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Online display advertising for CPG brands: (When) does it work?

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A B S T R A C T

This study examines how online display ads, alone or in combination with more conventional media (television and print), can help drive sales in the consumer packaged goods (CPG) sector. It also assesses how the combined sales effect of online and offline ads depends on the volatility of their expenditures over time. We explore these relations for 154 brands across 68 Dutch CPG product categories. We find that, even though display ads are not effective for the “average” CPG brand, they do have a significant impact for a sizable, and considerably larger than expected by chance, subset of brands. Importantly, this impact depends on the type of product. While display ads are found to be ineffective for low-involvement utilitarian products, they can significantly enhance sales for other CPG product types. Moreover, the effect depends on whether they are used in combination with other media: while display ads are best used as a stand-alone medium for high-involvement utilitarian products, it is better to combine them with traditional media for hedonic products. Finally, the long-term effectiveness of display messages increases significantly when they are spread more evenly in time.

1. Introduction

Advertising spending in online media is on the rise. In 2019, digital ad spending already accounted for 50.3% of the total media ad spending, and is projected to grow to 56.1% (62.6%) in 2021 (2024). Next to search ads, the largest portion of online media spending goes to online display advertising. Online ads, and display ads in particular, have become especially popular in automotive, financial service and telecom markets. Recently, CPG brands have also started to venture into the use of display advertising. Display ad spending by CPG companies reached approximately $4 billion in the US in 2016, which corresponded to 68% of the industry’s total online spending (eMarketer, 2016). In the Netherlands, brands at the forefront of this development were, among others, Coca-Cola, which allocated more than €500,000 to display advertising during 2016 and 2017, and Nivea Haircare, which stepped up their display-advertising spending to a similar amount in 2017. Still, many CPG brands – including leading brands like Ariel (a well-known laundry detergent brand) and Warsteiner (a globally distributed beer brand) – were more hesitant to jump on the digital bandwagon. More strikingly, others have been reducing their investments in the medium. For instance, in 2017, Procter & Gamble cut $200 million in digital ads, which they considered to be “largely ineffective” (Adweek, 2018). According to industry sources, this move “…echo[es] marketing executives’ mounting concerns around the
efficacy of online advertising and the growing perception that they are wasting money on online ads that never reach their intended audience” (The Wall Street Journal, 2017). This raises the question: is that so? Do display ads present CPG brands with a great opportunity? Or, conversely, are such ad investments for CPG brands merely a hype and, in the end, not sales-effective?

Through display-ad investments, proponents of the medium hope to improve their brands’ performance. Previous studies have suggested that online advertising may allow brands to widen their reach, generate brand awareness, and act as a purchase reminder (Binet & Field, 2018) in a more flexible and cost-effective way than conventional media (Drèze & Hussherr, 2003). However, when it comes to the actual impact of display advertising on brand sales, empirical evidence is still scant. Prior meta-analytic evidence on advertising elasticities pertains to offline media only (Frison, Dekimpe, Croux, & De Maeyer, 2014; Sethuraman, Tellis, & Briesch, 2011; Shapiro, Hitsch, & Tuchman, 2020), while extant studies on display ads mostly focus on a select set of non-grocery products like apparel (Dinner, van Heerde, & Neslin, 2014), books (Breuer, Brettel, & Engelen, 2011), cars (Naik & Peters, 2009), or health-care, beauty and non-prescription drugs (Manchanda, Dubé, Goh, & Chintagunta, 2006). Given that consumers’ response to ad messages is shaped by their decision-making process (Draganska, Hartmann, & Stanglein, 2012), the dynamic interplay among online and offline media is not yet well documented. The few studies that do consider such interactions again tend to remain focused mainly on non-CPG brands, and produce mixed results on the presence and direction of the effects (Kolsarici & Vakratsas, 2018; Naik & Peters, 2009; Taylor et al., 2013). Little is known as to whether and under what circumstances display ads and conventional media like print and TV work synergistically or counteract one another in CPG markets. Are those effects more likely to occur among certain media? For certain brands? And: do these effects materialize in all CPG categories alike, or do they depend on product-category characteristics?

In addressing this question, it is important to note that online ads are rarely used in isolation. The combined use of display ads with more traditional media such as print or TV ads could create interaction effects. On the one hand, (positive) synergies may arise (Binet & Field, 2009, 2018), for example, online banner ads may complement a TV campaign by transmitting its core message to the audience in a different manner. Conversely, the use of multiple media might also lead to negative interactions, due to duplicate reach, incongruence or irritation/overload (Burmester, Becker, van Heerde, & Clement, 2015; Taylor et al., 2013). Moreover, to the extent that the impact of advertising expenditures on sales carries over to subsequent periods, such cross-media effects may depend not only on concurrent, but also on past expenditures in other media.

Even though the notion of sales-advertising interactions between media is well-accepted in the marketing literature (see, e.g., Batra & Keller, 2016) and empirically supported for traditional media (e.g., Kolsarici & Vakratsas, 2018; Naik & Raman, 2003), the dynamic interplay among online and offline media is not yet well documented. The few studies that do consider such interactions again tend to remain focused mainly on non-CPG brands, and produce mixed results on the presence and direction of the effects (Kolsarici & Vakratsas, 2018; Naik & Peters, 2009; Taylor et al., 2013). Little is known as to whether and under what circumstances display ads and conventional media like print and TV work synergistically or counteract one another in CPG markets. Are those effects more likely to occur among certain media? For certain brands? And: do these effects materialize in all CPG categories alike, or do they depend on product-category characteristics?

The current research sets out to address these issues. We study how spending in online media (i.e., display ads) and offline media (i.e., print and TV) drives offline sales in the short and the long run, across a large set of (over 150) brands from a broad (68) range of CPG categories, using data from the Dutch market. We assess whether synergistic or antagonistic cross-media effects occur, thereby allowing this interplay to materialize within as well as across periods. We then document how both the stand-alone and combined sales effect of online and offline ads depend on the product category, and on the volatility of advertising spending in each medium.

2. Theoretical background and research questions

The effectiveness of (offline and/or online) advertising spending has been studied in two broad research streams. A first set of studies has focused on the idiosyncratic characteristics of different media to identify, in an experimental setting, the underlying reasons/processes why certain media may be more or less appropriate in certain contexts. Even though the insights from these studies will be instrumental in our subsequent theorizing, our work is situated more in the second research stream, where secondary data from real-life settings are used to quantify, through econometric techniques, the effectiveness of one or more advertising media. Web Appendix A positions our study vis-a-vis four sets of studies in that second tradition: (i) large-scale econometric studies on advertising’s effectiveness in CPG markets, (ii) empirical studies focusing on the sales effectiveness of display advertising, (iii) empirical studies on the interplay between different media, and (iv) studies on category-related differences in (on- or offline) media effectiveness. For each set, it offers a (by no means exhaustive) list of representative studies. In the subsequent sections, we discuss how we draw on the various research streams, and highlight our contributions relative to these earlier studies.

2.1. Effectiveness of display ads

Display advertising has already been a topic of interest to several scholars, not only because of its increased usage, but also because the medium, by virtue of its idiosyncratic characteristics, may produce different outcomes than more traditional media. A number of prior studies have looked at the properties of this medium (relative to offline media) and the response mechanisms that it triggers in an experimental setting (Dijkstra, Buijlets, & van Raaij, 2005; Drèze & Hussherr, 2003). As these studies indicate, display advertising is a fairly low-cost, high-reach and targetable medium that differs from other media in terms of (i) modality (use of sensory modes, static vs. dynamic), (ii) information quantity, and (iii) pacing (where an important distinction is that between “retrieval” media – for which the consumer determines whether and when to access the information that is presented – and “display” media, where the presentation is more immediate and based on the consumer’s attention).
and for how long – and “delivery” media – for which the speed and sequence of information transfer is controlled much more by the sender (Van Raaij, 1998).

Display advertisements often use only visual stimuli – unlike TV, which is a multi-sensory medium – and the ads as such are very low on content – especially compared to print. Moreover, display advertising is a retrieval medium that typically has only limited “bandwidth”, i.e., covers only a minor portion of the webpage that the consumer is viewing, leaving the larger part for website content. At the same time, display ads typically allow consumers to control the pacing (time spent looking at the ad) and to collect extra information (by clicking on the ad).

These properties lead proponents of display advertising to advocate its effectiveness. The simplicity of the message allows for fluent processing. Interested consumers can click on the ads to get more information about the brand if and when they see fit. But also consumers who do not process the ad may be influenced. The ad may leave a memory trace that primes them on subsequent advertising exposures: even if they do not remember having seen the ad, they may find it familiar (Drèze & Huss herr, 2003) and this familiarity may translate into brand liking (Chatterjee, 2012). As such, display ads could create awareness (Hoban & Bucklin, 2015), serve as a reminder (Manchanda et al., 2006), activate consumers to buy the brand (Binet & Field, 2018), and even have a brand-building function and improve performance in the long run (Draganska et al., 2014). Finally, this medium may be able to reach a larger part of the population than traditional (offline) media. Hence, adding display ads to the media mix may result in higher sales (Abraham, 2008).

