**How advertising and retail drivers grow brand health online**

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**Abstract**

Sellers on online marketplaces such as Amazon.com use a variety of retail and advertising services to improve their brand performance, including awareness, consideration and sales. However, frequent success metrics on such funnel stages are needed to quantify their response to different advertising and retail drivers – such as advertising impressions and campaign tactics. For over 122,000 brands and product category combinations, we leverage weekly data from Amazon Brand Index which automatically and regularly measures 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 to the recommended allocation based on the model’s coefficients. We find that new product launches and upper-funnel advertising products are particularly effective for brands of low level of consideration, while those brands have yet to fully take advantage of these opportunities. Medium and large brands benefit most from lower-funnel advertising. As to funnel stages, all three metrics benefit from number of new reviews, % discount, negative keyword and geo reach campaigns. Furthermore, they all improve with high-traffic shopping events such as Prime Day and Thanksgiving. Interestingly, new product launches and remarketing campaigns only significantly drive brand awareness, suggesting other product and retail factors could determine consideration and revenue. In general, we find fewer drivers for revenue, potentially due to the off-Amazon factors such as word-of-mouth or alternative options at other retails we have no access of data. These results are robust across different product categories, but we find interesting differences in how upper- and middle-funnel ad products succeed in driving sales.

*Key Words*: Brand Awareness, Brand Consideration, Brand Conversion, Digital Advertising, Online Advertising, Online Retailing

**1.** **Introduction**

Global e-commerce rose from 15% of total retail sales in 2019 to 21% in 2021, and the total e-commerce market is estimated to increase from $3.3 trillion in 2022 to $5.4 trillion in 2026. As the pillars of online retailing, online marketplaces continue to play an essential role in facilitating transactions by connecting sellers and consumers on their mediums. In July 2022, the most popular online marketplace worldwide, Amazon, generated 5.3 billion monthly visits.[[1]](#footnote-2) Online marketplaces offer sellers a wide variety of retail and advertising services to improve their brand performance. For example, Amazon.com offers sellers many options to grow their brands, covering the 4Ps of marketing: Product (launching new products, denoted by ASIN which stands for Amazon Standard Identification Number), Price (selling prices and discounts), Place (product position), and Promotion (ad impressions, audience segments and campaign goals). Therefore, it is imperative for advertisers to understand the effects of different types of advertising and retail drivers on the growth of brand performance. Indeed, sellers on the online marketplaces have yet to fully understand which actions are most likely to grow the number of shoppers who are aware of, and considering their brands. Moreover, online marketplaces offer a rich portfolio of targeting including location-based reach and negative keywords that filter out irrelevant searches. Finally, online marketplaces also use advanced machine learning algorithms to predict which products may benefit most from advertising so advertisers can prioritize among their product lines. To sellers, these prolific new ad formats and retail options are both intriguing and often overwhelming (Masters 2022). Hence, our research question is: which advertising and retail factors matter most for brand growth to sellers on Amazon?

This question remains unanswered in prior literature for multiple reasons. The first challenge lies in the unique context of the online marketplace where insights from traditional offline settings may no longer apply. Sellers on the online marketplaces have many more types of advertising in addition to their ability to directly set retail prices. In contrast, in the offline retail stores, retailers choose the prices, and in-store ad options are limited. The second challenge is data availability as it is difficult to collect data on both advertising and brand performance, and track them over time. Finally, the abundance of potential ad and retail drivers combined with sparse previous literature, suggests an Empirics-First approach (Golder et al. 2022), where the empirical results lead and form the basis of potential explanations, and calls for theory development later.

In this paper, we study the impact of advertising and retail drivers on brand performance in the context of Amazon’s online marketplace. We leverage a unique data set from the Amazon Brand Index, which measures brand-level awareness, consideration and retail revenue, based on shopper behaviors. We also collect ad and retail factors as potential drivers for those brand growth metrics. Specifically, we analyze weekly data in the period between January 1, 2021, and May 16, 2022, which includes 122,000 U.S. brand/product category combinations among the largest categories within verticals of Hardlines (HL), Softlines (SL), and Consumables (CPG). We use a fixed effects panel model which controls for the potential endogeneity problem to explain weekly changes in three Amazon Brand Indices (ABI): brand awareness, brand consideration, and brand revenue.

