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ORIGINAL ARTICLE

Data-driven budget allocation of retail media by ad product, funnel metric, and brand size

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Abstract
Sellers on online marketplaces such as Amazon.com use a variety of retail and retail media advertising services to improve their brand performance, including awareness, consideration, and revenue. But how can they measure their progress and drive these metrics? For 122,000 brands, we measure Amazon shoppers' brand awareness, consideration, and purchases and test how they change with ad and retail actions. Furthermore, we compare these brands' past media mix with the recommended allocation based on the model's coefficients. We find that new product launches and upper-funnel retail media advertising are particularly effective for small brands. Medium-sized and large brands benefit most from lower-funnel advertising. For the funnel stages, all three metrics benefit from the number of new reviews, % discount, negative keywords, and geo-reach campaigns. These results are robust across different product categories, but we find notable differences in how upper- and middle-funnel ad products succeed in driving sales.

Keywords Retail media · Budget allocation · Brand awareness · Brand consideration · Brand revenue · Digital advertising · Online retail · Brand building

Introduction

Global e-commerce is estimated to increase from $3.3 trillion in 2022 to $5.4 trillion in 2026 (Giuditta 2022). As the pillars of online retail, online marketplaces continue to play an essential role in facilitating transactions by connecting sellers and consumers. For example, Amazon[1] offers sellers many options to grow their brands, covering the 4Ps of marketing: product launch, price (selling prices and discounts), place (search rank position), and promotion (ad impressions, audience segments, and campaign goals). Such promotion is widely known as "retail media," which currently represents $125.7 billion of advertising spend and is expected to overtake TV advertising by 2028 (Davey 2023). At the same time, online marketplaces offer a rich portfolio of targeting, including location-based reach and negative keywords that filter out irrelevant searches. While negative keywords are widely discussed in practice (a Google search reveals 536 million results on October 24, 2023), published scientific results are lacking. To sellers, these prolific new ad formats and retail options are both intriguing and often overwhelming (Masters 2022). Against this background, our research question is: which advertising and retail factors matter most for brand growth to sellers on Amazon?

This question remains unanswered in the existing literature for several reasons. The first lies in the unique context of the online marketplace, in which insights from traditional offline settings may not apply. Sellers on online marketplaces have access to many more types of advertising in addition to their ability to directly set retail prices. By contrast, in offline retail stores, retailers choose the prices, and in-store ad options are limited. Thus, while marketing literature on budget allocation among mass media advertising is rich, it shows a large gap for online retail media. The second

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[1] In July 2022, Amazon.com, the most popular online marketplace in the United States, generated 5.3 billion monthly visits; eBay, the second most visited shopping site, had 3 billion visits. In addition, both Amazon and eBay were the world's top online retailers in terms of mobile web traffic (https://www.statista.com/statistics/1155246/leading-online-marketplaces-usa-average-monthly-visits/).

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challenge is data availability, as collecting data on both advertising and brand performance and tracking them over time are difficult. This gap is especially pronounced for new ad forms, such as retail media; for new targeting options, such as negative keywords; and in the context of the full 4Ps of retail media. Finally, advertisers differ in important ways, such as existing brand sizes and advertiser goals across purchase funnels. We follow the empirics-first approach (Golder et al. 2022), in which analysis of an abundance of potential ad and retail drivers yields empirical results, which form the basis of potential explanations and offer suggestions for theory development.

In this research, we examine the impact of advertising and retail drivers on brand performance in the context of Amazon's online marketplace. We leverage a unique dataset from the Amazon Brand Index (ABI), which measures brand-level awareness, consideration, and revenue, based on shopper behaviors. We also collect ad and retail factors as potential drivers for brand growth metrics. Specifically, we analyze weekly data in the period between January 1, 2021, and May 16, 2022, which includes more than 122,000 US brand/product category combinations among the largest categories within verticals of hardlines, softlines, and consumables (consumer packaged goods). We use a fixed-effects panel model, which controls for the potential endogeneity problem to explain weekly changes in the three ABIs: brand awareness, brand consideration, and brand revenue. From the results, we calculate the optimal budget allocation across ad products based on funnel metric and brand size.

Our contributions are fourfold. First, we find that growth in all three brand metrics was driven by advertising impressions from Sponsored Brands (SBs), Sponsored Brands video (SBv), Sponsored Display (SD), and Sponsored Products (SPs), suggesting robust performances of Amazon sponsored ads on all brand metrics. For campaign strategies, the total number of ads and ads with negative keywords or geo reach significantly improved all three metrics. Negative keywords allow marketers to prevent a shopper's search query from triggering an ad impression when it is not desired, by a specific list of suppression terms. For example, a seller of adult diapers may specify "babies" as a negative keyword to avoid serving ads to consumers looking for diapers for babies. In terms of retail factors, both the count of newly available reviews in that week and the percentage of discount had significant impacts on ABI. In addition, all three brand-building metrics displayed significantly positive changes on Prime Day and during the Thanksgiving week.

Second, we identified key performance indicator– (KPI-) specific drivers. For example, while Fire TV and Owned & Operated (O&O) Display impressions increased both awareness and revenue, they did not show a significant impact on consideration. Remarketing, lifestyle/in-market segments, and ads optimized for purchase significantly improved awareness. Furthermore, ads optimized for click-through rate (CTR) significantly improved consideration. Drawing on the performance from each ad format, known at Amazon as "ad products," we also calculated the optimal media mix to contrast with the current mix, recommending an increase in budget for Fire TV, O&O Display, SBs, and SBv to grow brand revenue.

Third, we find notable differences in advertising drivers for brand awareness based on brand sizes. Upper-funnel advertising products (e.g., Streaming TV [STV]) were especially effective for small brands, though those brands have yet to fully take advantage of these opportunities. For medium-sized and large brands, both SBs and SBv significantly improved brand awareness. We find little differentiation across brand sizes in brand consideration and revenue drivers.

Fourth, we also find differences among top advertising products as ABI drivers across product categories. Upper-funnel products (i.e., Fire TV, STV) had a significant impact in Clothing, Shoes & Jewelry; Grocery & Gourmet Food; Sports & Outdoors; Electronics; Toys & Games; and Pet Supplies. Middle-funnel products (i.e., O&O and Demand-Side Platform [DSP] Displays) had significant impacts in Grocery & Gourmet Food, Tools & Home Improvement, and Health & Household. By contrast, sponsored ads showed a significant impact on brand revenues in all product categories, with SBs and SBv having the largest effect sizes.

Taken together, these results indicate that both retail and advertising actions help grow brands, and they have differential impacts depending on brand sizes and success metrics. As a result, to improve their brand performance, sellers need to choose their priority actions according to which brand metrics they want to improve, as well as their current brand sizes and the product categories in which they operate.

The remainder of this paper is organized as follows: we first review the related literature streams and integrate them into our conceptual framework. Then, we specify data and measurement. After detailing our method, we estimate it and report on the results. Finally, we leverage the empirical results to calculate the optimal budget allocation across ad products, for different brand sizes and advertising goals.

Literature review

This study investigates how different advertising and retail drivers improve brand awareness, consideration, and revenue. Therefore, we contribute to the literature streams on brand attitude metrics, e-commerce, the impact of advertising, and how it differs across ad products, brands, and categories.

Prior research shows that *consumer attitudes* toward a brand influence the association between advertising and brand outcomes (Chaudhuri 2002), highlighting the importance of consumer perceptions in determining ad effectiveness (Buil et al. 2013). In their theory of buying behavior, Howard and Sheth (1969, p. 14) note, "Attitude is an input into executive decisions because many marketing decisions, including advertising, can be more adequately evaluated or measured in terms of attitude than of purchase behavior." However, this perspective has been challenged by psychology literature (e.g., Ajzen and Fishbein 1977). Consistent with this literature, Pauwels and van Ewijk's (2020 recent marketing study confirmed the low correlations between general attitudes and behavior, unless the measurement context maps onto the behavior in a very specific way. We propose that retail media offers such *specific mapping*, because retail site visitors leave specific behavioral clues as to their attitudes toward the brands and products they are browsing, searching, and examining. Indeed, behavior can be viewed as an *action* (e.g., a purchase) directed at a *target* (e.g., a brand), performed in a *given context*, at a certain *point in time* (Ajzen and Fishbein 1977). The principle of compatibility requires that measures of attitude and behavior involve the same action, target, context, and time elements, as Krauss (1995) shows across eight studies.