Opponents of the medium, however, emphasize the downsides. Because of the low “bandwidth”, consumers may overlook, or even avoid looking at, the display ads while focusing on the remaining website content (Burke, Hornof, Nilsen, & Gorman, 2005). For lack of attention and information content, consumers may not learn about or elaborate on the properties of the brand, which would make the message effect less enduring (Chatterjee, 2012). Especially if there is a delay between the ad and the actual purchase occasion, this might jeopardize the ability of display ads to enhance brand sales.

While the above response mechanisms have been discussed conceptually and explored experimentally, or used to explain the impact of display advertising on a number of intermediate metrics such as site visits (Chae, Bruno, & Feinberg, 2019; Hoban & Bucklin, 2015), clicks (Bruce, Murthi, & Rao, 2017), or purchase intent (Goldfarb & Tucker, 2011), only a limited set of studies have assessed the relation between brand sales and display ads in the field (e.g., Danaher & Dagg er, 2013; Li & Kannan, 2014; Lob schat, Osinga, & Reinartz, 2017 – see Web Appendix A), and even fewer have done so in a CPG setting – a gap that we intend to fill. In so doing, we also complement earlier large-scale econometric analyses (e.g., Frison et al., 2014; Shapiro et al., 2020) on the use of offline media to stimulate CPG sales.

2.2. Role of product-category characteristics

As indicated by Draganska et al. (2014), the (relative) response to advertising messages depends on consumers’ typical decision-making process in the category. This process, in turn, is governed by the level of involvement, and by the category’s hedonic (“feel”) vs. functional nature (“think”). An extensive literature (see, for example, Del Barrio-Garcia, Kamakura, & Luque-Martínez, 2019 for a recent review) has looked into the way consumers process advertising messages in categories that differ along these two dimensions – the well-known “FCB” grid (Ratchford & Vaughn, 1989). While this category grid has mainly served as a framework to decide on message content and media usage, it also serves as a useful basis to form expectations on media effectiveness (see, e.g., Bart, Stephen, & Sarvary, 2014).

In low-involvement categories, consumers may not notice, or even deliberately try to avoid, advertising messages (Dijkstra et al., 2005). Whether that happens depends on the pacing (intrusiveness) and modality (number of sensory modes) of the medium. Television, as a delivery medium that uses multiple sensory modes, is likely to affect even low- or uninvolved consumers (Buchholz & Smith, 1991). Print and display advertising, being retrieval media, allow consumers to more easily skip the message. Hence, these media are less apt to influence less involved consumers. Especially for low-bandwidth display messages, this ad avoidance or lack of attention may be a problem – display-message processing in low-involvement categories being mostly pre-attentive (Dijkstra et al., 2005), and click-through rates very low (Drèze & Huss herr, 2003).

The category’s hedonic vs. utilitarian nature, in turn, determines the amount and type of information that consumers respond to, and the way they process this information. Hedonic categories call for (audio-) visual (rather than verbal) stimuli, which allow conveying brand imagery and experiential cues, and are typically processed in a more emotional fashion (Del Barrio-Garcia et al., 2019; Macinnis & Jaworski, 1989). Whereas print media have limited ability to transmit such affective signals, TV has high communication power and may more readily transfer moods, feelings, and images that facilitate affective responses (Chauduri & Buck, 1995). Display advertising can be situated somewhere in-between: it typically has more visual content than print, but is more static than TV and often does not include auditive information. Hence, for hedonic products, display ads are anticipated to generate stronger consumer reactions than print, but weaker reactions than TV.

For functional, utilitarian, products, consumers are better served with verbal information on product attributes (Del Barrio-Garcia et al., 2019; Macinnis & Jaworski, 1989). Whether consumers actually attend to and use that information will, again, depend on their involvement with the product. While they are less inclined to use it (and stick to their routinely behavior) in low-involvement settings, they are likely to process this information analytically for high-involvement categories. Because of its transient character, television does not make it easy for consumers to retain and rehearse the presented information. Therefore,

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2 The FCB grid was originally developed by Vaughn for Foote, Cone and Belding Advertising.
rather than triggering cognitive processing. TV ads are bound to entail primarily global evaluative consumer responses (Pieters & van Raaij, 1992). In contrast, print and display advertising allow consumers to process information at their own pace, and to retain the information for later use. Even if display ads as such are not informative, they allow involved consumers to request more information. This implies that for high involvement, utilitarian products, print and display ads may lead to more elaborate, cognitive, message processing (Dijkstra et al., 2005), and be more impactful than TV.

2.3. Cross-media effects

Display ads seldom constitute the single medium-of-choice. As such, online advertising elasticities should not be considered in isolation: if a brand allocates its resources to more than one advertising channel, the effectiveness of each medium may well depend on the other media used (Naik & Raman, 2003; Naik, Schultz, & Srinivasan, 2007). This interplay may be positive or negative, and it is unclear as of yet which effects to expect (Sridhar, Germann, Kang, & Grewal, 2016).

Synergistic, or positive, cross-media effects arise if the combined effect of two media exceeds the sum of their individual effects (Naik, 2007). Different media may reach consumers in a different context (time and place) or in different modes (audio, text, visual). As such, they may convey the advertising message in a complementary way, and/or operate on different outcome metrics (Batra & Keller, 2016; Dijkstra et al., 2005). For instance, print advertising appears particularly well-suited to convey detailed brand information, TV advertising may be better at creating awareness, interest, and brand imagery, and display ads may be well-suited to generate or maintain brand salience, and serve as a reminder and activation tool (Batra & Keller, 2016; Pfeiffer & Zinnbauer, 2010). Transmitting the advertising message using different media may therefore stimulate message processing and memorization throughout the purchase funnel (Edell & Keller, 1989) while avoiding tedium (Chatterjee, 2012), and thus lead to superior brand performance. Synergistic effects have initially been documented for offline advertising media. For instance, combining print and TV ads has been shown to boost sales for clothing (Naik & Raman, 2003). Positive cross-effects may also materialize among offline and online media. For instance, in a study involving (four) consumer goods and (two) services, Chang and Thorson (2004) show that combining TV and display ads lift the consumer’s level of attention, while Naik and Peters (2009) find that it increases purchase consideration for a car brand. Pauwels, Demirci, Yildirim, and Srinivasan (2016), in turn, observe synergistic effects on traffic and revenues for (five) services, furniture and apparel brands. Print and display ads, too, may complement each other. For example, their joint use may enhance brand recall and attitude, as shown by Chatterjee (2012) for credit cards and car rentals, and increase website visits, as found by Rosenkranz and Myers (2013) for a non-profit service.

Conversely, also antagonistic, or negative, cross-media effects may arise. In such a case, the combined effect of two media is lower than the sum of their individual effects: instead of amplifying each other, the media weaken each other (Burmester et al., 2015). Dinner et al. (2014), for example, found that a high-fashion retailer’s traditional advertising reduced its online click-through rates, which could be attributed to an information-substitution effect, in that the former already provided information that one otherwise would try to obtain by click-throughs. In an increasingly digital world, consumers’ simultaneous use of several media (“multiplexing”) may inhibit attention to the brand’s advertising across these media (Jeong, Hwang, & Fishbein, 2010). The exposure to multiple media may also lead to redundancies (duplicate reach; Taylor et al., 2013) which could distract the consumer and create confusion (Assael, 2011). Moreover, multiple-media exposure may induce supersaturation and reactance (Kolsarici & Vakratsas, 2018). Empirical evidence on such antagonistic effects has been found by Taylor et al. (2013) in two CPG categories, and Kolsarici and Vakratsas (2018) for selected durable and packaged-goods brands.

In sum, extant studies underscore the potential for cross-effects between offline and online media. However, the few studies that empirically document this interplay (i) typically consider only few categories and brands, (ii) do so in a non-CPG setting, (iii) often focus on intermediate metrics like attention and consideration, and (iv) have produced conflicting results. Hence, it is fair to say that the presence of synergistic vs. antagonistic effects, between online and offline media, on brand sales across CPG categories, are not well-documented yet.

On an additional note, consumers’ advertising response across media can depend on both concurrent and earlier messages (Batra & Keller, 2016). The latter has typically been ignored in extant studies, which have mostly focused on cross-media spillovers at the same point in time. Our analysis will accommodate dynamic interdependencies in consumers’ cross-media response, and will assess to what extent the presence, extent, and nature (positive or negative) of these interactions varies across different product types.