We highlight a few major findings. First, we find that positive changes in all three brand indices were driven by advertising impressions from Sponsored Brands (SB), Sponsored Brands video (SBv), Sponsored Display (SD), and Sponsored Products (SP), suggesting robust performances of Amazon sponsored ads on all brand metrics. As for campaign strategies, the total number of ads, ads with negative keywords or geo reach significantly improved all three metrics. On the side of the retail factors, the count of newly available reviews in that week and the percentage of discount both had significant impacts on ABI. In addition, all three brand-building metrics displayed significantly positive changes on Prime Day (PD) and in 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 the clickthrough rate (CTR) significantly improved consideration. Based on 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, Owned & Operated (O&O) Display, and SBv to grow brand revenue.

Third, we find several interesting differences based on brand sizes. First, average ratings improved brand metrics for small and medium brands but not large brands, suggesting that the former two groups benefited more from additional information provided by reviews. Second, newly launched ASINs in the past month were more likely to drive small and medium brands’ metrics. Fourth, upper- and middle-funnel advertising products (e.g., Fire TV, O&O Display) were especially effective for small and medium brands, while those brands have yet to fully take advantage of these opportunities. Although large brands had more reviews on average, weekly new reviews still made a significant impact on all metrics, suggesting a positive momentum from shopper demand. For large brands that were on average more retail-ready, leveraging different ad products was particularly important. For example, all sponsored ads (SP, SB, SBv, and SD) positively impacted large brands’ awareness and consideration, whereas O&O Display were effective revenue drivers. In terms of campaign goals and audience segments, ads optimized for purchase goals worked the best for small brands, and remarketing worked the best for medium brands. In addition to the two ad types above, campaigns aimed at increasing consideration, such as those with lifestyle audience, negative keywords, and ads optimized for CTR, all worked effectively for large brands. Finally, small brands obtained a greater boost from pre-Prime Day advertising, though brands of all sizes benefited from a Prime Day lead-up period.

Last but not least, we also find differences among top advertising products as ABI drivers across product categories. Upper-funnel products (i.e., Fire TV, Steaming TV ads denoted by STV) had significant influence in Clothing, Shoes & Jewelry, Grocery & Gourmet Food, Sports & Outdoors, Electronics, Pet Supplies, and Toys & Games. Middle-funnel products (i.e., O&O, DSP Display) had significant impacts in Grocery & Gourmet Food, Health & Household, and Tools & Home Improvement. By contrast, sponsored ads showed a significant impact on all product categories’ conversions, with SB and SBv having the biggest effect sizes.

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

**2.** **Literature Review**

Our paper investigates how different advertising and retail drivers improve brand awareness, consideration and revenue. Therefore, we contribute to the following streams of literature: 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* about a brand influence the relationship 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) noted, “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.” Empirically, 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 over and above long-term marketing effects (Bruce, Peters, and Naik 2012; Hanssens et al. 2014; Petersen et al. 2018; Srinivasan, Vanhuele, and Pauwels 2010; Kumar et al. 2019). These studies note, however, that it is costly to continuously track high-quality funnel metrics with surveys, which requires representative sampling and survey procedures for hundreds, 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, they are less, or even not, sensitive to the well-documented survey issues of memory, mere measurement, and social desirability biases (Morwitz, Johnson, and Schmittlein 1993; Simmons, Bickart, and Lynch, Jr. 1993; Tourangeau, Rips, and Rasinski 2000).

As 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 (Li et al. 2020). Several empirical papers have shown that such online behavior metrics convert to sales and are responsive to marketing actions (Colicev et al. 2018; De Vries, Gensler, and Leeflang 2017; Srinivasan, Rutz, and Pauwels 2016), but this is typically done for a single or for a few brands. In this paper, we leverage weekly data, for over 122,000 brands and product category combinations, from the Amazon Brand Index which automatically and regularly measures Amazon shoppers’ brand awareness, consideration, and purchases. This data set allows us to uncover more generalized insights across brands with different characteristics.

As for *advertising’s impact*, different ads likely have different effects on specific brand metrics (Batra and Keller 2016). Depending on the context, advertising could influence some but not all brand metrics. For one, Buil et al. (2013) find that advertising spend improves brand awareness but not the perceived quality. For another, Dehaan et al. (2016) find that content-separated advertising (such as remarketing) is effective in driving traffic to an online retailer, but that content-integrated advertising (such as ads for products directly relevant to a search query) is more likely to convert to purchase. Furthermore, advertising effectiveness research has examined budget allocation from different angles, including short-term vs. long-term ad effectiveness (Vakratsas and Ma 2005), different types of online advertising (Breuer et al. 2011), and search platforms (Zia and Rao 2019). One key finding is that the effect 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 paper incorporates various ad and retail factors to evaluate their impact across brands of different sizes and in different categories.