In marketing, researchers have assessed important concepts such as brand awareness and consideration with purchase (Vakratsas and Ambler 1999). Market response models have shown that such metrics predict sales above and beyond long-term marketing effects (Hanssens et al. 2014; Kumar et al. 2019; Petersen et al. 2018; Srinivasan et al. 2010). These studies note, however, that continuously tracking high-quality funnel metrics with surveys is costly, as they require representative sampling and survey procedures for hundreds and often thousands of consumers. Therefore, they call for further research on the explanatory power of online behavior metrics, which are inexpensive to collect and unobtrusive to prospective customers (Lecinski 2011). As such, these metrics are less, or even not, sensitive to the well-documented survey issues of memory, mere measurement, and social desirability biases (Morwitz et al. 1993; Simmons et al. 1993; Tourangeau et al. 2000).

For e-commerce, the internet has generated many new metrics recommended to managers when evaluating marketing effectiveness and assessing how consumers think, feel, and act regarding their brand (Colicev et al. 2018; Yadav and Pavlou 2014). Generic and branded search, website page views, and reviews are key examples of consumers' brand-related actions. Several empirical articles have shown that such online behavior metrics convert to sales and are responsive to marketing actions (Colicev et al. 2018; De Vries et al. 2017; Srinivasan et al. 2016), but this is typically done for a single or a small number of brands. By contrast, large-scale studies focus on a particular (retail media) ad product, such as Sponsored Video, and do not investigate brand building (Pauwels et al. 2023). In this study, we leverage weekly data, for more than 122,000 brands and product category combinations, from the ABI, which automatically and regularly measures Amazon shoppers' brand awareness, consideration, and purchases. This dataset allows us to uncover more generalized insights across a large number of brands with different characteristics.

Regarding advertising's impact, different ads likely have different impacts on specific brand metrics (Batra and Keller 2016). Depending on the context, advertising could influence some but not all brand metrics. Buil et al. (2013) find that advertising spend improves brand awareness but not perceived quality. In addition, De Haan et al. (2016) show that content-separated advertising (e.g., remarketing) is effective in driving traffic to an online retailer but that content-integrated advertising (e.g., ads for products directly relevant to a search query) is more likely to convert to purchase. Research on newer advertising tactics, such as negative keywords, focuses on how to select them (Peltonen et al. 2017; Tavşanoğlu 2018) instead of their impact on outcomes such as brand metrics and sales. Finally, advertising effectiveness research has examined budget allocation from different angles, including short- versus long-term ad effectiveness (Vakratsas and Ma 2005), different types of online advertising (Breuer et al. 2011), and search platforms (Zia and Rao 2019). A key finding is that the effects of both advertising and retail factors, such as product assortment, price, review volume, and valence, likely depend on the product category and the brand size (Colicev et al. 2018; Pauwels et al. 2016; You et al. 2015). Consistent with this line of literature, our research incorporates various ad and retail factors to evaluate their impact across brands of different sizes and in different categories.

Conceptual development

While the literature review guides our analysis, we do not derive hypotheses from a unified theory. Instead, we address our research question in an empirics-first approach, defined by Golder et al. (2022) as research that "(1) is grounded in (originates from) a real-world marketing phenomenon, problem, or observation; (2) involves obtaining and analyzing data over multiple categories; and (3) produces valid marketing-relevant insights without necessarily developing or testing a theory" (p. 319). To guide these insights, we provide a conceptual framework on the dimensions by which digital advertising effectiveness may differ and explore how these dimensions translate into metrics in our empirical setting.

First, the purchase funnel (Srinivasan et al. 2010) is a key concept in marketing literature. Before deciding on a brand, consumers first become aware of the brand and then consider it for purchase. In the awareness stage, consumers may notice the brand and search for it. However, they may not yet have a clear idea of what the brand stands for or whether its products are serious contenders for the purchase decision. In the consideration stage, consumers research and become informed about the brand and product specifics. This information enables the evaluation and subsequent purchase decision. Therefore, the number of consumers considering a brand should predict brand sales, and the number of consumers aware of the brand should predict brand consideration.

Second, research has long treated brand familiarity as a driver of consumer response to marketing (Aaker et al. 2013). Consumers perceive less risk in a familiar brand and are more likely to pay attention to its call-to-action (lower-funnel) marketing. For example, price promotions by familiar brands such as Coca-Cola generate a much stronger response than the same discount for unfamiliar brands (Lichtenstein et al. 1991; Mela et al. 1997). As a result, less familiar brands typically try to build awareness and consideration through upper-funnel and middle-funnel advertising, respectively. Outside marketing communication, product innovation, and price discounts also help bring an unfamiliar brand to the attention of potential customers (Slotegraaf and Pauwels 2008).

Third, word of mouth is a key post-purchase metric with substantial power to influence potential customers' awareness, consideration, and purchases (Trusov et al. 2009). In e-commerce, reviews are easy to access and search. Prior research has demonstrated separate effects of review (star) ratings and the number of reviews (You et al. 2015). The former indicates the product quality and the latter its popularity and the confidence a potential customer has in the review rating (You et al. 2015). On Amazon, a minimum of 3.5 stars and 15 reviews signal that product quality and popularity are sufficient to start advertising (Ibarra 2020).

Fourth, we consider both the number of ad impressions and the number of ad campaigns. For the former, a larger number of impressions increases the likelihood that consumers are exposed to the brand's message and thus become aware of its offering (Keller and Lehmann 2006; Tellis 2003). For the latter, different campaigns provide variety in ad messaging and execution, which can help maintain consumers' interest in the brand, especially if it is familiar to them (Pauwels et al. 2022). We include ad impressions and the number of campaigns by ad format, as their impact may differ across upper-, middle-, and lower-funnel advertising.

Finally, digital advertisers have many new options in both ad formats and metrics. For the former, ad relevance to the reached audience can be enhanced through the use of *negative keywords* (e.g., "babies" when offering diapers for adult incontinence) and by lifestyle, being "in-market," and geographic (geo-) location. Moreover, audiences that browsed the category previously can be retargeted (e.g., De Haan et al. 2016), labeled as "remarketing" on Amazon. Campaigns can be optimized for CTR or for purchase conversion. For metrics, Amazon offers a 0/1 coded "ad readiness score" (previously called "retail readiness"), which simplifies the click probability of a product in the absence of ads. A score of 1 indicates that the product detail pages include all the information necessary for consumers to make informed purchase decisions, including "informative, [search engine optimization–] rich titles, bullets, and product descriptions, clear imagery, engaging videos, customer ratings and reviews, and ample inventory" (Ibarra 2020). Because research has shown that advertising works well for high-quality products (Erdem and Swait 2004; Golder and Tellis 1997), an ad readiness score of 1 signals to sellers that their products are worthy of advertising.