2.4. Volatility as a driver of advertising effectiveness

Not only the (combined) use, but also the spending volatility may influence a medium’s sales impact – i.e., the extent to which the expenditures on that medium are “evenly spread” or fluctuate over time (Gijsenberg & Nijs, 2019). While “even” spending levels ensure a continuous advertising presence, pulsing schedules have been said to prevent wearout or tedium (i.e., avoid that the “even” stream of media messages no longer triggers attention or interest, and even produces reactance; e.g., Naik, Mantra, & Sawyer, 1998) or to optimally exploit the advertising dynamics (Dubé, Hitsch, & Manchanda, 2005). Which of these advantages prevails may be medium-specific – i.e., depend on the medium’s modality, information content and pacing, and on its carry-over effect – aspects that may well differ for offline and online media. For TV (which, as a multi-sensory delivery medium, is more engaging) or print (a more informative retrieval medium), advertising elaboration may enhance the duration of the message effect but also its wearout. In comparison, to the extent that display-ad processing is more inattentive, the impact of a single message is bound to be less enduring and tedium from repeated messages is expected to be lower (Chatterjee, 2012) – conditions that may
favor a more continued stream of messages.\textsuperscript{3} Hence, we expect display advertising to be more effective when ad spending is less volatile. This may particularly hold for low-involvement hedonic items, where ad processing is predominantly pre-attentive (Dijkstra et al., 2005) and display ads may serve to build or maintain brand salience rather than provide consumers with (new) brand information (Batra & Keller, 2016).

To conclude this section: we expect the impact of display ads relative to print and TV to depend on the involvement level and hedonic nature of the product category. While some of these links have been discussed conceptually, a rigorous empirical verification is, to the best of our knowledge, still lacking.\textsuperscript{4} Our large-scale empirical analysis will shed light on how the use of display ads – alone or combined with other media – affects brand sales for different types of CPG products, and on the role of volatility therein.

3. Data

3.1. Data sources and brand selection

Through AC Nielsen, we obtained high-frequency advertising-spending data on a broad cross-section of categories and brands in the Dutch CPG market. The advertising data cover a period of 117 weeks from January, 2016 to March, 2018, and are matched with GfK scanner panel data on household purchases and prices (also aggregated to the brand level). We considered all brands in that intersection with an average market share of at least 1% (for a similar cut-off rule, see Kohli & Sah, 2006). This resulted in a sample of 154 national brands across more than 60 product categories. For these brands, we quantify the effectiveness of their spending on a key online medium (display advertising) and two popular offline media (TV and print), provided that the brand used a given medium at least seven times during the observation period.\textsuperscript{5} If the medium was used less than seven times, the expenditures on the medium were added to a control variable that captures the combined spending in a variety of smaller, and only occasionally used, media such as billboard and cinema. Together, our three focal media represent the bulk (91.5%) of the brands’ advertising expenditures. The advertising expenditures are corrected for inflation using the Dutch Consumer Price Index (CPI).

3.2. Descriptives

Our dataset covers multiple product classes (i.e., beverages, food, household care, personal care and pet food), each involving a varied set of product categories (Table 1, Panel A). For instance, the “beverage” class includes categories like cola and tea, while the “food” class includes categories such as candy bars and yoghurt. These categories differ along multiple dimensions, such as national-brand concentration and private-label presence, and therefore allow us to address the effectiveness of the advertising media in quite different settings. Also within a given category, we observe considerable diversity in the nature and size of the brands (Table 1, Panel B), in that both more and less frequently purchased brands as well as more expensive and cheaper brands are studied (e.g., Clipper vs. Lipton in the tea category; Danone vs. Zuivelhoeve in the yoghurt category). This comprehensive dataset will enable us to not only obtain generalizable insights on the effectiveness of these three key media when used in CPG markets, but to also explore the heterogeneity, if any, in their effectiveness across categories and brands.

Table 2 provides descriptives on media usage. As can be seen from Panel A, nearly all CPG brands invest in TV advertising (85.71% of the brands), while about half of them do so in print advertising (50.65%). TV dominates by far in terms of expenditure level (86.68%). While online display ads still get a smaller share of the advertising budget, already 104 (67.53%) brands use the medium on a fairly regular basis (28 out of 117 weeks, on average), with several of them allocating as much (or even more) of their budget to this online medium than to print.

Most brands use a mix of advertising media (Panel B). Brands that use only one medium tend to favor offline media, in particular TV. Display ads are most often used in combination with one or both other media. This suggests that brand managers primarily assign a “supporting” role to this medium, and underscores the importance of studying potential synergies between the online and offline media.

Brands are also characterized by large differences in their volatility, as illustrated in Web Appendix B. While brand A (a leading coffee brand) employs TV ads quite frequently (77% of weeks), and maintains a rather constant spending level, brand B (a leading beer brand) advertises less often on TV (44% of weeks) and is characterized by extended periods of zero spending that alternate with periods of intense spending.

\textsuperscript{3} The pre-attentive ad processing turns click-through rates into ineffective performance measures (Drèze & Hüscher, 2003) such that, even if display ad frequency is negatively associated with click through (Försch & de Haan, 2018), this does not necessarily imply lower sales.

\textsuperscript{4} While Del Barrio-García et al. (2019) examine the actual usage of alternative online and offline media across these category types, they do not measure the actual effectiveness of these media.

\textsuperscript{5} Given our interest in cross-media effects, we require a higher number of spending occurrences than other recent studies (see, e.g., van Heerde et al., 2013), which required only two occurrences.
4. Methodology

Given our research objectives, our modelling approach involves three steps. First, we obtain the sales-advertising elasticities by medium – including cross-media effects – for each brand. Next, we combine these estimates to derive empirical generalizations. In a third and final step, we perform a moderator analysis to explain the observed differences in elasticities.

4.1. Measuring media effectiveness by brand

For each brand, we assess how effective each medium is at driving sales, and whether the joint use of the media results in synergistic or antagonistic effects. Several methodological challenges must be met here. First, the model should distinguish between short- and long-term advertising effectiveness, while accounting for medium- and brand-specific carryover effects.

Second, the specification must accommodate the potential interplay among different media, not only in the same period, but also across periods. Third, we should correct for possible endogeneity in media spending over time. To this end, we use the following sales equation:

$$\ln \text{SALES}_{ict} = \alpha^c + \sum_{k=1}^{K^c} \beta_k^c \text{ADSTOCK}_{ikt} + \sum_{k=1}^{K^c} \theta_{k,1}^c \text{ADSTOCK}_{ikt} + \rho^c_1 \text{TREND}_{it} + \rho^c_2 \text{SEAS}_\text{COS}_{it}$$

$$+ \rho^c_3 \text{SEAS}_\text{SIN}_{it} + \rho^c_4 \ln \left( \text{PRICE}^c_{it} \right) + \rho^c_5 \ln \left( \text{COMPPRICE}^c_{it} \right) + \rho^c_6 \text{OTHERADSTOCK}_{ict} + \rho^c_7 \text{COMPADSTOCK}_{ict}$$

$$+ \epsilon^c_{it},$$

where $\text{SALES}_{ict}$ denotes the volume sales of brand $i$ in category $c$ during week $t$, and $\epsilon^c_{it}$ are normally-distributed error terms. The use of a multiplicative functional form (with the natural logarithm of sales as dependent variable) facilitates interpretation of the coefficients and subsequent cross-brand comparisons.

We assess the media effectiveness using an Adstock framework, and thereby allow for advertising carryover effects over time (Broadbent, 1979). Similar to Dinner et al. (2014), we define a stock variable $\text{ADSTOCK}_{ikt}$ for medium $k$ of brand $i$ in category $c$ during week $t$ as:

$$\text{ADSTOCK}_{ikt} = \lambda^c_k \text{ADSTOCK}_{ikt-1} + \left( 1 - \lambda^c_k \right) \ln \left( \text{ADVERTISING}_{ikt} \right) + 1,$$

where $\text{ADVERTISING}_{ikt}$ denotes the expenditures on medium $k$ by brand $i$ in category $c$ during week $t$. As Eq. (2) shows, the

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Table 1
Brand and category descriptives.

| Panel A: Data overview | Examples of product categories | Examples of brands |
|------------------------|-------------------------------|-------------------|
| Product classes        |                              |                   |
| Beverages              | Coke                          | Coca-Cola, Pepsi |
|                        | Tea                           | Clipper, Lipton   |
| Food                   | Candy bars                    | Bros, Snickers    |
|                        | Yoghurt                       | Danone, Zuivelhoeve |
| Household care         | General cleaners              | Ajax, Cillit Bang |
|                        | Toilet paper                  | Edet, Page        |
| Personal care          | Deodorant                     | Axe, Dove         |
|                        | Hair colouring products       | L’Oréal, Syoss    |
| Pet food               | Wet cat food                  | Gourmet, Whiskas  |
|                        | Dry cat food                  | Perfect Fit, Purina |

| Panel B: Brand and category characteristics | Mean | Standard deviation | Percentiles |
|---------------------------------------------|------|--------------------|-------------|
| Brand characteristics                       |      |                    | 25          | 50          | 75          |
| Price premium                              | 0.953| 0.838              | 0.423       | 0.735       | 1.273       |
| Purchase frequency                         | 3.212| 1.526              | 2.100       | 2.659       | 4.127       |
| Category characteristics                    |      |                    |             |             |             |
| Market concentration                       | 0.483| 0.177              | 0.337       | 0.516       | 0.610       |
| Private label share                        | 0.398| 0.204              | 0.253       | 0.362       | 0.586       |

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6 As indicated before, we assess the effectiveness of a medium if the brand uses the medium during at least seven weeks. The number of media that satisfies this condition for a given brand $i$ in category $c$ is given by $K^c$.