**3. Conceptual development**

While the literature review guides our analysis, we do not derive hypotheses from a unified theory. Instead, we address the 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. To guide these insights, we provide a conceptual framework on the dimensions by which digital advertising effectiveness may differ, and how these dimensions translate into metrics in our empirical setting.

First, the purchase funnel (Srinivasan et al. 2010) or online decision journey (Court et al. 2009) is a key concept in marketing literature. Before deciding on a brand, a consumer first becomes aware of the brand and then considers it for purchase. In the awareness stage, consumers may notice the brand, and search for a brand they heard of. However, consumers 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 do such research and become informed about the brand and product specifics. This information enables the evaluation and the 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, *brand familiarity* has long been studied as a driver of consumer response to its marketing (Aaker et al. 2013). Consumers see less risk in a familiar brand, and are more likely to pay attention to its call-to-action (lower-funnel) marketing. For instance, price promotions by familiar brands such as Coca-Cola obtain 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 are typically advised to build awareness and consideration by respectively upper-funnel and mid-funnel advertising. Outside of marketing communication, product innovation and price discounts also help bring an unfamiliar brand to the attention of potential customers (Slotegraaf and Pauwels 2007).

Third, *word-of-mouth* is a key post-purchase metric with a substantial power to influence potential customers’ awareness, consideration, and purchase (Trusov et al. 2009). In e-commerce, reviews are easy to access and search. Past research has demonstrated separate effects of review (star) ratings and the number of reviews (You et al. 2015). The former indicates the product quality, the latter its popularity and the confidence a potential customer has in the review rating (ibid). On Amazon.com, 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 consumers are exposed to the brand’s message, and thus become aware of its offering (Tellis 2003, Keller and Lehmann 2006). For the latter, different campaigns provide variety in ad messaging and execution, which can help maintain consumer interest in the brand, especially if it is familiar to the consumer (Pauwels et al. 2022). We include ad impressions and the number of campaigns by ad format, as their impact may differ across upper-, mid-, and lower-funnel advertising.

Finally, digital advertisers have many new options in both the 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 geographical location (geo). Moreover, audiences who browsed the category can be retargeted (e.g., DeHaan et al. 2016), labelled as ‘remarketing’ on Amazon.com. Campaigns can be optimized for Click-Through Rate (CTR) or for purchase conversion. For metrics, Amazon offers a 0/1 coded ‘ad readiness score’ simplifying the click probability of a product in the absence of ads. Previously called ‘retail readiness’, a score of 1 demonstrates that the product detail pages include all the information necessary for consumers to make informed purchase decisions (Ibarra 2020), including “informative, SEO-rich titles, bullets, and product descriptions, clear imagery, engaging videos, customer ratings and reviews, and ample inventory”. Because research has shown that advertising works better for high quality products (Golder and Telis 1997, Erdem and Swait 2004), the ad readiness score of 1 signals to sellers that their products are worthy of advertising.

**3.** **Data and Measurement**

**3.1 Data and Sample Selection**

To ensure the generalizability of our results, we start with more than thirty product categories across three consumer verticals (Hardlines, Softlines, and Consumables) on Amazon.com. Among the product categories included in the Amazon Brand Index (ABI), we retain the top twelve categories based on the number of Amazon Standard Identification Numbers (ASIN)[[2]](#footnote-3). 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) versus hedonic (e.g. Toys & Games) nature (Li et al. 2020). As ABI is updated at the weekly level for each brand, we merge brand-level retail and advertising data with ABI from 1/1/2021 to 5/16/2022. Because retail and advertising data are both at the ASIN / daily level, we aggregate them to brand/product category by weekly 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, whereas for advertising spend, we sum up all ASINs spend at the brand level (see Table 1). Because we are mostly interested in what explains the movement in ABI, we only keep brand/product categories with at least 28 weeks of data. This length of time ensures sufficient variability in the data to uncover the significant impact of advertising 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 *over 122,000 brand/product category combinations with over 6.4 million observations* in total.

|  |  |
| --- | --- |
| Underlying Variable (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 at 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 |
| Sponsored Products readiness score (average) | Binary coded showing the click probability when using Sponsored Products |
| Ad impressions by types (sum) | Fire Tablet, Kindle, video, Fire TV, O&O Display, DSP Display, Audio, Streaming TV ads, IMDB, and sponsored ads (including Sponsored Products, Sponsored Brands, Sponsored Brands video, and Sponsored Display) |
| Number of campaigns by types (sum) | Remarketing, Lifestyle/In-Market (LSIM), Contextual, Negative keywords, Geo-reach, Click Through Rate (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 1: Key Variables and Their Explanation**