Data and measurement

Data and sample selection

To ensure the generalizability of our results, we begin with more than 30 product categories across three consumer verticals (hardlines, softlines, and consumables) on Amazon. Of the product categories included in the ABI, we retain the top 12 categories based on the number of Amazon Standard Identification Numbers (ASINs).[2] Specifically, we select the following product categories: Home & Kitchen; Clothing, Shoes & Jewelry; Grocery & Gourmet Food; Electronics; Arts, Crafts & Sewing; Sports & Outdoors; Tools & Home Improvement; Health & Household; Beauty & Personal Care; Toys & Games; Patio, Lawn & Garden; and Pet Supplies. These categories differ on many dimensions, including their utilitarian (e.g., Tools & Home Improvement) and hedonic (e.g., Toys & Games) nature (Li et al. 2020). As ABI is updated on a weekly basis for each brand, we merge brand-level retail and advertising data with ABI from January 1, 2021, to May 16, 2022. Because retail and advertising data are both at the ASIN/daily level, we aggregate them to the brand/product category weekly level to be consistent with the ABI cadence. Specific aggregation depends on the metrics. For example, for the percentage of discount of retail price, we take the average of all ASINs within a brand to be the brand-level proxy, and for advertising spend, we sum up all ASIN spend at the brand level (see Table 1). Because we are mostly interested in the drivers that explain the movement in ABI, we only keep brand/product categories with at least 28 weeks of our variables, dropping less than 10% of the data. This time frame ensures sufficient variability in the data to uncover the significant impact of advertising

[2] This is equivalent to the stock-keeping unit (SKU) in a traditional retail setting.

Table 1 Key variables and their explanation

Underlying variables (aggregation)	Operationalization and explanation
New products launched (sum)	The number of new ASINs launched in the last month
% discount	Average % discount across all ASINs of a brand
Overall visible review ratings (average)	Overall ratings displayed
New ratings in each week (average)	New ratings added that could reflect shopper momentum at a given time
Search rank (average)	Page number on which ASINs of the brand are shown
Ad readiness score (average)	Binary coded showing the click probability of a product in the absence of ads
SP readiness score (average)	Binary coded showing the click probability when using SPs
Ad impressions by types (sum)	Fire tablet, Kindle, video, Fire TV, O&O Display, DSP Display, audio, STV, IMDb, and sponsored ads (including SBs, SBv, SD, and SPs)
Number of campaigns by types (sum)	Remarketing, lifestyle/in-market, contextual, negative keywords, geo reach, CTR optimization, and conversion optimization
Amazon Brand Awareness Index	Number of consumers likely aware of the brand, calculated as a weighted index of searches and non-ad retail impressions
Amazon Brand Consideration Index	Number of consumers likely considering the brand, calculated as a weighted index of detail page views and dwell time
Amazon brand revenues	Brand sales revenue on Amazon.com

Table 2 Analysis steps

Analysis step	Question addressed	Result
Ordinary least squares	Are the residuals heteroskedastic?	Need for panel model
Augmented Dickey–Fuller test	Are variables mean stationary (have a fixed mean) or evolving?	Amazon Brand Metrics evolve, so take difference
Hausman test	Random- or fixed-effects model?	Fixed effects
Elasticity	What is the % impact for a 1% change in the driver variable?	SBv drives all three ad goals, Fire TV, O&O Display, and SBs drive brand revenue only
Ratio of elasticities	What is the optimal allocation across ad products for smaller and for larger brands?	Smaller brands should allocate more to STV and SD, larger brands to SBv

and retail drivers. To measure ad investment, we use the number of impressions instead of dollar spend, because the former has fewer missing values and is less subject to inaccuracies (e.g., currency conversion, negotiation). The final sample contains more than 122,000 brand/product category combinations with over 6.4 million observations in total at the weekly level.

ABI calculation and brand size categorization

In our sample, key dependent variables such as awareness, consideration, and revenue are ABIs at the brand/product category level updated weekly. ABIs, computed using Amazon first-party data, are predictive of the downstream impact not only on Amazon but also on surveys measuring customer perceptions (Pauwels and van Ewijk 2020). To meet the leading performance indicator criteria in Hanssens et al. (2014), we optimally selected and weighed the brand awareness metrics to predict brand consideration, and the brand consideration metrics to predict sales. The Awareness Index metrics include consumer actions revealing that they both are aware of the brand (e.g., branded search) and have been exposed to the brand (non-ad retail impressions). The Consideration Index metrics include the number of detail page views and dwell time (time spent on the detail page). Both metrics indicate that the consumer is actively evaluating products for purchase (Li et al. 2020). Furthermore, we categorize brands by sizes using the Consideration Index because it has the highest correlation with both awareness and revenue ($r \geq 0.72$). Specifically, we categorize brands as small, medium-sized, and large if they belong to the bottom 33%, middle 33%, or top 33% in the Consideration Index, respectively.

Analysis and results

Table 2 overviews the analysis steps with the addressed question and result for each step.

Model selection

First, we run ordinary least squares regressions of the change in brand metrics on ad and retail drivers. The residual plots clearly show their correlation with the predicted ABI values (i.e., the significant presence of heteroskedasticity). Thus, we establish the need for a panel model that accounts for within-brand variations. Second, we conduct the augmented Dickey–Fuller test because stationarity is a requirement for longitudinal data modeling. Using Python's Statsmodel package for 30 randomly selected brand/product categories, we find that 30% were evolving. As a result, we take the first-order difference of ABI (i.e., changes in ABI as values of the current period minus those of the previous period) and use that as the dependent variables for all brands. The augmented Dickey–Fuller tests further revealed that all first-order differences are stationary, suggesting no need for second-order differencing. Third, we use the Hausman test to select between the random- and fixed-effects models. Given that all the tests reject the null hypothesis that the random-effects estimator is consistent (i.e., assuming errors are not correlated with the regressors, and thus there is no endogeneity problem), we report only the results with the fixed-effects estimators. However, we also test the random-effects model as a robustness check and find quantitatively similar results.

The resulting fixed-effects model specification is

$$\begin{aligned}\Delta(ABI)^j_{i,t} = \beta_0 &+ \beta_1 Ad_{i,t} + \beta_2 NPD_{i,t} + \beta_3 Ratings_{i,t}\\ &+ \beta_4 SearchRank_{i,t} + \beta_4 Campaign_{i,t}\\ &+ \beta_6 Readiness_{i,t} + \beta_7 PD_t + \beta_8 Thanksgiving_t\\ &+ \alpha_i + \epsilon_{i,t}, fort = 1, \dots, 28, j = 1, 2, 3,\end{aligned}$$

where $\Delta(ABI)^j_{i,t}$ is the difference of j th ABI feature for brand i between week $t-1$ and week t, where $j = 1, 2, 3$ for the three ABI features (awareness, consideration, and revenue); $Ad_{i,t}$ is the advertising spending of brand i in week t, including all Amazon Ads such as SBs, SBv, and DSP Display (see Table 1 for ad types); $NPD_{i,t}$ are the number of new products launched one month before week t by brand i; $Rating_{i,t}$ are the overall visible and newly added ratings for brand i in week t, respectively; $Searchrank_{i,t}$ is the average page number of search results across all SKUs by brand i in week t; $Campaign_{i,t}$ is the number of campaigns of brand i in week t (see Table 1 for types); $Readiness_{i,t}$ is the click probability across all SKUs for a brand with or without any ad; PD_t, $Thanksgiving_t$ are indicator functions for the weeks of Prime Day and Thanksgiving; and α_i is the brand-level fixed effect for brand i. We estimate this model with the Linearmodels Python package.

Media mix calculation

Ever since Dorfman and Steiner (1954) derived the optimal marketing allocation, marketing literature has validated the profit-maximizing allocation spend on ad products on the basis of their sales elasticities, that is, the percentage of sales increase from a 1% increase in the ad investment. This formula is the basis for the generalizable findings in research (e.g., Hanssens 2015). In a first step, we estimate the preferred model (fixed effects in our case) to extract statistically significant coefficients of ad products' impressions. Second, together with the descriptive statistics on impression levels, we calculate the elasticity of each KPI to each ad spend. Third, we derive the optimal budget allocation from the magnitude of elasticities to contrast with the current allocation on average across all applicable brands to make media mix recommendations (for a similar procedure, see De Haan et al. 2016). The exact steps are as follows:

1. Calculate KPI's elasticity by ad product: elasticity = coefficient estimated from the model × average (ad impressions)/average (KPI). For example, suppose that the estimated regression coefficient is 1 (i.e., each ad impression increases awareness by 1). If the average ad impressions are 10 and average awareness is 100, the elasticity is 0.1. In other words, a 1% increase in ad impressions increases awareness by 0.1%.
2. Sum up elasticities from the first step and divide each by the total, to generate the recommended percentage of allocation of impression by ad product.
3. Contrast the second step with the current allocation as the suggestion for that KPI.

