increases performance by .28%. Thus, regional advertising's effectiveness appears to have decreased in the latter period of our observational timeframe, rationalizing firm actions toward reducing regional advertising. Notably, national and online advertising effectiveness remain stable and significant in the full time frame as well as in the shorter (more recent) time frame, again rationalizing firms' decisions to increase spending emphasis in these media options.

Next, to understand the role of the negative interaction effects among the media vehicles (national, regional, and online), we calculated the change in effectiveness in one form of advertising that results from an increase in spending in the other two types of advertising. In Table 7, Panel B, we show that for the average firm in our sample, we observe that a 1% increase in national advertising (1) decreases regional advertising effectiveness by .08% and (2) decreases online advertising effectiveness by .43%. Furthermore, a 1% increase in regional advertising (1) decreases national advertising effectiveness by .35% and (2) decreases online advertising effectiveness by .36%. Finally, a 1% increase in online advertising (1) decreases national advertising effectiveness by .15% and (2) decreases regional advertising by .03%.

This means that while spending 1% more on national, regional, and online media increases performance by .12%, .76%, and .32%, respectively, by virtue of the main effects, it also negates performance by .20%, .15%, and .04%, respectively, by virtue of subadditive effects. Thus, the joint effect of increasing spending in all three media by 1% is a 1.2% total increase in performance through main effects (.12% + .76% + .32%) but also a .39% decrease in performance through subadditive effects (−.2% − .15% − .04%). Therefore, the subadditive effects jointly erode the total performance of media spending by approximately 33% (.39%/1.2%).

Managers should be wary of these subadditive effects, especially if the firm has a compartmentalized view of the advertising media functions. Importantly, managers should carefully monitor the subadditive effects and try to maintain them at zero. So how can this be accomplished? We offer the following recommendations.

First, the subadditive effects likely capture opportunity costs of poor tactical and strategic integration across media. Indeed, as Sheehan and Doherty (2001) espoused more than a decade ago, there is a need for both strategic and tactical integration of multiple media to achieve positive interaction effects. Strategic integration might involve the use of just one overarching communication theme with national, regional, and online media, thematically integrated and customized to the target audiences so that a synergistic effect of the communication can emerge. Indeed, communicating a single, focused, clear message across the three media types might help differentiate a firm's brand from those of its competitors. Tactical integration, in turn, refers to building consistency in retrieval cues (e.g., key visuals) across all media, so as to build strong brand images and avoid confusion effects. Thus, managers should strive to better integrate their media portfolio and build a cohesive message and narrative across all media vehicles to increase the individual and joint impact of those vehicles.

Second, firms may also want to take a close look at their advertising agencies and/or their agencies' responsibilities. Indeed, disagreements among or within agencies can be a significant source of strategic and tactical integration issues. For example, some firms employ separate agencies for their online and more traditional advertising, often resulting in either "turf battles" among the involved agencies or lack of integration. Indeed, considering the negative interaction effects among the media discussed previously, it appears that online advertising's effectiveness is most negatively affected by the other two media vehicles, resonating with the notion that firms are still struggling to integrate online advertising into their traditional advertising allocation strategy (Danaher and Dagger 2013). However, it does not have to be that way. BMW's "X3 matchup" campaign provides one example of how firms could integrate their traditional and online advertising into one media campaign.[9] In general, managers should try to better align their online, regional, and national advertising to prevent subadditive effects and hopefully attain superadditive benefits among their chosen advertising vehicles.

Finally, managers should also strive to make their message more unique and, if possible, not emphasize the same features as their competitors, thereby making it more difficult to poach their message and media spending. For example, Sketchers advertised its rocker bottom ("Shape Up") shoes during Super Bowl 2011, and not surprisingly, online searches for the term "Shape Ups" subsequently increased significantly. Notably, however, Reebok, maker of the "Easy Tone" rocker bottom shoes, seemed to have been able to take advantage of Sketchers's multimillion-dollar investment in Super Bowl commercials by poaching on the keyword "Shape Ups" to advertise its own competing model (e.g., Sayedi, Jerath, and Srinivasan 2014).

[9]Consumers were asked to rebuild the new X3 introduced with a television commercial using BMW's online car configurator. Consumers could rewatch the commercial over and over on BMW.com, Facebook, and YouTube and could win a two-year lease of the car if their configuration matched that of the X3 shown in the commercial.

Limitations

We close by noting some limitations of our study, which present avenues for further research. First, we assumed that all 18 media vehicles offered a financial benefit to firms, though some media vehicles are likely more advantageous to some firms and less so to others. For example, a firm that targets the Hispanic market should benefit more from advertising in a Hispanic magazine than a B2B manufacturer with a wider target. Further research should consider the suitability of the various media vehicles for the sample firms and test whether our predictions hold. Second, we included only publicly traded manufacturing firms in our sample; our theory applies to a broad set of firms, but our conclusions are limited to our sample. Additional research could analyze whether our predictions hold in other samples, such as service firms. Third, our results are conservative, in that they reflect environments in which media budgets have little leeway to increase. Fourth, our theorization and empirical findings are limited to firms that (usually) advertise nationally, locally, and online. Thus, our findings cannot be generalized to small, local firms that do not advertise nationally. Fifth, although we focused on establishing the effectiveness of media spending, we did not try to explain substitution patterns among media, which future studies could explore.[10] Finally, although we offer potential explanations for the identified subadditive effects among the three media types, we did not identify the concrete source(s) of these effects. Thus, as have already mentioned, we hope that future studies will further explore the source(s) of the identified negative interaction effects.

[10]We thank the area editor for highlighting this research avenue.

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