**3.2 ABI Calculation and Brand Size Categorization**

In our sample, key dependent variables such as awareness, consideration, and conversion are Amazon Brand Indices (ABI) at the brand/product category level updated weekly. ABI are computed using Amazon first-party data and are predictive of the downstream impact not only on Amazon but also on surveys measuring customer perceptions (Pauwels and van Ewijk 2020). For example, the brand consideration metrics were optimally selected and weighted to predict sales. The Awareness Index metrics include both consumer actions revealing they 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 (DPV) and dwell time (time spent on the detail page). Both metrics indicated 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 conversion (r > = 0.72). Specifically, we categorize brands as small, medium, and large if they belong to the bottom 33%, middle 33%, or top 33% in the Consideration Index, respectively.

**4. Analysis and Results**

**4.1. Model Selection**

First, we run ordinary least squares regressions (OLS) of the change in brand metrics on ad and retail drivers. The residuals plots clearly show their correlation with the predicted ABI values, i.e., the significant presence of heteroscedasticity. Thus, we establish the needs for the panel model that accounts for within-brand variations. Second, we conduct the Augmented Dickey Fuller (ADF) test as stationarity is a requirement for longitudinal data modelling. Among the 30 brand/product categories we randomly selected, 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. Further, ADF tests revealed all first-order differences are stationary, suggesting no needs for the second-order differencing. Third, we use the Hausman test to select between the random effect (RE) vs. fixed effect (FE) models. Given that all the tests reject the null hypothesis that the random effect estimator is consistent (i.e., assuming errors are not correlated with the regressors, and thus there is no endogeneity problem), we only report results with the fixed-effect estimators. However, we do test random effects model as a robustness check and results are quantitively similar.

**4.2. Media Mix Calculation**

Ever since Dorfman and Steiner (1954) derived the optimal marketing allocation, marketing literature validated that the profit-maximizing allocation spend on ad products should be based on their sales elasticities, i.e., the percentage of sales increase from a 1% increase in the ad investment. This formula is the basis for generalizable findings such as Hanssens (2015) titled “Empirical Generalizations about Marking Impact” published by the Marketing Science Institute. In the first step, we estimate the preferred model (fixed effects in our case) to extract statistically significant coefficients of ad products’ impressions. Then together with descriptive statistics on impression levels, we calculate the elasticity of each KPI to each ad spend. Next, we derive the optimal budget allocation based on the magnitude of elasticities to contrast with the current allocation on average across all applicable brands to make media mix recommendations (see De Haan et al. 2016 for a similar procedure). The exact formulas are given below:

1. calculate KPI’s elasticity by ad product: elasticity = coefficient estimated from the model \* average (ad impressions)/average (KPI)
2. Sum up elasticities from 1) and divide each by the total, to generate the recommended percentage of allocation of impression by ad product
3. Contrast 2) with the current allocation as the suggestion for that KPI

**4.3. Model Fit, Coefficients and Media Mix Allocation for all brands**

*Overall model significance*. Fixed effect models explain Amazon Brand Indices reasonably well, with both F-statistics and its robust standard error version at p < 0.001 for all KPIs. The explanatory power is highest for Clothing, Shoes and Jewelry, and the lowest for Grocery and Gourmet Food, with 2x difference, suggesting product category differences. Across the brand metrics, the explanatory power is twice as high for changes in awareness than for changes in conversion, consistent with the literature that advertising is a more powerful driver of upper-funnel than for lower-funnel metrics (Srinivasan et al. 2010, Pauwels et al. 2013).

*Model Coefficients.* We report the fixed effect model coefficients for the retail and ad campaign actions in Table 2.

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Brand awareness**  | **Brand consideration**  | **Brand revenue**  |
| Number of new products launched last month  | 0.1181\* | Ns | Ns |
| % of discount  | 1362.7\*\*\* | 987.2\*\*\* | 3434.9\*\*\* |
| Weekly new reviews  | 126.7\*\*\* | 10.858\*\*\* | 71.802\*\*\* |
| Search results page number  | -304.76\*\*\* | -6.8825\*\*\* | -74.713\*\*\* |
| Number of remarketing campaigns  | 0.0386\*\*\* | Ns | Ns |
| Number of lifestyle/in-market campaigns  | 0.0829\*\*\* | 0.0023\* | Ns |
| Number of negative keyword campaigns  | 0.0321\*\*\* | 0.0056\*\*\* | 0.0248\*\*\* |
| Number of geo reach campaigns  | 0.0168\*\*\* | 0.0062\*\*\* | 0.0303\*\*\* |
| Number of campaigns optimized for CTR | Ns | 0.0018\*\*\* | Ns |
| Number of campaigns optimized for purchase | 0.0265\*\*\* | Ns | Ns |
|  |  |  |  |
| The week of Prime Day  | 2835.3\*\*\* | 271.38\*\*\* | 1096\*\*\* |
| The week of Thanksgiving  | 1134.5\*\*\* | 116.68\*\*\* | 549.4\*\*\* |