As an example of two ad products with elasticities of 0.2 and 0.1, respectively, two-thirds of the budget should be allocated to the former and one-third to the latter.

Model fit, coefficients, and media mix allocation for all brands

Overall model fit

Fixed-effects models explain ABIs reasonably well, with F-statistics (including F-stats with robust standard errors) with $p \leq 0.01$ for all KPIs. The explanatory power is highest for Clothing, Shoes & Jewelry and lowest for Grocery & Gourmet Food (with a two-times difference), suggesting product category differences. The average explanatory power of the variance between panel units is 0.12 for brand awareness, 0.11 for brand consideration, and 0.07 for brand revenue. These R-squares are significant and substantial and, at the same time, show that most metrics are explained by factors other than Amazon Ads during the studied period. Such

Table 3 Fixed-effects model results: Campaigns and retail actions coefficients

	Brand awareness	Brand consideration	Brand revenue
Number of new products launched last month	0.1181 (0.0694)*	*ns*	*ns*
% discount	1362.7 (225.05)***	987.2 (24.629)***	3434.9 (121.31)***
Weekly new reviews	126.7 (5.9177)***	10.858 (0.6476)***	71.802 (3.1898)***
Search results page number	− 304.76 (14.515)***	− 6.8825 (1.5884)***	− 74.713 (7.8239)***
Number of remarketing campaigns	0.0386 (0.0062)***	*ns*	*ns*
Number of lifestyle/in-market campaigns	0.0829 (0.015)***	0.0023 (0.0013)*	*ns*
Number of negative keyword campaigns	0.0321 (0.0051)***	0.0056 (0.0006)***	0.0248 (0.0028)***
Number of geo-reach campaigns	0.0168 (0.0038)***	0.0062 (0.0004)***	0.0303 (0.0021)***
Number of campaigns optimized for CTR	*ns*	0.0018 (0.0004)***	*ns*
Number of campaigns optimized for purchase	0.0265 (0.0062)***	*ns*	*ns*
The week of Prime Day	2835.3 (75.765)***	271.38 (8.2914)***	1096 (40.84)***
The week of Thanksgiving	1134.5 (73.801)***	116.68 (8.0764)***	549.4 (39.781)***

Standard errors are in parenthesis and disclosed only for review purposes. Amazon Ads do not approve public disclosure

ns non-significant at the 10% confidence level

*$p<0.10$, **$p<0.05$, ***$p<0.001$

factors may include product quality, competitive actions, and the reputational impact of brand marketing before the period. Across the brand metrics, the explanatory power is highest for changes in awareness, followed by consideration and then revenue, consistent with prior research that finds that advertising is a more powerful driver of upper- than lower-funnel metrics (Pauwels et al. 2013; Srinivasan et al. 2010).

Model coefficients

We report the fixed-effects model coefficients for the retail and ad campaign actions in Table 3. First, we note that funnel drivers in the general marketing literature also apply at Amazon. Launching new products is crucial to increase brand awareness, and price discounts work for all KPIs, as do new reviews, indicating the importance of word of mouth (Rojas-Lamorena et al. 2022; Srinivasan et al. 2010; You et al. 2015). Moreover, brands appearing high in the search rank garner greater brand awareness, which translates into more consideration and revenue (Bertozzi et al. 2022; Rutz and Bucklin 2011). New results appear for the campaign variables. While the number of remarketing and lifestyle/in-market campaigns raise brand awareness, we find no significant increase in brand revenue. By contrast, the use of negative keywords and geolocation campaigns is associated with higher performance on all three KPIs. While campaigns optimized for CTR significantly increase brand consideration, those optimized for purchase mainly increase awareness. Across the board, we observe that digital marketing, which once was relegated to lower-funnel activation, is effective at increasing brand awareness and consideration, consistent with the conceptual arguments of Batra and Keller (2016) and the results of Pauwels and van Ewijk (2020). Finally, both Amazon's Prime Day and the Thanksgiving week (Black Friday/Cyber Monday) boost brand awareness, consideration, and revenue, with Prime Day enjoying about double the effect of Thanksgiving.

How should advertisers adjust their main digital marketing allocation? Table 4 shows the coefficients for the advertising products that we can compare with current allocations, because advertisers have sufficiently spent in our data. As the table shows, SBv is a significant driver of all three dependent variables: brand awareness, consideration, and revenue. By contrast, Fire TV, O&O Display, and SBs (non-video) are significant drivers of brand revenue only.

Table 4 Fixed-effects model results: Ad product coefficients for media allocation calculation

Dependent variable	Ad product	Coefficient	Average weekly impressions[a]
Brand awareness	SBv	0.0132***	1860
Brand consideration	SBv	0.0006***	1860
Brand revenue	SBv	0.0030***	1860
	Fire TV	1.7758**	5530
	O&O Display	0.0386***	119
	SBs	0.0013***	10,800

Only coefficients used to calculate the media mix are shown. Although other ad impressions are significant, their effects on ad mix are too small to be included

[a]Average impressions and KPIs are not approved by Amazon Ads to disclose beyond the scope of review. This column is for reviewers only

*$p<0.10$, **$p<0.05$, ***$p<0.001$

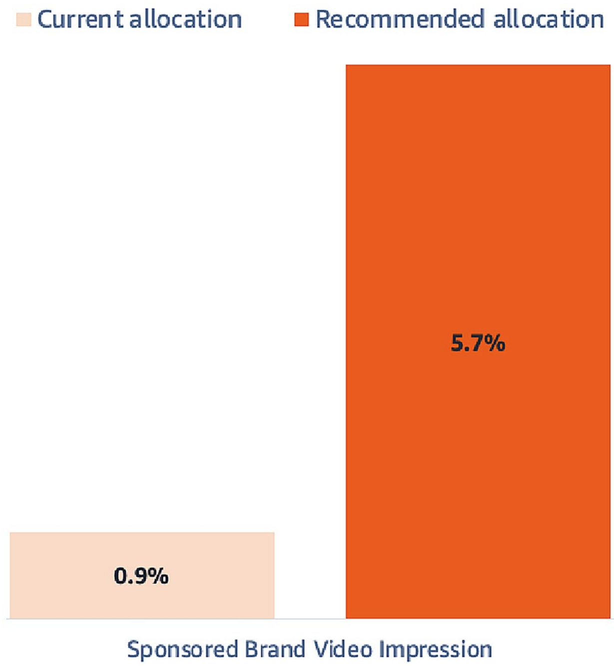

Fig. 1 Increasing SBv for brand awareness

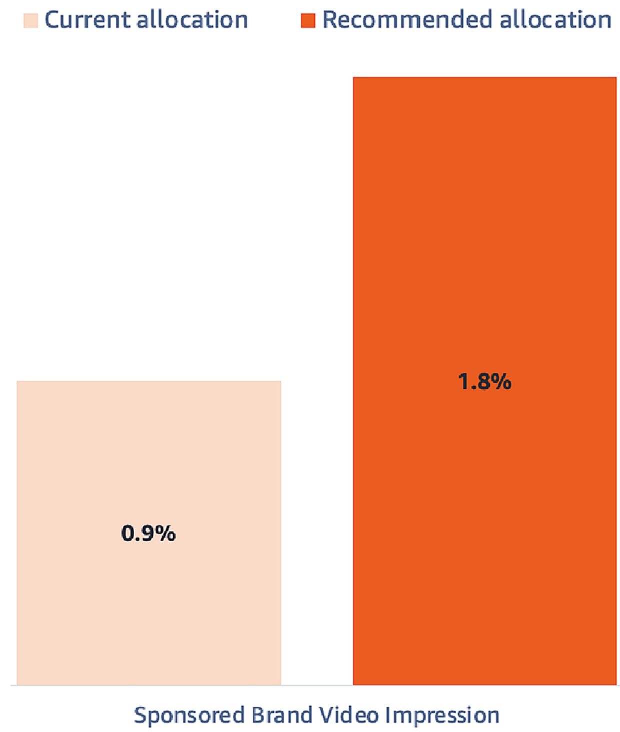

Fig. 2 Increasing SBv for brand consideration

With the model coefficients, we can calculate the ratio of elasticities that summarizes our model's recommendation on ad product allocation (De Haan et al. 2016; Dorfman and Steiner 1954; Wright 2009). Comparing the current advertising spending with this model-based advice shows managers the gap between reality and recommendation. We begin with our general recommendations and then differentiate by advertiser size because adoptions of different ad products vary with this variable.