7 A value of “1” is added to all advertising observations to accommodate zero values for a brand’s ad spending in certain media in a particular week.

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Adstock variable is a geometrically-weighted average of the current- and previous-period advertising expenditures on a given medium, and depends on the value of the carryover parameter (“decay rate”) \( \lambda_{kic} \) (0 ≤ \( \lambda_{kic} \) < 1). We allow for a separate decay rate per medium \( k \) and per brand \( i \) (in category \( c \)). The former is needed given that advertising media differ on multiple dimensions (e.g., the way in which information is presented and/or the speed at which information is transferred by the medium, Dijkstra et al., 2005) that may shape the duration of their effects. As for the latter, both characteristics of the brand (e.g., their purchase frequency) and characteristics of the category to which the brand belongs (e.g., market concentration) may influence the degree of carryover. Similar to Dinner et al. (2014), the ADSTOCK\(_{kic} \) variable is initialized by the log-transformed ad expenditure of the first week (full details on all operationalisations are provided in Table 3).

Like previous meta-analytic and large-scale empirical studies (e.g., Frison et al., 2014; Sethuraman et al., 2011), we express advertising effectiveness in terms of sales elasticities. To allow for potential cross-media effects in these elasticities, we include interaction terms. Cross-media effects have traditionally been studied through interactions between contemporaneous media spending levels (e.g., budgets spent on two different media within the same week). Technically, this approach hampers the assessment of cross-effects for media with a rather sparse data structure (as is often the case with online spending in a CPG setting), and for high-frequency data in general.\(^8\) Moreover, this approach may not fully capture the dynamic interplay between media. To the extent that past spending on a medium still affects consumers’ current purchase behavior, it can also influence consumers’ current response to other media. In line with Onishi and Manchanda (2012) and Dinner et al. (2014), we therefore construct the interactions among the stock variables, instead of among the advertising expenditures themselves. In this way, the effect of spending on one medium can depend not only on concurrent, but also on past spending in another medium.\(^9\)

To more cleanly separate out the advertising effects, we add several control variables. We include a trend variable (TREND\(_t \)), constructed to range between −1 (for the first week) and +1 (for the final week) such that the media-effect estimates pertain to the mid-observation period. We control parsimoniously for seasonality by including two trigonometric terms (SEAS_COS\(_t \) and SEAS_SIN\(_t \) (Hanssens, Parsons, & Schultz, 2001; see Table 3 for details on the operationalization). To capture the impact of price

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\(^8\) This approach was also used to test for synergy effects in the error-correction specification of Frison et al. (2014). While 231 of their brands used TV advertising and 117 used billboard advertising, many (> 40) brands never had a joint (i.e., same-week) occurrence of non-zero spending in both media.

\(^9\) Eq. (1) only includes two-way interactions between the media Adstock variables. Of the 154 brands in our dataset, 54 used all three media (display advertising, TV and print). For those brands, we also considered a model including a three-way interaction between the Adstock variables for these media. Only for 9% of those brands, this extra interaction was significant at the 10% level – a proportion smaller than chance. Moreover, also the meta-analytic estimate for this three-way interaction effect was highly insignificant (\( p = .497 \)).
changes, we add the (natural logarithm of the) price of brand $i$ in category $c$ at time $t$ ($\text{PRICEx}_t$), as well as the (natural logarithm of the) competitors’ price ($\text{COMPPRICE}_{x}$), obtained as a market-share weighted average of the price of other brands in the same category.\footnote{All brand prices are winsorized to remove outliers (see Kurt & Hulland, 2013 or Gim et al., 2018 for a similar practice), and corrected for inflation using the Dutch Consumer Price Index.} We account for the influence of other, smaller media by a stock variable reflecting the brand’s combined expenditures on those media ($\text{OTHERADV}_{x}$). The impact of competitive advertising is addressed by including a stock variable ($\text{COMPADSTOCK}_{x}$) that is also defined according to Eq. (2), but where advertising refers to the combined expenditures (across all media) by brand $i$’s competitors in category $c$ ($\text{COMPADV}_{x}$).

The parameter $\beta_{x}^{c}$ represents the long-term effect of medium $k$ for brand $i$ in category $c$, i.e., the % cumulative sales impact across time that results from a 1% change in the medium’s advertising expenditures ($\text{Dinner et al., 2014}$), absent (current and/or earlier) spending on other media. The corresponding short-term (immediate) effect is given by: $\beta_{x}^{c}(1 - \lambda_{x}^{c})$ (See Web Appendix C). We will refer to these expressions as the “stand-alone” advertising elasticities henceforth. However, given that most brands employ multiple media, these stand-alone effects do not paint the full picture when cross-media interactions arise.

Accounting for cross-media effects ($\theta_{x}$), we derive the “total” long-term ($\varepsilon_{x}^{c,LR}$) and short-term ($\varepsilon_{x}^{c,SR}$) advertising elasticity of medium $k$ for brand $i$ in category $c$ at the average Adstock level of the other focal media $l$ ($\text{ADSTOCK}_{kl}$) that are used by brand $i$. As shown in Web Appendix C, this (average) total long-term elasticity is given by: $\varepsilon_{x}^{c,LR} = \beta_{x}^{c} + \sum_{l=1, l\neq k}^{K} \theta_{x}^{c} \text{ADSTOCK}_{kl}$, while the corresponding short-term elasticity is obtained as: $\varepsilon_{x}^{c,SR} = \varepsilon_{x}^{c,LR} (1-\lambda_{x}^{c})$.

### 4.1.2. Estimation procedure

Estimation of the model proceeds in five steps. In a first step, Eq. (1) is estimated nonlinearly to assess the parameters $\lambda$, $\alpha$, $\beta$, $\theta$ and $\rho$. Starting values for these parameters are inspired by extant literature.\footnote{For each adstock variable $\text{Adstock}_{x}$, the corresponding copula is obtained as $\text{Copula}_{x}^{c} = \Phi^{-1}(H(\text{Adstock}_{x}))$, where $\Phi^{-1}(.)$ is the inverse of the normal cumulative density function, and $H(.)$ is the empirical distribution function of the Adstock variable (see, e.g., Papies et al., 2017).} In the second step, copula variables are created for the Adstock variables and the price variable; Eq. (1) is extended with the copula variables one-at-a-time, and those that have a significant impact ($p < .10$) are retained (for a similar practice, see Gielens, Geyssens, Deleersnyder, & Nohe, 2018; Gim, Tuli, & Dekimpe, 2018). In the third step, Eq. (1) is re-estimated nonlinearly including the set of retained copula variables. Since the carryover parameter(s) may take on a (slightly) different value after the re-estimation, the Adstock variable(s) may change somewhat as well. In the fourth step, we therefore re-construct the copulas to make them consistent with the Adstock variables from the third step, and re-estimate Eq. (1) with the set of retained copula variables. In the fifth and final step, we allow for contemporaneous correlations between the error terms of brands that belong to the same category, by re-estimating the equations of brands in the same category jointly using seemingly unrelated regressions (SUR). If the correlations reveal significant based on a likelihood ratio test, we retain these SUR estimates as our final estimates.

### 4.2. Empirical generalizations on media effectiveness

Having obtained the total short- and long-term elasticity by brand for our three focal media, our next step will be to derive empirical generalizations. In so doing, because most brands only use a subset of media, we must apply a correction for possible self-selection bias.