Ns = Non-significant at the 10% confidence level, \*p<0.10, \*\*p<0.05, \*\*\*p<0.001

**Table 2: Campaigns and Retail Actions Coefficients**

First, we note that funnel drivers in the general marketing literature also apply at Amazon.com. Launching new products is key to increase brand awareness, price discounts work for all KPIs, as do new reviews, indicating the importance of word-of-mouth (Rojas-Lamorena et al. 2022, You et al. 2015, Srinivasan et al. 2010). Moreover, brands appearing high in the Search rank obtain better brand awareness, which translates into more consideration and conversion (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 raises brand awareness, we do not find a significant increase in conversion. In contrast, the use of negative keyword and of geolocation campaigns is associated with higher performance on all 3 KPIs. While campaigns optimized for click-through rate significantly increase brand consideration, those optimized for purchase appear to 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 the Thanksgiving week (Black Friday/Cyber Monday) as Amazon’s Prime Day lift brand awareness, consideration and revenues – with Prime Day enjoying about double the effect of Thanksgiving.

But how should advertisers adjust their main digital marketing allocation? Table 3 show the coefficients for the advertising products that we can compare to current allocations because advertisers have sufficiently spent in our data.

|  |  |  |  |
| --- | --- | --- | --- |
| Dependent Variable | Ad product  | Coefficient  | Average weekly impressions[[3]](#footnote-4)  |
| 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 |
| SB | 0.0013\*\*\* | 10800 |

\*p<0.10, \*\*p<0.05, \*\*\*p<0.001. Only coefficients used to calculate media mix are shown here. Though other ad impressions are significant, their effects on ad mix are too small to be included.

**Table 3: Ad Products for Media Allocation Calculation**

As shown in Table 3, Sponsored Brand Video was a significant driver of all three dependent variables: Brand Awareness, Consideration and Revenue. In contrast, Fire TV, Owned & Operated Display and Sponsored Brands (non-video) are significant drivers of Brand Revenue only.

Based on the model coefficients, we can calculate the ratio of elasticities that summarizes our model’s recommendation on ad product allocation (Dorfman and Steiner 1954, Wright 2009, DeHaan et al. 2016). It is managerially important to compare the current advertising spending with this model-based. We start with our general recommendations, and then differentiate by advertiser size because adoptions of different ad products vary a lot with this variable.

For the average advertiser in our data, Figures 1-3 compare our recommended media mix with the current allocation.



**Figure 1. Increasing SBv for Brand Awareness**



**Figure 2. Increasing SBv for Brand Consideration**



**Figure 3. Adopting Fire TV and O&O Display, and increasing SB and SBv for Brand Revenue**

First, the current allocation of 0.9 % of the media budget to Sponsored Brand Video 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, Sponsored Brands allocation should increase from 4.99% to 6.94%. Likewise, upper funnel Fire TV and Owned & Operated Display should be added as respectively 0.01% and 0.02% of the budget, coming from the dominant spending on the lower funnel ad product Sponsored Products.

**4.4. Coefficients for Advertising Mix by Brand Size**

Next, we show the model coefficients by brand size, and their recommended vs. current media mix. See Table 4 for the coefficients, and Figures 4a to 4c for media mix depending on brand sizes, using brand awareness as an example.

|  |  |  |  |
| --- | --- | --- | --- |
| Ad product  | Coefficient  | Average weekly impressions | Brand Size  |
| STV | 0.008\* | 21 | Small Brand |
| SB | 0.0027\*\*\* | 3371 |
| SD | 0.0135\*\*\* | 646 |
| SB | 0.0016\*\*\* | 10066 | Medium Brand  |
| SBV | 0.0076\*\*\* | 1847 |
| SB | 0.0029\*\*\* | 20984 | Large brand |
| SBv | 0.0162\*\*\* | 3276 |