For the average advertiser in our data, Figs. 1, 2, and 3 compare our recommended media mix with the current allocation. First, the current allocation of 0.9% of the media budget to SBv is insufficient: the model suggests it should increase to 5.9% for awareness goals, 1.8% for consideration goals, and 2.7% for revenue goals. Second, SBs allocation should increase from 4.99% to 6.94%. Likewise, upper-funnel Fire TV and O&O Display should reflect 0.01% and 0.02% of the budget, respectively, coming from the dominant spending on the lower-funnel ad product SPs. Note that the elasticities show that brands should optimally spend more on the analyzed ad products. Because we do not have data on other brand communication channels, we do not know their elasticities, which are needed to advise for reallocation of funds to Amazon Ads or increasing the overall budget. The likelihood of managers to follow such advice is partly based on their decision authority to only reallocate an existing budget or to also change the budget size (Hanssens and Pauwels 2016).

Coefficients for advertising mix by brand size

Next, we show the model coefficients by brand size and their recommended versus current media mix. Table 5 provides the coefficients, and panels A–C of Fig. 4 depict the media mix, depending on brand sizes, using brand awareness as an example.

Consistent with marketing theory and research findings (e.g., Hanssens et al. 2014; Pauwels et al. 2016), small brands have more potential to increase awareness and thus show a higher elasticity to upper-funnel advertising actions such as STV and SD. As a result, our model recommends that these brands allocate 0.2% of the budget to STV and 8.6% to SD. Moreover, middle-funnel ad product SBs should receive 9.0% of media mix allocation, more than for any other advertiser size. By contrast, SBs are already close to optimal for medium-sized and large brands, which we recommend increase to 5.1% and 7.2% of the budget, respectively. The greatest opportunity for these brands lies in SBv, as the model recommends increasing the current 0.9% allocation to 4.5% and 6.2%, respectively.

Top three advertising and retail drivers by product category

In this section, we present the top three drivers for brand growth for each product category focusing on brand revenue. To enhance exposition, we summarize the results in Table 6.

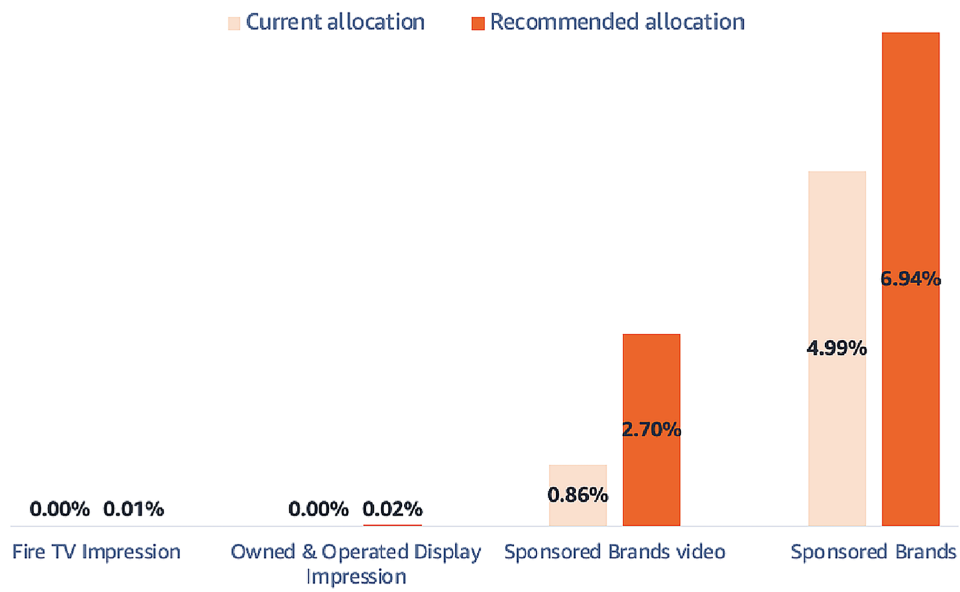

Fig. 3 Adopting Fire TV and O&O Display, and increasing SBs and SBv for brand revenue

Table 5 Fixed-effects model results: Ad product coefficients for brand awareness by brand size

Ad product	Coefficient	Average weekly impressions	Brand size
STV	0.008*	21	Small
SBs	0.0027***	3371	
SD	0.0135***	646	
SBs	0.0016***	10,066	Medium-sized
SBv	0.0076***	1847	
SBs	0.0029***	20,984	Large
SBv	0.0162***	3276	

$*p<0.10$, $**p<0.05$, $***p<0.001$

First, the most effective retail drivers and advertising drivers differ across product categories. Upper-funnel products (i.e., Fire TV, STV) have a significant impact on Clothing, Shoes & Jewelry; Grocery & Gourmet Food; Electronics; Sports & Outdoors; Toys & Games; and Pet Supplies. Middle-funnel products (i.e., O&O and DSP Display) have a significant impact on Grocery & Gourmet Food, Tools & Home Improvement, and Health & Household. By contrast, sponsored ads have a significant impact on brand revenues in all studied product categories, with SBs and SBv having the largest effect sizes.

Second, the number of new reviews is the most effective retail driver across most product categories across the purchase funnel, expanding the finding of Li et al. (2020) that reviews matter outside the immediate purchase context. This result highlights the power of the most recent reviews to shape consumer behavior, consistent with previous findings across categories and countries (Kübler et al. 2018; You et al. 2015).

Third, the total number of ads is the most effective advertising driver across most product categories. A larger number of ads typically means more consumer exposure. This result highlights the importance of the informative role of advertising in facilitating the focal brands' entry into consumers' consideration set. Regarding specific advertising tactics, remarketing only shows up as a top-three driver for Clothing, Shoes & Jewelry. Negative keyword ads are a top driver for Electronics and Health & Household. Lifestyle/in-market matters for Home & Kitchen; Clothing, Shoes & Jewelry; Arts, Crafts & Sewing; and Patio, Lawn & Garden. Ads optimized for CTR are a top-three driver for Sports & Outdoors and Patio, Lawn & Garden. Finally, ads optimized for purchase are a top-three driver for Pet Supplies.