#### 4.2.1. Endogeneity due to self-selection

In setting up their advertising strategy, brand managers may select the advertising media they expect to be most effective. If unaccounted for, such self-selection may lead to a biased assessment of the media effectiveness across brands. To account for

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this potential bias, we follow Frison et al. (2014) and implement Heckman’s two-stage method. This method starts with the estimation of a probit selection model to assess the likelihood of the adoption of a particular medium (0/1) by a specific brand. The probability that medium \( k \) is used by brand \( i \) in category \( c \) is specified as a function of category-specific instruments:

\[
P\left( s_k^c = 1 \mid z_k^c \right) = \Phi\left( z_k^c \delta_k \right),
\]

(3)

where \( s_k^c \) equals 1 (0) if medium \( k \) is (not) used by brand \( i \) in category \( c \), \( z_k^c \) represents the instruments, and \( \Phi \) is the normal cumulative density function. We consider two sets of instruments. The first set considers, for each brand \( i \) in category \( c \), the group of brands of the same product class (i.e., beverage, food, household care, personal care, pet food) as brand \( i \), but excluding brand \( i \) itself and all its direct (same-category) competitors. For each medium (display advertising, print, TV), it then calculates the share of those brands within the same product class that use the medium. The second set considers, for each brand \( i \) in category \( c \), a comparable group of brands within the same product class (i.e., beverage, food, household care, personal care, pet food) in the Belgian CPG market. The Belgian and Dutch (CPG) market are highly similar in terms of several key characteristics, such as GDP per capita, annual inflation, online ad spending and private-label share. Again, for each medium, we then calculate the fraction of those brands that use the medium. \( z_k^c \) thus contains 6 instruments: 2 sets by 3 media. By construction, because they pertain to brands in another product category (first set) and/or country (second set) (for a similar reasoning, see, e.g., Germann, Ebbes, & Grewal, 2015; Sotgiu & Gielens, 2015), these variables are unlikely to influence the brands’ own advertising elasticities, and thus represent valid instruments. They also constitute strong instruments, as evidenced by the highly significant (\( p < .001 \) for every medium) likelihood ratio tests on their significance in Eq. (3). Based on the estimates of the probit model, we construct an inverse Mills ratio for each medium that enables us to account for the selection bias when deriving meta-analytic effectiveness inferences.

4.2.2. Meta-analytic models

Similar to Frison et al. (2014), we construct meta-analytic regressions that allow us to derive the average short- and long-term advertising elasticity of medium \( k \):

\[
\begin{align*}
\bar{e}_{k,SR}^c &= \bar{e}_{k,LR}^{TOT} + \sum_i \gamma_{k,SR}^i \tau_{i}^{ic} + u_{k,SR}^c, \\
\bar{e}_{k,LR}^c &= \bar{e}_{k,LR}^{TOT} + \sum_i \gamma_{k,LR}^i \tau_{i}^{ic} + u_{k,LR}^c,
\end{align*}
\]

(4)

where \( \tau_{i}^{ic} \) denotes the inverse Mills ratios for display advertising (\( l = D \)), print (\( l = P \)) and TV (\( l = TV \), with associated coefficients \( \gamma \). The error terms \( u_{k,SR}^c \) and \( u_{k,LR}^c \) are normally distributed. Eq. (4) is defined for each medium: display advertising (\( k = D \)), print (\( k = P \)) and TV (\( k = TV \). Both in the short and the long run, the equation is estimated simultaneously (pooled) across media. Since the total elasticities account for cross-media effects, we need to address not only possible self-selection induced by the focal medium, but also by the media the focal medium interacts with. To that end, Eq. (4) includes each time as regressors the inverse Mills correction factors pertaining to all three media. The estimated values for \( \bar{e}_{k,SR}^{TOT} \) and \( \bar{e}_{k,LR}^{TOT} \) then represent the expected total long-term (short-term) effectiveness of medium \( k \) for an average CPG brand.

Because the dependent variables are estimated quantities (with surrounding uncertainty), we estimate Eq. (4) with Weighted Least Squares, using the inverse of the variance of the brand-specific elasticity estimates (obtained with the delta rule) as weights. Given that also the inverse Mills ratios are estimated quantities, we apply jackknife resampling to acquire reliable standard errors for the model parameters. If an inverse Mills ratio is not significant (i.e., does not point to a significant selection bias), the ratio is (in line with the recommendations of Papiès et al., 2017) dropped from the model specification, and the equation is re-estimated. Also for the stand-alone elasticities, short- and long-term empirical generalizations will be derived for each medium \( k \) (denoted as \( \bar{e}_{k,SR}^{TOT} \) and \( \bar{e}_{k,LR}^{TOT} \) respectively), using models similar to Eq.(4).

4.3. Explaining heterogeneity in media effectiveness across brands and categories

In a final step, we will consider to what extent differences in a medium’s advertising effectiveness are systematically and predictably related to the brand’s category characteristics and to its spending volatility. Focusing on the total long-run elasticity, we augment Eq. (4) by adding a medium-specific effect of (i) the level of involvement in the brand’s product category (INV\(^c\)), the hedonic (vs. utilitarian) nature of the category (HED\(^c\)), and the interaction between the two (INV\(^c\) * HED\(^c\)), and (ii) the volatility of the brand’s advertising spending on that medium (VOL\(^c\)). To facilitate interpretation, we mean-center these category characteristics. Because previous studies show that advertising effectiveness may well differ between more or less ‘popular’

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brands (e.g., Draganska et al., 2014; van Heerde, Gijsenberg, Dekimpe, & Steenkamp, 2013), we allow medium-specific effects of the brand’s market share (BSHARE$t_k$) as controls. The following model is thus estimated across the three media:

$$\bar{e}_{k,LR}^t = \mu_{k,LR} + \sum_{i} \gamma_{k,LR} \text{INV}^i + \alpha_{1,k}\text{HED}^i + \alpha_{2,k}\text{INV}^i \cdot \text{HED}^i + \omega_{k,\text{VOL}}^i + \eta_{k}\text{BSHARE}^i + \epsilon_{k,LR}^t$$

Similar to Eq. (4), the self-selection issue is managed by the inclusion of three sets of inverse Mills ratios, derived from Eq. (3). Since the dependent variable and the inverse Mills ratios are estimated quantities, we again estimate Eq. (5) using Weighted Least Squares and correct the standard errors of the parameters using jackknife resampling. As before, if an inverse Mills ratio is not significant, it is dropped from the model and the equation re-estimated.

5. Results

5.1. First-stage results: Advertising media effectiveness

We first consider the results of the brand-sales models in Eq. (1). The median VIF value is 2.26 overall – far below the rule-of-thumb cutoff value of 10 (Hair, Black, Babin, & Anderson, 2014), which indicates that multicollinearity is not an issue. Moreover, the coefficients of the control variables are in the expected direction (see Web Appendix D for a summary) – attesting to the validity of the estimates. Our focus, though, is on the impact of the different media, which we discuss below.

5.1.1. Total effectiveness

The estimates for the total elasticities are summarized in Table 4 (Panel A). The table provides information on the distribution of the elasticities across brands (left section), the significance of brand-specific coefficients (middle section) and the meta-analytic findings (right section). Zooming in on the latter first, we observe that for the average brand, TV has a significant positive

| Variable | Operationalization |
|----------|-------------------|
| Sales-advertising relation | Total (volume) sales for brand $i$ in category $c$ during week $t$. |
| Sales (SALES$^c$) | Expenditures (in €) on medium $k$ (Display adv, Print, or TV) for brand $i$ in category $c$ during week $t$, deflated by the Consumer Price Index (CPI). |
| Advertising (ADVERTISING$^c_k$) | Stock variable for medium $k$ of brand $i$ in category $c$ during week $t$, defined by Eq. (2). |
| Adstock (ADSTOCK$^c_k$) | Market-share weighted average price of competitors of brand $i$ in category $c$ during week $t$. |
| Trend (TREND$^c_k$) | Expenditures on smaller and less frequently used media (< 7) for brand $i$ in category $c$ during week $t$. |
| Seasonality (SEAS_COS$^c_k$, SEAS_SIN$^c_k$) | Total expenditures on display advertising, print, TV and other media by competitors of brand $i$ during the observation period. |
| Price (PRICE$^c_k$) | Items rated on a 7 point scale, from 1=‘strongly disagree’ to 7=‘strongly agree’. |
| Competitive price (COMP_PRICE$^c_k$) | Items based on Steenkamp, van Heerde, and Geyskens (2010): “This product category is very important to me”, “This product category interests me a lot”. |
| Other advertising (OTHERADV$^c_k$) | Summed scale of hedonic vs. utilitarian nature of the category. The utilitarian scores were reverse-scaled before averaging (Cronbach alpha = 0.81). Items based on Voss, Spangenberg, and Grohmann (2003). For hedonicity: “Products in this category are fun”, “Products in this category are delightful”, “Products in this category are exciting”. For utilitarian nature: “Products in this category are functional”, “Products in this category are necessary”, “Products in this category are practical”. |
| Competitive advertising (COMP_ADVERTISING$^c_k$) | Coeficients of the control variables are in the expected direction (see Web Appendix D for a summary) – attesting to the validity of the estimates. Our focus, though, is on the impact of the different media, which we discuss below. |
| Involvement (INV$^c_k$) | Coeficients (middle section) and the meta-analytic findings (right section). Zooming in on the latter first, we observe that for the average brand, TV has a significant positive

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15 As a robustness check, we also included the brand and category characteristics as additional explanatory variables in Eq. (3), and derived the inverse Mills ratios from that regression. The results were very similar.