\*p<0.10, \*\*p<0.05, \*\*\*p<0.001

**Table 4: Ad Products for Media Allocation Calculation for Brand Awareness by Size**



**Figure 4a. Increasing Small Brands’ Awareness**



**Figure 4b. Increasing Medium Brands’ Awareness**



**Figure 4b. Increasing Large Brands’ Awareness**

Consistent with marketing theory and findings (e.g. Hanssens et al. 2014, Pauwels et al. 2016), small brands have more potential to grow awareness and hence show a higher elasticity to upper funnel advertising actions such as Streaming TV (STV) and Sponsored Display (SD). As a result, our model recommends them to allocate .2% of the budget to STV and 8.6% to SD. Moreover, mid-funnel ad product Sponsored Brands (SB) should receive 9.0% of media mix allocation – more than for any other advertiser size. In contrast, the SB is already close to optimal for medium and large brands, which are recommend to increase it to respectively 5.1% and 7.2% of the budget. The large opportunity for these brands lies in Sponsored Brand Video, as the model recommends increasing the current 0.9% allocation to respectively 4.5% and 6.2%.

**4.5. 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 the following table.

|  |  |  |
| --- | --- | --- |
| Product categories | Top 3 retail drivers | Top 3 advertising drivers |
| Home & Kitchen | Number of new reviews\*\*\*, percentage of ASINs with 5+ reviews\*\*\*, percentage of price discount\*\*\* | Total # ads\*\*\*, # of LSIM ads\*\*\*, # of geo ads\*\*\* |
| Clothing, Shoes & Jewelry | Number of new reviews\*\*\*, count of total visible reviews\*\*, new ASINs launches\* | Total # ads\*\*, # of LSIM 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\*\* |
| 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\*\*\* |
| Arts, Crafts & Sewing | percentage discount\*\*\* | SBv impressions\*\*\*, # of LSIM ads\*\*\*, # of geo ads\*\*\* |
| Health & Household | Count of new reviews\*\*\*, percentage of price discount\*\*\* | Total # ads\*\*, # of negative keyword ads\*\*\*, Owned & Operated Display\*\*\* |
| Tools & Home Improvement | Count of new reviews\*, 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 LSIM ads\*\*\*, # of geo ads\*, # of ads optimized for CTR\*\*\* |
| Beauty & Personal Care | Count of total visible reviews\*, percentage of price discount\* | Total # ads\*\*\*, # of contextual ads\*\*\*, # of geo ads\*\*\* |
| Electronics | Count of new reviews\*\*\*, # new ASIN launches\*, percentage of price discount\*\*\* | Total # ads\*\*\*, # of geo ads\*\*\*, # of negative keyword ads\*\*\* |
| Pet Supplies | NA | Total # ads\*\*\*, # of ads optimized for purchase\*\*, STV impressions\*\* |

\*p<0.10, \*\*p<0.05, \*\*\*p<0.001

**Table 5: Top Three Drivers for Each Product Category**

First, the most effective retail drivers and advertising drivers differ across product categories. Upper-funnel products (i.e., Fire TV, STV) have significant influence on clothing, shoes & Jewelry, Grocery & Gourmet Food, Sports & Outdoors, Electronics, Pet Supplies, and Toys & Games. Middle funnel products (i.e., Owned & Operated Display, DSP Display) have a significant impact on Grocery & Gourmet Food, Health & Household, and Tools & Home Improvement. In contrast, *Sponsored Ads* have a significant impact on all product categories’ conversions, especially with SB and SBV having the biggest effect sizes.

Second, *the number of new reviews* seems to be 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 in shaping consumers’ 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 which facilitates the focal brands’ entry into consumers’ consideration set. As to specific advertising tactics, *remarketing* only shows up as a top 3 driver for Clothing, Shoes & Jewelry. Negative keyword ads are a top driver for Health & Household and for Electronics. Lifestyle/in Market (LSIM) matters for Arts, Crafts & Sewing, Clothing, Shoes & Jewelry, Home & Kitchen, Patio, Lawn & Garden. Interestingly, ads optimized for click-through rate are a top 3 driver for Sports & Outdoors, and for Patio, Lawn & Garden. In contrast, ads optimized for purchase are top 3 driver for Pet Supplies.

**5. Discussion**

Our new findings shows that digital advertising and retail drivers are not only specific to brand funnel metrics, but also differ by advertiser size and product category. These results raise several questions for marketing theory and practice, which we discuss below.

 First, why are new product launches and upper-funnel advertising products particularly effective for brands of low and medium level of consideration? New product launches build brand awareness (Srinivasan et al. 2009), especially for relatively small brands, where this funnel metric has more room to grow (Hanssens et al. 2014). Larger brands are more likely to be well-known, and potentially benefit less from any new information. Because smaller brands tend to have fewer products, we speculate that each new addition to their product lines influences consumers’ perception about the focal brand to a greater extent compared to larger brands. To put differently, it is in consumers’ best interest to pay more attention to new product launches by smaller brands because a richer amount of information will be revealed about the focal brand. Consistent with this rationale, ee also find upper-funnel advertising aimed at increasing brand recognition such as Streaming TV ads improve small brands’ awareness but not for larger brands.