Discussion

We show that digital advertising and retail drivers not only are specific to brand funnel metrics but also differ by advertiser size and product category. These results raise several questions for marketing theory and practice. First, why are new product launches and upper-funnel advertising products particularly effective for brands of low- and medium-level consideration? New product launches build brand awareness (Srinivasan et al. 2009), especially for relatively small brands, for which this funnel metric has more room to grow (Hanssens et al. 2014). Larger brands are more likely to be well-known and thus potentially benefit less from any new information. Because smaller brands tend to have fewer products, we speculate that each new addition to their

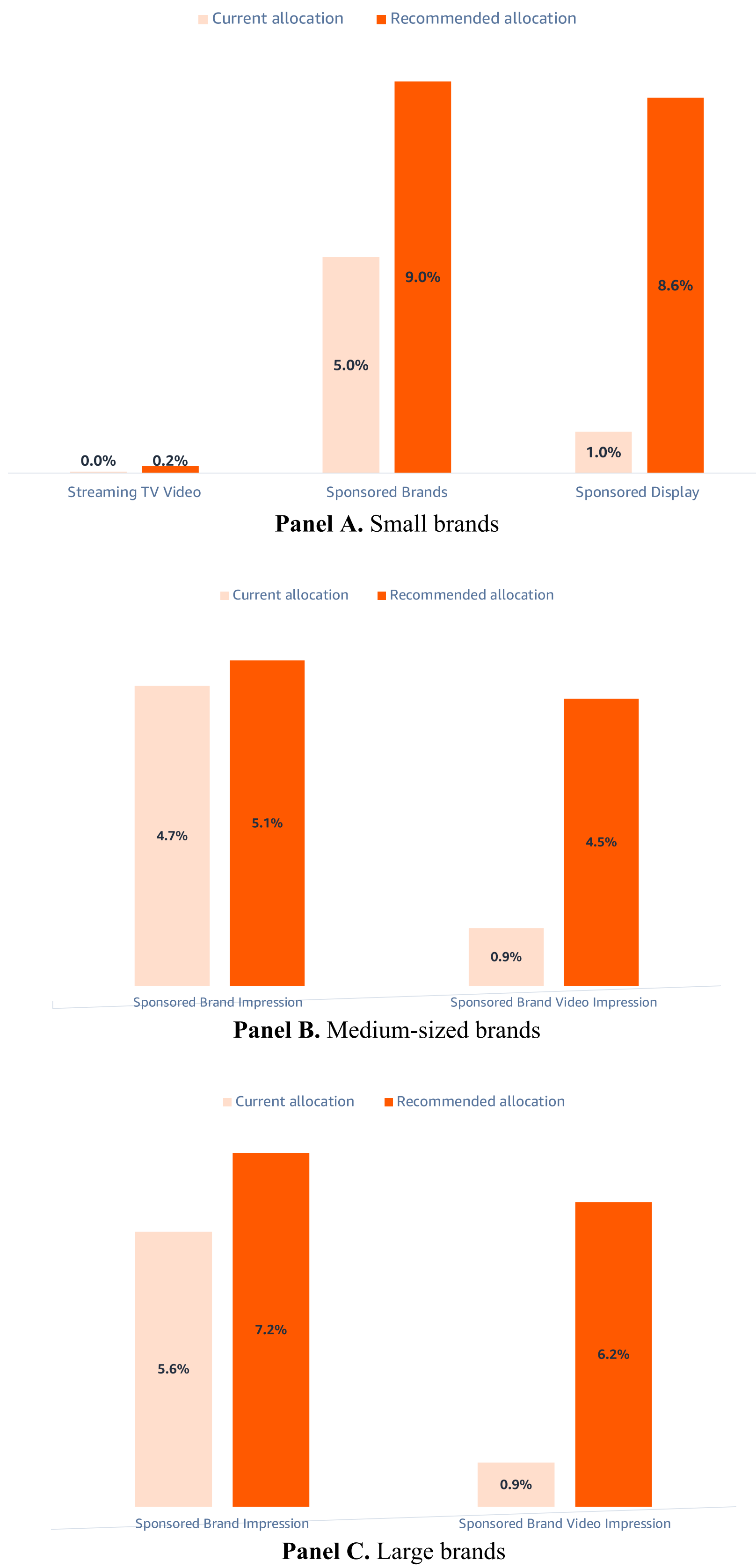

Fig. 4 Increasing awareness. **A** Small brands. **B** Medium-sized brands. **C** Large brands

Table 6 Top three drivers for each product category

Product categories	Top three retail drivers	Top three advertising drivers
Home & Kitchen	Number of new reviews***, percentage of ASINs with 5 + reviews***, percentage of price discount***	Total # ads***, # of lifestyle/in-market ads***, # of geo ads***
Clothing, Shoes & Jewelry	Number of new reviews***, count of total visible reviews**, new ASINs launches*	Total # ads**, # of lifestyle/in-market ads***, # of remarketing ads**
Grocery & Gourmet Food	Ratings of new reviews*, new ASINs launches***, percentage of price discount***	Fire TV impressions***, # contextual ads***, # ads with geo reach**
Electronics	Count of new reviews***, # new ASIN launches*, percentage of price discount***	Total # ads***, # of geo ads***, # of negative keyword ads***
Arts, Crafts & Sewing	Percentage discount***	SBv impressions***, # of lifestyle/in-market ads***, # of geo ads***
Sports & Outdoors	Count of new reviews**, ratings of total visible reviews**, percentage of price discount***	Fire TV impressions***, total # ads*, # of ad optimized for CTR*** or purchase***
Tools & Home Improvement	Count of new reviews*, count of total visible reviews*, percentage of price discount***	Total # ads*, # of contextual ads**, # of geo ads*
Health & Household	Count of new reviews***, percentage of price discount***	Total # ads**, # of negative keyword ads***, O&O Display***
Beauty & Personal Care	Count of total visible reviews*, percentage of price discount*	Total # ads***, # of contextual ads***, # of geo ads***
Toys & Games	Count of new reviews*, percentage of price discount***	Total # ads**, # of contextual ads*, DSP impressions**
Patio, Lawn & Garden	Count of total visible reviews*, percentage of price discount*	# of lifestyle/in-market ads***, # of geo ads*, # of ads optimized for CTR***
Pet Supplies	NA	Total # ads***, # of ads optimized for purchase**, STV impressions**

*$p < 0.10$, **$p < 0.05$, ***$p < 0.001$

product lines influences consumers' perception of the focal brand to a greater extent than larger brands. In other words, paying more attention to new product launches by smaller brands is in consumers' best interest because a richer amount of information will be revealed about the focal brand. Consistent with this rationale, we also find that upper-funnel advertising intended to increase brand recognition, such as STV ads, improves awareness of small brands but not large brands.

Second, why do % discount and remarketing ads increase awareness more than consideration? The first finding highlights the power of discounts to attract consumer attention, as Slotegraaf and Pauwels (2008) demonstrate in fast-moving consumer goods categories. However, discounts alone do not suffice to keep consumers' interest, as operationalized by the dwell time on the product's detail page to obtain information (consideration). The same holds for remarketing ads: while they get consumers (again) in the funnel, they are less effective in evoking consideration and purchase. As De Haan et al. (2016) demonstrate for a Dutch online retailer, the likely reason is that remarketing is content-separated (i.e., shown on web pages, which consumers do not visit for the purpose of the remarketed product). Instead, they find higher revenue for consumers who come in through content-integrated ads, referred to as "contextual advertising."

Consistent with this contextual rationale, we observe strong effects for campaigns using *negative keywords* and *geolocation*. Negative keywords help advertisers avoid audiences focused on other products and thus increase the chances that the ad-exposed audience is interested in the advertised product. This advertising tactic is a top-three brand revenue driver in the Electronics and Health & Household categories. Likewise, geolocation allows advertisers to reach audiences at the right place and at the right time. Because they are seeing ads relevant to their real-time location, consumers are more likely to pay attention to, consider, and ultimately purchase the advertised product.

The effectiveness of *new reviews* shows the importance of this word-of-mouth metric as a demand-perspective indicator of product quality. At the same time, ad readiness indicates product quality from a supply side perspective. Thus, advertisers should ensure that product detail pages include all the necessary information for consumers, such as search engine optimization – rich titles, bullets, and product descriptions; clear imagery; engaging videos; customer ratings and reviews; and ample inventory.