16 Value across all brands and variables, in a model excluding interactions (following Disatnik & Sivan, 2016). The separate values for our three focal adstock variables are similar: 5.16 for banner, 3.04 for print, and 2.93 for TV. Still, we want to point out that in our meta-analytic estimates in Table 3, and our second stage results, we always correct for the standard errors of the first-stage estimates. This implies that, in the few instances where less-reliable estimates are obtained (e.g., in the occasional instances where the VIF values exceeded 10), these estimates will receive only a low weight, and hardly influence our main findings.

17 A histogram of the total elasticities is given in Web Appendix E, Panel A.
impact on brand sales, in the short run \( \varepsilon_{TOT;SR} = 0.002, p < .01 \) as well as the long run \( \varepsilon_{TOT;LR} = 0.008, p < .01 \)\(^{18} \). These estimates are comparable to the meta-analytic results from Frison et al. (2014) for the Belgian CPG market (0.003 and 0.004, respectively) and to the findings of Shapiro et al. (2020) across 288 CPG brands in the US (who report a median long-run TV advertising elasticity of 0.014). The total elasticities for print are also significant, in both the short run \( \varepsilon_{P;SR} = 0.003, p < .01 \) and the long run \( \varepsilon_{P;LR} = 0.007, p < .05 \). Frison et al. (2014) distinguished two types of print media (newspaper and magazine), and found an insignificant short- and long-term elasticity for the former, but a small significant effect for magazine (0.002 and 0.004, respectively). As such, our findings for the offline media are largely in line with theirs, giving face validity to our results.

As for display advertising, which was not studied in Frison et al. (2014), we observe no significant meta-analytic total effects \( \varepsilon_{TOT;SR} = 0.000, \varepsilon_{TOT;LR} = 0.003, p > .10 \). This suggests that, for the typical CPG brand, using display advertising does not enhance brand sales – corroborating earlier concerns that consumers may not (or insufficiently) notice display ads (Burke et al., 2005). However, these total elasticities capture the impact of display ads as they are used in practice – in combination with other media (see Table 2). As indicated by Dijkstra et al. (2005), too many media in a campaign may result in lower attention and reduce medium effectiveness. The question then becomes: would the use as a stand-alone medium make display ads effective for the “prototypical” CPG brand?

### 5.1.2. Stand-alone effectiveness and media interactions

The results for the stand-alone elasticities are presented in Panel B of Table 4\(^{19} \). Not accounting for cross-media effects reduces the impact of TV and print advertising in the short run (to \( \varepsilon_{TV;SR} = 0.001, p < .01 \) and \( \varepsilon_{P;SR} = 0.002, p < .10 \)), yet increases the impact of these media in the long run (to \( \varepsilon_{TV;LR} = 0.009, p < .01 \) and \( \varepsilon_{P;LR} = 0.011, p < .01 \)). For display ads, we again find no evidence of a significant sales impact in the short run \( \varepsilon_{D;SR} = -0.000, p > .10 \), but we do find a significant stand-alone effect in the long run \( \varepsilon_{D;LR} = 0.042, p < .01 \).

To acquire more insights into the interactions by media pair across the different brands, Table 5 summarizes the distribution of the cross-media parameters (i.e., the theta’s in Eq. (1)), along with their signs and significance.\(^{20} \) By working with the cross-period interactions (i.e., interactions between the Adstock variables), we can estimate cross-media effects for all media pair users.\(^{21} \) For

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**Table 4**

| Medium | Number of users\(^{a} \) | Percentiles | Brand-specific findings\(^{b} \) | Meta-analytic findings\(^{c} \) | Estimate | p-value |
|--------|--------------------------|-------------|-------------------|---------------------------|---------|--------|
|        |                          | 25          | 50                | 75                        | Number of significant positive effects | Share of significant positive effects (%) |
| **Panel A: Total elasticities** | | | | | | |
| Short-term | | | | | | |
| Display adv | 104 | -0.0049 | 0.0012 | 0.0102 | 22 | 21.15 | 0.0001 | 0.4647 |
| Print | 78 | -0.0026 | 0.0033 | 0.0165 | 24 | 30.77 | 0.0028 | 0.0006 |
| TV | 132 | -0.0029 | 0.0025 | 0.0095 | 40 | 30.30 | 0.0016 | 0.0013 |
| Long-term | | | | | | |
| Display adv | 104 | -0.0664 | 0.0089 | 0.1147 | 17 | 16.35 | 0.0030 | 0.1727 |
| Print | 78 | -0.0463 | 0.0183 | 0.0854 | 14 | 17.95 | 0.0067 | 0.0181 |
| TV | 132 | -0.0295 | 0.0080 | 0.0569 | 34 | 25.76 | 0.0075 | <0.0001 |
| **Panel B: Stand-alone elasticities** | | | | | | |
| Short-term | | | | | | |
| Display adv | 104 | -0.0104 | 0.0025 | 0.0211 | 23 | 22.12 | -0.0003 | 0.3493 |
| Print | 78 | -0.0063 | 0.0035 | 0.0214 | 18 | 23.08 | 0.0019 | 0.0526 |
| TV | 132 | -0.0050 | 0.0018 | 0.0105 | 34 | 25.76 | 0.0012 | 0.0063 |
| Long-term | | | | | | |
| Display adv | 104 | -0.1643 | 0.0243 | 0.1544 | 17 | 16.35 | 0.0419 | 0.0004 |
| Print | 78 | -0.0969 | 0.0129 | 0.1382 | 14 | 17.95 | 0.0114 | 0.0030 |
| TV | 132 | -0.0413 | 0.0074 | 0.0652 | 29 | 21.97 | 0.0089 | 0.0001 |

\(^{a} \) ‘Users’ are brands that use the given medium at least seven times during the observation period.

\(^{b} \) Significance based on one-sided test, \( p < .10 \).

\(^{c} \) Significance based on standard errors from Jackknife resampling, \( p \)-values for one-sided test.

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\(^{18} \) Given the clear directional hypothesis on the sign of advertising elasticities (Hanssens, 2015), we use one-sided tests here.

\(^{19} \) A histogram of the stand-alone elasticities is given in Web Appendix E, Panel B.

\(^{20} \) We used two-sided tests for the cross-media parameters, given that theoretical arguments can be given (discussed before) for both synergistic and antagonistic effects.

\(^{21} \) Had we only considered same-period interactions (as is common in prior work), this number would have dropped from 58 to 20 for display advertising and print, from 90 to 76 for display advertising and TV, and from 66 to 27 for print and TV.
both cross-media effects that involve display ads, we find that the share of significant positive and negative cross-media parameters is larger than chance. Combining display ads with print and/or TV ads may thus yield additional sales, but it is at least as likely to retract from the effectiveness of these media – an intriguing finding that we explore in more detail in the subsequent sections.

To conclude this section: whereas print and TV enhance sales for a typical CPG brand in the long run, this does not hold for display ads – the (meta-analytic) total sales elasticity of which remains insignificant. However, this does not imply that the medium cannot be effective. There is a substantial subset of brands (a proportion larger than chance) for which the total display-advertising elasticity is significantly positive, in the short (21%) and the long (16%) run. Hence, the meta-analytic elasticities appear to conceal quite some variation across brands and/or categories. This is confirmed by means of the chi-square homogeneity test (Rosenthal, 1991), which evaluates the significance of the variance in effect sizes for the long-term total elasticities. For each medium, we find evidence that there is significant ($p < .01$) heterogeneity among their estimated elasticities. Importantly, the stand-alone elasticities and cross-media parameters reveal that using the media alone or in combination makes a difference, with media interactions being positive in some instances but negative in others.

5.2. Second-stage results: Drivers of the total long-term display-advertising, print and TV effectiveness

To explore this variability in advertising effectiveness, we proceed to our moderation analysis, by estimating Eq. (5). Table 6 presents the estimation results.

The medium-specific coefficients of brand share indicate that TV advertising is less effective for already more popular brands ($\eta_{TV} = −0.023, p < .01$) – consistent with earlier findings. Interestingly, the opposite pattern holds for print: print advertising being less effective for low-share brands ($\eta_p = 0.066, p < .05$). The impact of display ads does not differ between high and low share brands ($\eta_d = 0.012, p > .10$). As for the category characteristics, category involvement and hedonicity enhance the display-advertising effect ($\omega_1 = 0.024, p < .05; \omega_2 = 0.010, p < .10$). Print appears less impactful in higher-involvement categories ($\omega_3 = −0.019, p < .10$), while TV has a more positive effect in more hedonic categories, and especially those with higher involvement levels ($\omega_2, \nu = 0.004, p < .10; \omega_3, \nu = 0.013, p < .05$). For volatility, we only find a significant effect for display ads ($\omega_d = −0.015, p < .10$). The negative coefficient suggests that a more even, sustained spending pattern is appropriate for this medium.

