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Advertising non-premium products as if they were premium: The impact of advertising up on advertising elasticity and brand equity☆

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ABSTRACT

Non-premium brands occasionally emulate their premium counterparts by using ads that emphasize premium characteristics such as superior performance and exclusivity. We define this practice as "advertising up" and develop hypotheses about its short- and long-term impact on advertising elasticity and brand equity respectively. We test the hypotheses in two large-scale empirical studies using a comprehensive dataset from the automotive industry that includes, among others, the content of 2317 television ads broadcast over a period of 45 months. The results indicate that advertising up increases (decreases) short-term advertising elasticity for non-premium products with a low (high) market share. The results also show that an intensive use of advertising up over time leads to long-term improvements (reductions) in brand equity for expensive (cheap) non-premium products. Furthermore, an inconsistent use of advertising up leads to reductions in brand equity. The results imply that managers of non-premium products with a low market share can use advertising up to increase advertising effectiveness in the short run. However, advertising up will only generate long-term improvements in brand equity for expensive non-premium products. Finally, to avoid long-term reductions in brand equity, advertising up should be consistently used over time.

1. Introduction

Many product categories contain vertically differentiated brands at different price points. In the automotive market, premium brands,[1] such as BMW or Mercedes, position themselves above non-premium brands, such as Hyundai or Skoda. Similarly, in fashion, Ralph Lauren positions itself above Zara; in mobile devices, Apple positions itself above Huawei; in the hotel industry, Ritz-Carlton positions itself above Holiday Inn. The consequences of vertical differentiation can be observed in numerous marketing decision areas, such as price, channel, and product design. Premium brands are routinely higher priced, retailed through more exclusive channels, and better designed than non-premium brands. In this paper, we focus on the effects of a marketing decision that is frequently overlooked, namely the decision that a brand makes regarding the content of its advertising. Specifically, we investigate how mimicking the content of premium brand ads affects the effectiveness of non-premium brand ads.

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[1] In this paper, we define a premium brand as a brand that delivers superior functional and symbolic value at a higher price compared to other brands in the category.

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Advertising by premium brands routinely includes elements such as exclusivity, superior quality, and exceptional design. For example, BMW's ad campaigns under the tagline "The Ultimate Driving Machine" consistently stress the performance and exclusivity of its cars. Non-premium brands typically emphasize other elements, such as price discounts and reliability, which tend to be more relevant for value conscious consumers. However, sometimes non-premium brands try to emulate premium brand advertising by including symbolic and functional elements that are commonly used by their premium counterparts. We refer to this tactic as "*advertising up*". Recent examples (2015) include Hyundai's ads that have emphasized the steering precision of its Sonata[2] and Kia's ads that have emphasized how the design of its Sorento helps "unleash consumers' confidence".[3]

Formally, we define "advertising up" as the degree to which an ad broadcast by a non-premium brand resembles the ads generally used by premium brands. Managers may decide to use advertising up with the goals of increasing the effectiveness of their ads in the short run and enhancing the brand equity of their products in the long run. However, it is not clear from a theoretical point of view whether advertising up actually helps achieving these goals. On the one hand, literature on hedonic consumption (Bagwell & Bernheim, 1996; Hirschman & Holbrook, 1982) supports the notion that advertising up should be effective because it contributes to building and fortifying the functional and symbolic value of the product. On the other hand, persuasion knowledge (Darke & Ritchie, 2007; Kirmani & Zhu, 2007) and the functional theory of attitudes (Katz, 1960) support the notion that advertising up may not be effective, and may even backfire, because advertising up may not match the attitudes that consumers hold about non-premium brands and might even be perceived as deceptive. Hence, despite the extended use of advertising up in some product categories, it is not clear, a priori, which of these effects dominate or under what conditions advertising up may be effective.