Finally, we observe similar retail drivers across categories, with the number of new reviews, % discount within the top three drivers, and new product launches critical for Home & Kitchen; Clothing, Shoes & Jewelry, and

Electronics. Likewise, the number of ad campaigns matters across categories, with SBs and SBv showing the largest effect sizes. Beyond sponsored ads, (O&O and DSP) Display has a significant impact in Grocery & Gourmet Food, Tools & Home Improvement, and Health & Household. Future research is necessary to shed light on the reasons behind this effectiveness. One possible explanation is that these categories are rather *utilitarian* in nature and therefore engender deeper information processing, often starting several weeks before purchase (Mathwick et al. 2001; Park et al. 2018). Consumers prefer online search because of its ease of comparison, which reduces brand differentiation (Noble et al. 2005), increasing the potential for Display to influence the purchase funnel. By contrast, upper-funnel ad products (i.e., Fire TV, STV) have a significant impact on Clothing, Shoes & Jewelry; Grocery & Gourmet Food; Electronics; Sports & Outdoors; Toys & Games; and Pet Supplies. Many of these product categories are rather *hedonic* in nature, which enhances the appeal of fun, surprise, variety, and adventure in consumers' shopping journey (Arnold and Reynolds 2003; Novak et al. 2003). Li et al. (2020) find that hedonic purchases involve more product page views of the target retailers up to two weeks before conversion, providing a funneling effect of final purchases.

Conclusion

In this research, we analyze the impact of different retail and advertising actions on brand growth. Two typical challenges are the difficulty of measuring brand metrics and the difficulty of combining advertising information and brand performance. Focusing on the empirical context of Amazon.com, we overcome these challenges by leveraging a unique dataset from ABI, which automatically and regularly measures Amazon shoppers' brand awareness and brand consideration, and by combining it with different advertising and retail drivers. Our data start on January 1, 2021, and end on May 16, 2022, and include 122,000 US brand/product category combinations across the largest categories within the verticals of hardlines, softlines, and consumables. Specifically, weekly changes of brand awareness, brand consideration, and brand revenue are all documented by ABI. This comprehensive dataset allows us to confidently address our focal research question with a fixed-effects panel model.

Our fixed-effects panel model includes both retail and advertising variables, after controlling for the potential endogeneity problem (i.e., regressors might be correlated with the error terms). We find that retail and advertising actions differentially increase brand awareness, consideration, and revenue. In particular, SBv improves brand awareness and consideration, whereas STV, SBs, and SD are especially helpful for brand revenue. For small brands, we suggest increased investment in STV, SBs, and SD for awareness; STV, SBv, and SD for consideration; and SBs and SBv for revenue. For medium-sized and large brands, we recommend SBs and SBv for all metrics. We also recommend that sellers choose their priority actions according to which ABIs they want to improve, as well as their current brand sizes.

We highlight three main findings and their corresponding managerial recommendations. First, different advertising products drive different brand metrics. We find that increasing SBv investment is crucial for brand awareness and consideration while adopting STV, together with increasing the budget for SBs and SD, is particularly helpful for brand revenue. Second, specific recommendations for advertising products depend on brands' sizes. For small brands, STV, SBs, SBv, and SD can help improve brand metrics. For medium-sized and large brands, we recommend prioritizing increasing budgets for SBs and SBv. Third, the recommendation for advertising products depends on the product category. Upper-funnel products (i.e., Fire TV, STV) have significant impacts on Clothing, Shoes & Jewelry; Grocery & Gourmet Food; Electronics; Sports & Outdoors; Toys & Games; and Pet Supplies. Middle-funnel products (i.e., O&O and DSP Display) have a significant impact on Grocery & Gourmet Food, Tools & Home Improvement, and Health & Household. Finally, sponsored ads have a significant impact on all product categories' revenues, with SBs and SBv having the largest effect sizes.

Despite using a large dataset that combines advertising, retail, and brand performance, our study has some limitations. First, owing to data collection limitations, we analyze only advertisers on Amazon's marketplace. Future research could examine our research question in different empirical contexts. Second, our research focuses on the impact of online ads and retail actions on brand performance online. Future research could assess the impact of advertising and retail drivers on both online and offline brand performance. Third, we include the effect of the 4Ps, such as new product introductions, but do not study whether larger or smaller brands show different effects of relative changes. One possible direction is to integrate brand size directly into the model. Fourth, multinational corporations are interested in understanding the differences in different markets. Thus, analyzing the impact of advertising and retail drivers on brand performance in non-US markets would be worthwhile. Finally, we do not have information on brands' contribution margin or profits. While budget allocation optimization does not require this information, optimizing brands' overall budget does (e.g., Dorfman and Steiner 1954; Wright 2009).

Of the considerable digital advertising spending in the United States, \$189.8 (of \$248.8) billion is in digital video advertising, and retail media is on the rise and likely to hit \$100 billion by 2026 (Adgate 2022). Our study sheds new light on how advertising and retail factors drive growth of different brands, and we hope to inspire exciting new research in this area.

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Data availability The data are confidential to the data provider, given its contract with its customers.

Declarations

Conflict of interest All authors worked at Amazon Ads during the research. No other conflicts of interest are present.

References

Aaker, D.A., A.L. Biel, and A. Biel. 2013. *Brand equity & advertising: Advertising's role in building strong brands*. New York: Psychology Press.

Adgate, B. 2022. Retail media networks are the next big advertising channel, *Forbes*, 1 December. https://www.forbes.com/sites/bradadgate/2022/12/01/retail-media-networks-are-the-next-big-advertising-channel/?sh=1a65cee6346c.

Ajzen, I., and M. Fishbein. 1977. Attitude-behavior relations: A theoretical analysis and review of empirical research. *Psychological Bulletin* 84 (5): 888–918.

Arnold, M.J., and K.E. Reynolds. 2003. Hedonic shopping motivations. *Journal of Retailing* 79 (2): 77–95.

Batra, R., and K.L. Keller. 2016. Integrating marketing communications: New findings, new lessons, and new ideas. *Journal of Marketing* 80 (6): 122–145.

Bertozzi, G., S.R. Bagheri, B. Graham, P. Knowles, O. Netzer, and K. Pauwels. 2022. How much does digital advertising accelerate new product success? *Applied Marketing Analytics* 7 (4): 318–328.

Breuer, R., M. Brettel, and A. Engelen. 2011. Incorporating long-term effects in determining the effectiveness of different types of online advertising. *Marketing Letters* 22: 327–340.

Buil, I., L. De Chernatony, and E. Martínez. 2013. Examining the role of advertising and sales promotions in brand equity creation. *Journal of Business Research* 66 (1): 115–122.

Chaudhuri, A. 2002. How brand reputation affects the advertising-brand equity link. *Journal of Advertising Research* 42 (3): 33–43.

Colicev, A., A. Malshe, and K. Pauwels. 2018. Social media and customer-based brand equity: An empirical investigation in retail industry. *Administrative Sciences* 8 (3): 55.

Davey, J. 2023. Retail media ad revenue forecast to surpass TV by 2028. *Reuters*, 12 June, https://www.reuters.com/business/retail-consumer/retail-media-ad-revenue-forecast-surpass-tv-by-2028-2023-06-12/.

De Haan, E., T. Wiesel, and K. Pauwels. 2016. The effectiveness of different forms of online advertising for purchase conversion in a multiple-channel attribution framework. *International Journal of Research in Marketing* 33 (3): 491–507.

De Vries, L., S. Gensler, and P. Leeflang. 2017. Effects of traditional advertising and social messages on brand-building metrics and customer acquisition. *Journal of Marketing* 81 (5): 1–15.

Dorfman, R., and P.O. Steiner. 1954. Optimal advertising and optimal quality. *American Economic Review* 44 (5): 826–836.

Erdem, T., and J. Swait. 2004. Brand credibility, brand consideration, and choice. *Journal of Consumer Research* 31 (1): 191–198.

Giuditta, K. 2022. The future of ecommerce demands a better understanding of online consumer journeys. retailTouchPoints, 10 November, https://www.retailtouchpoints.com/topics/digital-commerce/the-future-of-ecommerce-demands-a-better-understanding-of-online-consumer-journeys.

Golder, P.N., M.G. Dekimpe, J.T. An, H.J. van Heerde, D.S. Kim, and J.W. Alba. 2022. Learning from data: An empirics-first approach to relevant knowledge generation. *Journal of Marketing* 87 (3): 319–336.

Golder, P.N., and G.J. Tellis. 1997. Will it ever fly? Modeling the takeoff of really new consumer durables. *Marketing Science* 16 (3): 256–270.