5.2.1. Total long-term elasticities by category type

To get a feel for the impact of category characteristics, we conduct a spotlight analysis (as in Datta et al., 2017). Building on our conceptual discussion (and similar to Del Barrio-Garcia et al., 2019), we first distinguish between four category types, based on a median split along the low vs. high involvement dimension, and the hedonic vs. utilitarian dimension. For each category type, we then use the estimates from Table 6, Panel C, to obtain the average total long-term elasticity for each advertising medium, across brands in that type of category that use the medium, along with its significance level. We do so for mean levels of brand share and spending volatility.

As Fig. 1 shows, display advertising significantly enhances sales for brands in high-involvement, hedonic categories, with an average elasticity of $\varepsilon_{TOT}^{D, high, he} = 0.013 (p < .05)$. In those categories, its impact is similar to that of TV ($\varepsilon_{TOT}^{TV, high, he} = 0.019, p < .05$) and print ($\varepsilon_{TOT}^{P, high, he} = 0.010, p < .10$) – the differences between media being statistically insignificant ($p > .10$). This positive effect of display ads is consistent with the observation that for hedonic (“feel”) products, consumers tend to engage in peripheral processing of mostly visual information, while a high level of category involvement reduces their tendency to deliberately avoid or be irritated by the (display) ad. In all other category types, display ads do not seem to generate a significant sales increase. This stands in sharp contrast with print and TV, which exert a significant positive effect in low involvement categories, irrespective of their utilitarian or hedonic nature. So, based on Fig. 1, the “opponents” of display advertising appear to be proven right – the medium generating only a small positive impact for one particular type of CPG products, and representing spoiled arms in all other instances. However, such conclusion would ignore managers’ discretion to use display advertising either as a stand-alone medium or alongside other media.
from the synergies with other media. Further exploration shows that these positive cross-effects especially hold for higher-share lift when used as a stand-alone medium (utilitarian products, where the total display-advertising elasticity was insignificantly small). The opposite occurs for high-involvement – antagonistic effects, such combined use may have driven down the display-advertising elasticity. To explore this further, we re-estimate Eq. (5) with the stand-alone (instead of the total) long-term display-advertising elasticity as dependent variable, and again consider the impact by category type. In low-involvement categories, as anticipated, display advertising still fails to produce a positive sales effect (while print and TV continue to generate a sales lift). In high-involvement categories, we observe an interesting reversal. For high-involvement hedonic products, display advertising is not effective by itself (for low-involvement utilitarian products, display advertising continues to be ineffective no matter the temporal spread. In each of the other cases, display ads can generate a significant sales lift provided that the volatility is sufficiently low (i.e., up to 1.65 for low-involvement hedonic categories, 1.74 for high-involvement hedonic categories, and 2.05 for high-involvement hedonic categories). Hence, if one acknowledges the role of the temporal budget spread, the picture becomes much less bleak, and rather consumers seeking out information in response to individual media (e.g., by clicking on the display ad), and rather becoming confused or irritated when confronted with multiple media. Closer analysis (cf. footnote 22) revealed that display and print advertising, in particular, interact negatively (the meta-analytic estimate for their cross-effect is negative and significant).

5.2.2. The role of media interactions

The results in Fig. 1 capture the impact of the medium as currently deployed, that is: often in combination with traditional media. In case of antagonistic effects, such combined use may have driven down the display-advertising elasticity. To explore this further, we re-estimate Eq. (5) with the stand-alone (instead of the total) long-term display-advertising elasticity as dependent variable, and again consider the impact by category type. In low-involvement categories, as anticipated, display advertising still fails to produce a positive sales effect (while print and TV continue to generate a sales lift). In high-involvement categories, we observe an interesting reversal. For high-involvement hedonic products, display advertising is not effective by itself (for low-involvement utilitarian products, display advertising continues to be ineffective no matter the temporal spread. In each of the other cases, display ads can generate a significant sales lift provided that the volatility is sufficiently low (i.e., up to 1.65 for low-involvement hedonic categories, 1.74 for high-involvement hedonic categories, and 2.05 for high-involvement hedonic categories). Hence, if one acknowledges the role of the temporal budget spread, the picture becomes much less bleak, and rather

5.2.3. The role of spending volatility

So far, we considered the media impact for average volatility levels as observed in the data. However, our estimates in Table 6 showed that for display advertising, changes in the temporal spread of expenditures may significantly alter the advertising effect. As an additional probe, we re-ran the second-stage (weighted) regressions with the same drivers as in Eq. (5), but with the cross-media parameters as dependent variables, and with parameters specific to each media pair.

We also estimated a version of Eq. (5) in which we added interactions between volatility and the category characteristics, for each medium. This did not improve the R2 significantly, indicating that the impact of volatility does not differ between category types.

Table 6
Drivers of total long-term effectiveness.a

| Variable          | Estimate | t-Statistic | p-value b |
|-------------------|----------|-------------|-----------|
| Display adv       | 0.002    | 0.322       | 0.748     |
| Print             | 0.011    | 2.536       | 0.012     |
| TV                | 0.012    | 5.840       | 0.000     |
| Display adv * Involvement | 0.024    | 2.146       | 0.033     |
| * Hedonic         | 0.010    | 1.814       | 0.071     |
| * Involvement*Hedonic | −0.016   | −1.233      | 0.219     |
| Print             | −0.019   | −1.697      | 0.091     |
| * Hedonic         | 0.005    | 1.026       | 0.306     |
| * Involvement*Hedonic | 0.014    | 1.123       | 0.262     |
| TV                | 0.001    | 0.282       | 0.778     |
| * Hedonic         | 0.004    | 1.918       | 0.056     |
| * Involvement*Hedonic | 0.013    | 2.392       | 0.017     |
| Display adv * Volatility | −0.015   | −1.663      | 0.097     |
| Print * Volatility | 0.002    | 0.403       | 0.687     |
| TV * Volatility   | 0.001    | 0.244       | 0.807     |
| Display adv * Brand Share | 0.012   | 0.689       | 0.491     |
| Print * Brand Share | 0.066    | 2.201       | 0.029     |
| TV * Brand Share  | −0.023   | −2.888      | 0.004     |
| R2                | 0.186    |             |           |
| R2adj             | 0.137    |             |           |

a Product category characteristics mean centered across categories in the dataset. Brand share and volatility mean centered by medium.

b p-values based on two-sided test.

22 As an additional probe, we re-ran the second-stage (weighted) regressions with the same drivers as in Eq. (5), but with the cross-media parameters as dependent variables, and with parameters specific to each media pair.

23 We also estimated a version of Eq. (5) in which we added interactions between volatility and the category characteristics, for each medium. This did not improve the R2 significantly, indicating that the impact of volatility does not differ between category types.
proves the proponents of display advertising right. Continued (even) exposure enhances the impact of display advertising (in line with the experimental findings of Drèze & Hussherr, 2003), and turns it into an effective medium for three out of the four category types.

6. Conclusions, implications and future research

Display advertising is becoming an increasingly important medium in brand managers' toolkit, with expenditures rising at astounding rates. As emphasized by Sridhar et al. (2016, p. 39), “online advertising has moved from a peripheral to a central advertising medium”. Yet, when it comes to CPG brands, the role of display ads is not yet clear. Not only are there huge differences in the adoption of this medium between brands, practitioners also appear to hold conflicting views on its ability to increase brand sales. While advocates proclaim that they “see the banner’s influence again and again” (AdAge, 2014), sceptics consider it a waste of good money and describe it as “one of the most misguided and destructive technologies of the Internet age” (The New York Times, 2014).

With very few empirical studies to go on, the jury is still out on whether, and when, display ads can improve the performance for CPG brands. Importantly, to fully evaluate the impact of display ads, one should assess not only the medium's ‘stand-alone’ effect, but also its ‘total’ effect in interaction with other media. Yet, achieving individual-medium and combined media-effectiveness in a multimedia advertising spending is far from trivial (Sridhar et al., 2016). What further complicates matters is that the effects are bound to differ between product categories, depending on consumers’ decision-making process in those categories. This lead Draganska et al. (2014) to explicitly call for more research on the interplay between category characteristics and media effectiveness.

Our study addressed this call, by conducting a large scale analysis of the impact of display ads on brand sales in different types of CPG categories, alone or in combination with other media, and with due attention to the spending volatility. Below, we summarize the key findings, and highlight important managerial takeaways.

6.1. Findings

We find that for the average CPG brand, unlike TV (and, to some extent, print) advertising, display ads by themselves do not exert a significant impact on brand sales, in the short nor the long run. Moreover, we find that interdependencies between display ads on the one hand, and offline media on the other, are negative in as many instances as they are positive. It follows that even

| Product Category | Hedonic | Utilitarian |
|------------------|---------|-------------|
| High Involvement | ![Graph](image1.png) | ![Graph](image2.png) |
| Low Involvement  | ![Graph](image3.png) | ![Graph](image4.png) |

Fig. 1. Total long-term elasticity for display advertising, print and TV advertising, by type of product category. Spending volatility set at the mean for each medium. *p < .10, one sided.
within a multi-media setting, display ads are not guaranteed to enhance sales for the typical CPG brand. This appears to confirm recent managerial concerns that investments in online ads for CPG are largely ineffective.