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

 Consistent with this contextual rationale, we observe strong effects for campaigns leveraging *geolocation* and *negative keywords*. Geolocation allows advertisers to reach audiences at the right place and right time. Because they are seeing ads relevant to their real-time location, consumers are more likely to pay attention, consider and ultimately purchase the advertised product. Likewise, negative keywords help the advertiser to avoid audiences that are 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 3 brand revenue drivers in the Health & Household and Electronics categories.

 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, it is important for advertisers to ensure the product detail pages include all the necessary information for consumers, such as SEO-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 number of new reviews and % discount within the top 3 drivers, and new product launches key in Electronics, Home & Kitchen, Clothing, Shoes & Jewelry. Likewise, the number of ad campaigns matters across categories, with Sponsored Brands and Sponsored Brands Video showing the biggest effect sizes. Beyond Sponsored Ads, (Owned & Operated and DSP) Display has a significant impact in Grocery & Gourmet Food, Health & Household and Tools & Home Improvement. Future research is needed to shed light on the reasons behind this effectiveness. One possible explanation is that these categories are rather *utilitarian* in nature, and therefore evoke deeper information processing, often starting several weeks before purchase (Mathwick, Malhotra, and Rigdon 2001; Park et al. 2018). Consumers prefer online search due to its ease of comparison, which reduces brand differentiation (Noble, Griffith, and Weinberger 2005), increasing the potential for Display to influence the purchase funnel. In contrast, upper-funnel ad products (i.e., Fire TV, STV) have significant influence on Clothing, shoes & Jewelry, Grocery & Gourmet Food, Sports & Outdoors, Electronics, Pet Supplies, and Toys & Games. Many of these product categories are rather *hedonic* in nature, which enhances the consumer appeal of fun, surprise, variety and adventure in their journey shopping (Arnold and Reynolds 2003; Novak, Hoffman, and Duhachek 2003). Li et al. (2020) find that hedonic purchases involve more product page views on the target retailers up to two weeks before the conversion, presenting a funneling effect toward to the final purchases.

**6. Conclusion**

In this paper, we analyzed the impact of different retail and advertising actions on brand growth. Two typical challenges include the difficulty to measure brand metrics and the difficulty to combine advertising information and brand performance. Focusing on the empirical context of Amazon.com, we overcome these challenges by leveraging a unique data set from Amazon Brand Index, which automatically and regularly measures Amazon shoppers’ brand awareness and brand consideration, and combining it with different advertising and retail drivers. Our data starts on January 1, 2021 and ends on May 16, 2022 and includes 122,000 U.S. brand/product category[[4]](#footnote-5) combinations across the largest categories within the verticals of Hardlines (HL), Softlines (SL), and Consumables (CPG). Specifically, weekly changes of Brand Awareness, Brand Consideration, and Brand Conversion (i.e., retail revenue) are all documented by Amazon Brand Indices (ABI). This comprehensive dataset allows us to confidently address the 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 grow Brand Awareness, Brand Consideration, and Brand Revenue. In particular, SBV improves brand awareness and consideration, whereas STV, SB and SD are especially helpful for brand revenue. For small brands, we suggest investment increases in STV, SB, and SD for awareness, STV, SBV, and SD for consideration, and SB and SBV for revenue. For medium and large brands, we recommend SB and SBV for all metrics. We recommend sellers to choose their priority actions based on which Amazon Brand Indices they want to improve, as well as their current brand sizes. We highlight three main findings and offer the corresponding managerial recommendations below.

First, different advertising products drive different brand metrics. We find that increasing SBV investment was key in brand awareness and consideration, and adopting STV, together with increasing budget for SB and SD, is particularly helpful for brand revenue. These findings are also consistent with References [1] and [2].

Second, specific recommendation of advertising products depends on brands’ sizes. For small brands, STV, SB, SD, and SBV are recommended to improve brand metrics. For medium and large brands, we recommend prioritizing increasing budget for SB and SBV.

Third, recommendation of advertising products depends on product categories. Upper-funnel products (i.e., Fire TV, STV) have significant influence on clothing, shoes & Jewelry, Grocery & Gourmet Food, Sports & Outdoors, Electronics, Pet Supplies, and Toys & Games. Middle funnel products (i.e., Owned & Operated Display, DSP Display) have a significant impact on Grocery & Gourmet Food, Health & Household, and Tools & Home Improvement. In contrast, Sponsored Ads have a significant impact on all product categories’ conversions, especially with SB and SBV having the biggest effect sizes.