Hanssens, D.M., ed. 2015. *Empirical generalizations about marketing impact*, 2nd ed. Cambridge, MA: Marketing Science Institute.

Hanssens, D.M., and K.H. Pauwels. 2016. Demonstrating the value of marketing. *Journal of Marketing* 80 (6): 173–190.

Hanssens, D.M., G. Yildirim, S. Srinivasan, K.H. Pauwels, and M. Vanhuele. 2014. Consumer attitude metrics for guiding marketing mix decisions. *Marketing Science* 33 (4): 534–550.

Howard, J.A., and J.N. Sheth. 1969. *The theory of buyer behavior*. New York: Wiley.

Ibarra, C. 2020. What is Amazon Retail Readiness? Feedvisor, October 21, https://feedvisor.com/resources/amazon-marketing-advertising-strategies/what-is-amazon-retail-readiness/.

Keller, K.L., and D.R. Lehmann. 2006. Brands and branding: Research findings and future priorities. *Marketing Science* 25 (6): 740–759.

Kraus, S.J. 1995. Attitudes and the prediction of behavior: A meta-analysis of the empirical literature. *Personality and Social Psychology Bulletin* 21 (1): 58–75.

Kübler, R., K. Pauwels, G. Yildirim, and T. Fandrich. 2018. App popularity: Where in the world are consumers most sensitive to price and user ratings? *Journal of Marketing* 82 (5): 20–44.

Kumar, V., B. Rajan, R. Venkatesan, and J. Lecinski. 2019. Understanding the role of artificial intelligence in personalized engagement marketing. *California Management Review* 61 (4): 135–155.

Lecinski, J. 2011. *Winning the zero moment of truth (eBook)*. Mountain View, CA: Google Inc.

Lichtenstein, D.R., S. Burton, and E.J. Karson. 1991. The effect of semantic cues on consumer perceptions of reference price ads. *Journal of Consumer Research* 18 (3): 380–391.

Masters, K. 2022. Amazon just announced 7 new advertising features. Which ones matter most? *Forbes*, 26 October 26, https://www.forbes.com/sites/kirimasters/2022/10/26/amazon-just-announced-7-new-advertising-features-which-ones-matter-most/?sh=6af998e02c79.

Mathwick, C., N. Malhotra, and E. Rigdon. 2001. Experiential value: Conceptualization, measurement and application in the catalog and Internet shopping environment. *Journal of Retailing* 77 (1): 39–56.

Mela, C.F., S. Gupta, and D.R. Lehmann. 1997. The long-term impact of promotion and advertising on consumer brand choice. *Journal of Marketing Research* 34 (2): 248–261.

Morwitz, V.G., E. Johnson, and D. Schmittlein. 1993. Does measuring intent change behavior? *Journal of Consumer Research* 20 (1): 46–61.

Noble, S.M., D.A. Griffith, and M.G. Weinberger. 2005. Consumer derived utilitarian value and channel utilization in a multi-channel retail context. *Journal of Business Research* 58 (12): 1643–1651.

Novak, T.P., D.L. Hoffman, and A. Duhachek. 2003. The influence of goal-directed and experiential activities on online flow experiences. *Journal of Consumer Psychology* 13 (1/2): 3–16.

Park, E., R. Rishika, R. Janakiraman, M.B. Houston, and B. Yoo. 2018. Social dollars in online communities: The effect of product, user, and network characteristics. *Journal of Marketing* 82 (1): 93–114.

Pauwels, K., C. Demirci, G. Yildirim, and S. Srinivasan. 2016. The impact of brand familiarity on online and offline media synergy. *International Journal of Research in Marketing* 33 (4): 739–753.

Pauwels, K., S. Erguncu, and G. Yildirim. 2013. Winning hearts, minds and sales: How marketing communication enters the purchase process in emerging and mature markets. *International Journal of Research in Marketing* 30 (1): 57–68.

Pauwels, K., M. Peran, Z. Shah, G. Schnaidt, and D. Vercamer. 2023. Sponsored brands video rings up clicks and sales in the short and long run. *Journal of Marketing Analytics* 11 (3): 275–286.

Pauwels, K., B. Sud, R. Fisher, and K. Antia. 2022. Should you change your ad messaging or execution? It depends on brand age. *Applied Marketing Analytics* 8 (1): 43–54.

Pauwels, K., and B. van Ewijk. 2020. Enduring attitudes and contextual interest: When and why attitude surveys still matter in the online consumer decision journey. *Journal of Interactive Marketing* 52 (1): 20–34.

Peltonen, J., J. Strahl, and P. Floréen. 2017. Negative relevance feedback for exploratory search with visual interactive intent modeling. In: G.A. Papadopoulos and T. Kuflik (eds.) *Proceedings of the 22nd international conference on intelligent user interfaces*. New York: Association for Computing Machinery, pp. 149–159.

Petersen, J.A., V. Kumar, Y. Polo, and F.J. Sese. 2018. Unlocking the power of marketing: Understanding the links between customer mindset metrics, behavior, and profitability. *Journal of the Academy of Marketing Science* 46 (5): 813–836.

Rojas-Lamorena, Á.J., S. Del Barrio-García, and J.M. Alcántara-Pilar. 2022. A review of three decades of academic research on brand equity: A bibliometric approach using co-word analysis and bibliographic coupling. *Journal of Business Research* 139: 1067–1083.

Rutz, O.J., and R.E. Bucklin. 2011. From generic to branded: A model of spillover in paid search advertising. *Journal of Marketing Research* 48 (1): 87–102.

Simmons, C.J., B.A. Bickart, and J.G. Lynch Jr. 1993. Capturing and creating public opinion in survey research. *Journal of Consumer Research* 20 (2): 316–329.

Slotegraaf, R.J., and K. Pauwels. 2008. The impact of brand equity and innovation on the long-term effectiveness of promotions. *Journal of Marketing Research* 45 (3): 293–306.

Srinivasan, S., O.J. Rutz, and K.H. Pauwels. 2016. Paths to and off purchase: Quantifying the impact of traditional marketing and online consumer activity. *Journal of the Academy of Marketing Science* 44 (4): 440–453.

Srinivasan, S., M. Vanhuele, and K. Pauwels. 2010. Mind-set metrics in market response models: An integrative approach. *Journal of Marketing Research* 47 (4): 672–684.

Tavşanoğlu, B. 2018. Decision support system for search engine advertising campaign management by determining negative keywords. Doctoral dissertation, Sabancı University.

Tellis, G.J. 2003. *Effective advertising: Understanding when, how, and why advertising works*. Thousand Oaks, CA: SAGE.

Tourangeau, R., L.J. Rips, and K. Rasinski. 2000. *The psychology of survey response*. Cambridge: Cambridge University Press.

Trusov, M., R.E. Bucklin, and K. Pauwels. 2009. Effects of word-of-mouth versus traditional marketing: Findings from an internet social networking site. *Journal of Marketing* 73 (5): 90–102.

Vakratsas, D., and T. Ambler. 1999. How advertising works: What do we really know? *Journal of Marketing* 63 (1): 26–43.

Vakratsas, D., and Z. Ma. 2005. A look at the long-run effectiveness of multimedia advertising and its implications for budget allocation decisions. *Journal of Advertising Research* 45 (2): 241–254.

Wright, M. 2009. A new theorem for optimizing the advertising budget. *Journal of Advertising Research* 49 (2): 164–169.

Yadav, M.S., and P.A. Pavlou. 2014. Marketing in computer-mediated environments: Research synthesis and new directions. *Journal of Marketing* 78 (1): 20–40.

You, Y., G.G. Vadakkepatt, and A.M. Joshi. 2015. A meta-analysis of electronic word-of-mouth elasticity. *Journal of Marketing* 79 (2): 19–39.

Zia, M., and R.C. Rao. 2019. Search advertising: Budget allocation across search engines. *Marketing Science* 38 (6): 1023–1037.

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