Still, there is a significant subset of brands for which display ads do enhance (long-term) brand sales. Analysis of these heterogeneous effects generates interesting new insights. First and foremost, category characteristics matter. Display ads do not lift sales for low-involvement utilitarian products. For these products, display advertising may suffer from “double-jeopardy”: as a retrieval, low-bandwidth medium it can easily be circumvented by less-involved consumers (Chatterjee, 2012; Dijkstra et al., 2005); as a carrier of few and mostly visual cues, it provides hardly any factual information that might be relevant for these products. Conversely, display ads can lead to a significant increase in brand sales in high-involvement categories. For high-involvement products that are hedonic in nature, display advertising works best in combination with other media. This may be because combining display advertising and traditional-media results in higher levels of attention (Chang & Thorson, 2004). It is also in line with the different functionality of the media: while display ads are mainly restricted to visual modes and cannot transfer a lot of information as such, they can reinforce the brand imagery conveyed through other media – enhancing brand salience or creating a reminder effect (Batra & Keller, 2016; Drèze & Hussersh, 2003). Such positive interactions prevail especially for already established brands, where display ads can help the brand stay ‘above the radar’. Interestingly, for high-involvement utilitarian products, display advertising should not be used in combination with print media. In these categories, display ads offer consumers a unique opportunity to obtain detailed verbal and visual information by clicking on the ad, and to elaborate on that information at their own pace. It appears that in such setting, display ads are ‘self-sufficient’, rather than generating extra attention or conveying additional information, the combination with print messages leads to confusion and overload.

Moreover, much depends on how the display-advertising budget is allocated over time, i.e., on its volatility. Display-advertising elasticities are higher when investments in the medium are not pulsed, but more evenly spread in time. This appears consistent with the observation that display ads are less subject to tedium and wearout, and can play a role in multiple stages of the purchase funnel, i.e., in creating awareness, maintaining brand salience, and activating consumers to buy (Batra & Keller, 2016). With an even message stream, display messages can lift sales even for low-involvement hedonic items – corroborating that pre-attentive processing of the ads can accumulate into higher brand awareness, familiarity and liking (Chatterjee, 2012).

In all, these findings underscore that display ads can play a very diverse role in the advertising media-scape – more so than any other media. Neither the proponents nor the opponents are universally right: whether display-advertising investments are ‘spoiled arms’ or ‘money well spent’ critically depends on the product category they are used in as well as on the temporal spread, not only for the medium itself, but also in combination with other media.

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Table 7
Display advertising usage across category types.

| Product category  | Hedonic | Utilitarian |
|-------------------|---------|-------------|
| Share of display-advertising users | 72.2 | 74.1 |
| Display-advertising spending share | 8.1 | 8.2 |
| Users with low-enough volatility | 38.5 | 48.8 |
| Combined users: Display adv -Any | 92.3 | 93.0 |
| Display adv -Print | 60.2 | 48.8 |
| Display adv -TV | 84.6 | 93.0 |
| Share of display-advertising users | 65.1 | 46.7 |
| Display-advertising spending share | 6.2 | 20.0 |
| Users with low-enough volatility | 46.3 | 0.0 |
| Combined users: Display adv -Any | 92.7 | 57.1 |
| Display adv -Print | 61.0 | 57.1 |
| Display adv -TV | 85.4 | 42.9 |

Display-advertising spending share = share of display-advertising expenditures in total advertising expenditures by the brand on display advertising, print and TV, averaged across brands in the cell (%). Users with low-enough volatility = out of brands in the cell that use display advertising, % for which volatility is below effectiveness cutoff (see legend of Fig. 2). Combined users = out of brands in the cell that use display advertising, % that use it in combination with other media (with any other (print OR TV) media, with print and with TV).

6.2. Management implications

Our results have important implications for managers. First, they show that display ads are not the new panacea for enhancing CPG brand sales. For the average brand, they do not generate a marked sales increase. It follows that managers should not automatically imitate their competitors in an attempt to maintain competitive parity, and rush into using this medium without careful reflection on its overall effectiveness. Still, they should not prematurely dismiss it either. Display-advertising investments are more rewarding for some brands than for others, and a judicious allocation of budgets over time in combination with other media can make the difference between effective and non-effective ads.

Do managers make the right decisions? And: (how) can their decisions be improved? To shed more light on this issue, we consider the actual display spending patterns by brands in the four category types (Table 7 gives an overview), against our findings on the effectiveness of the online medium. We find that the share of display-advertising users is largest in the high-involvement categories (>70%), with a smaller share of users in the low-involvement hedonic (65.1%) or low-involvement utilitarian group (46.7%). This is consistent with our finding that display advertising is mostly effective in high-involvement categories. However, when we look at expenditure shares, the situation is different: the share of display advertising in the brands’ total advertising spending is highest in the low-involvement utilitarian categories (20%, compared to less than 10% for the remaining product types).24 Moreover, for about half of the brands in these categories, display advertising is the sole medium of choice. Given that – in contrast with print and TV – display-advertising effects for low-involvement utilitarian products are never significant, these products are spoiled arms. Managers of these products would do well to re-allocate their display ad budgets to the traditional offline media.

In the remaining three category types, most brands that adopt display advertising use it in combination with traditional media (>92%). For hedonic products, where synergies are found to prevail, such combined use is a good thing. However, only half of the low-involvement hedonic brands (46.3%) have a low-enough volatility to get a significant positive effect. The situation is worse for high-involvement hedonic items, where only 38.5% have a temporal spread for their display ads conducive to a lift in brand sales. Our results suggest that for these brands, more even (sustained) spending would yield more bang for the online buck. Turning to the high-involvement utilitarian products, we find for only half (21 out of 43) of the brands, display-spending volatility is low-enough to yield a significant positive effect with combined use. These brands, also, are advised to maintain a more even spending stream. Moreover, about half of these brands use display advertising along with print – a detrimental combination. Based on our findings, they would be better off using display advertising as a stand-alone medium for these products.

6.3. Limitations and future research

While it offers several novel insights, our study also has a number of limitations that open up new research opportunities. First, even though we implemented an econometric correction for self-selection in the brands’ use of certain media along with an endogeneity correction on the chosen levels of media expenditures, our study did not involve a random assignment of brands to the different conditions, making any causal inference conditional on the validity of these “corrective measures”. Second, we focused on display advertising. Future studies could look into the category-specific interactions between offline media and other online media with different characteristics, such as online video, which may be more (less) similar to TV (print) advertising than the display ads we studied. Third, like most previous studies, we considered the impact of advertising budgets, not content.

24 This figure is based on a small number of brands, so it has to be interpreted with caution.
The display-ad effect, and the direction and magnitude of offline-online media interactions, may be further shaped by the nature (or creative content) of the message (see, e.g., Braun & Moe, 2013; Bruce & Murthi, 2017), and its consistency across the different media carriers. A promising route would be to track the advertising impact across media for individual ad campaigns – an aspect that we leave for future analysis. Fourth, while we found clear impact of display volatility, we could only speculate on the response mechanisms driving that effect. Future studies considering individual-level process measures along the lines of Chae et al. (2019) could further explore this. For lack of data, we had to consider display ads as one medium, without distinguishing the specific websites on which the ads appeared. To the extent that the ad effects are influenced by the quality of the website (e.g., the number of "real" viewers that are CPG shoppers, or the brand fit with the website content), a more refined analysis would be worthwhile. Relatedly, like most previous studies on the brand-sales impact of different media, we did not have data on the consumers targeted by the brand ads, nor on the media’s audience overlap. Hence, in instances where we found no significant cross-media interplay, we could not ascertain whether this was due to non-overlapping audiences, or to the intrinsic absence of synergistic or antagonistic effects even among consumers confronted with the different media. We leave this as a topic for future study.

Finally, it is important to emphasize that the current spending levels for online ads, while rapidly rising, are still small for most CPG brands (with an average share of 1.82%; Table 2). It will be interesting to see whether (and how) these results change if the allocation to display ads grows larger. The ongoing Covid-19 pandemic may well accelerate this evolution, as industry analysts expect display advertising spending to increase as a result of intensified online shopping behavior. Will this lead to a growing consumer acceptance (and effectiveness) of online ads, or result in larger fractions of CPGs’ target population experiencing advertising weariness (Chae et al., 2019) with negative marginal effects of additional exposures? We leave this as a topic for future study.

Declaration of competing interest
None.

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Web Appendix. Supplementary data
Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijresmar.2020.08.004.

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