Despite using a large data set that combines advertising, retail and brand performance, our study has some limitations. First, owing to data collection limitations, only advertisers on Amazon’s marketplace are analyzed. Future research could examine our research question in different empirical contexts. Second, our research focuses on online ads and retail actions on brand performance online. Future research can look at the impact of advertising and retail drivers on both the online and the offline brand performance. Third, multinational corporations are interested in understanding the differences in different markets. It will be interesting to analyze the impact of advertising and retail drivers on brand performance in non-U.S. markets.

Within the large amount of digital advertising spending in the U.S., $189.8 (out of $248.8) billion is in digital video advertising, and retail media is on the rise and is expected to hit $100 billion by 2026.[[5]](#footnote-6) 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.

**References:**

Aaker, D. A., Biel, A. L., & Biel, A. (2013). *Brand equity & advertising: advertising’s role in building strong brands*. Psychology Press.

Berkowitz, D., Allaway, A., & D'souza, G. I. L. E. S. (2001). The impact of differential lag effects on the allocation of advertising budgets across media. *Journal of Advertising Research*, *41*(2), 27-27.

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

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

Buil, I., De Chernatony, L., & Martínez, E. (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., Malshe, A., & Pauwels, K. (2018). Social media and customer-based brand equity: An empirical investigation in retail industry. *Administrative Sciences*, *8*(3), 55.

de Haan, E., Wiesel, T., & Pauwels, K. (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.

Erdem, T., & Swait, J. (2004). Brand credibility, brand consideration, and choice. *Journal of consumer research*, 31(1), 191-198.

Golder, P. N., & Tellis, G. J. (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: Marketing Science Institute, Relevant Knowledge Series.

Ibarra, Catherine (2020), “What is Amazon Retail Readiness”, *Feedvisor*, October 21, <https://feedvisor.com/resources/amazon-marketing-advertising-strategies/what-is-amazon-retail-readiness/>

Kang, M. Y. (2020). Advertising allocation and impact of advertising on event ticket sales: Which product, where, and when. *International Journal of Market Research*, *62*(4), 483-498.

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

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

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

Masters, Kiri (2022), “Amazon just announced 7 new advertising features. Which ones matter most? “, *Forbes*, 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., Malhotra, N., & Rigdon, E. (2001). Experiential value: conceptualization, measurement and application in the catalog and Internet shopping environment☆. *Journal of retailing*, *77*(1), 39-56.

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

Naik, P. A., & Raman, K. (2003). Understanding the impact of synergy in multimedia communications. *Journal of Marketing Research*, *40*(4), 375-388.

Noble, Stephanie M., David A. Griffith, and Marc G. Weinberger (2005), “Consumer Derived Utilitarian Value and Channel Utilization in a Multi-Channel Retail Context,” *Journal of Business Research*, 58 (12), 1643–51.

Park, Eunho, Rishika Rishika, Ramkumar Janakiraman, Mark B. Houston, and Byungjoon Yoo (2018), “Social Dollars in Online Communities: The Effect of Product, User, and Network Characteristics,” Journal of Marketing, 82 (1), 93–114.

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

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

Rojas-Lamorena, Á. J., Del Barrio-García, S., & Alcántara-Pilar, J. M. (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., & Bucklin, R. E. (2011). From generic to branded: A model of spillover in paid search advertising. *Journal of Marketing Research*, *48*(1), 87-102.

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

Tellis, G. J. (2003). *Effective advertising: Understanding when, how, and why advertising works*. Sage Publications.

Vakratsas, D., & Ma, Z. (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.

Yang, Y., Zeng, D., Yang, Y., & Zhang, J. (2015). Optimal budget allocation across search advertising markets. *Informs Journal on Computing*, *27*(2), 285-300.

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

1. eBay, the second most visited shopping site, had three billion visits. In addition, both were also 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/> [↑](#footnote-ref-2)
2. This is equivalent to the stock keeping unit (SKU) in a traditional retail setting. [↑](#footnote-ref-3)
3. Note that average impressions and KPIs are not approved by Amazon Ads to disclose beyond the scope of review. This column is for reviewers only. [↑](#footnote-ref-4)
4. This is also referred to as product categories. [↑](#footnote-ref-5)
5. https://www.forbes.com/sites/bradadgate/2022/12/01/retail-media-networks-are-the-next-big-advertising-channel/ [↑](#footnote-ref-6)