This paper has two main objectives. First, we study the short-term impact of advertising up on advertising elasticity, identifying contextual boundaries that may act as moderators of the impact. Specifically, we consider the product's price, market share, and quality ratings as moderators because these characteristics may influence the attitudes that consumers hold about products and, thus, the extent to which advertising up could be perceived as deceptive. Second, we assess the long-term consequences of the use of advertising up over time on the brand equity of products. Specifically, we focus on how the *intensity* (i.e., the average level) and the *inconsistency* (i.e., the variation) in the use of advertising up affect brand equity because these two variables summarize how advertising up is used over time.

In our empirical application, we use a comprehensive dataset from the automotive industry. First, we operationalize advertising up using the content of 2317 television ads broadcast from January 2007 through September 2010. The ads used to create the advertising up metric represented a total expenditure of US$11.3B and accounted for 87.7% of the advertising expenditures of 85 different non-premium products. Subsequently, we use the sales, advertising expenditures, features, and quality ratings of these 85 products to conduct two field studies. In the first study, we specify a sales model that allows us to examine how advertising up impacts advertising elasticity and how product characteristics moderate this impact. In the second study, we elicit brand equity for three periods and then assess how the use of advertising up during the second period is related to changes in brand equity between the first and the third periods.

We find that the short-term effect of advertising up on advertising elasticity is positive for non-premium products with a low market share and negative for non-premium products with a high market share. We do not find any moderating effect of price or of quality. Additionally, we find that the intensity in the use of advertising up is associated with positive long-term changes in brand equity for expensive non-premium products but negative changes in brand equity for cheap non-premium products. Finally, we find that inconsistency in the use of advertising up over time leads to reductions in brand equity.

Our study makes the following contributions to the literature. First, we contribute to the literature on advertising content (Bass, Bruce, Majumdar, & Murthi, 2007; Bruce, 2008; Chandrasekaran, Srinivasan, & Sihi, 2017; Chandy, Tellis, MacInnis, & Thaivanich, 2001; Kopalle, Fisher, Sud, & Antia, 2017; Liaukonyte, Teixeira, & Wilbur, 2015; Xu, Wilbur, Siddarth, & Silva-Risso, 2014) by defining a new type of ad content (advertising up), developing new theory about its effect on advertising effectiveness, and empirically studying its impact in a large-scale study. Second, we contribute to the literature on brand equity (Ailawadi, Lehmann, & Neslin, 2003; Buil, de Chernatony, & Martínez, 2013; Sriram, Balachander, & Kalwani, 2007; Yoo, Donthu, & Lee, 2000) by documenting the impact that the intensity and inconsistency in the use of advertising up have on a product's long-term brand equity. To our knowledge, this study is the first to empirically demonstrate that consistency in advertising communications is key to improve brand equity in the long run.

2. Theory and hypotheses

2.1. Advertising up

We define advertising up as the degree to which an ad broadcast by a non-premium brand resembles the ads generally used by premium brands. This definition contains three important notions that differentiate advertising up from other theoretical constructs used in marketing (e.g., comparative advertising, deceptive advertising). First, advertising up refers to the similarity between a focal ad and a prototype from a different segment. Second, the focal ad is for a non-premium product whereas the prototype belongs to the premium segment. Finally, the definition implies that advertising up should be operationalized as a continuous measure (i.e., the "degree" of similarity), which is driven by the characteristics of the ad. The degree of similarity with the

2 https://www.youtube.com/watch?v=JPHVwT5DUvM
3 https://www.youtube.com/watch?v=RcLehEP2z5s

prototype may depend not only on the information contained in the ad but also on other ad characteristics such as the type of appeal, the music, the format, and the actors participating in the ad.

Our theorizing relies on the premise that consumers perceive the extent to which an ad resembles a premium ad (i.e., to get the “this looks premium” feeling when they watch an ad) and that this perception affects the extent to which the ad persuades them. This assumption is in line with prior research on schemas suggesting that consumers form prototypes of ads for product categories (Goodstein, 1993; McDaniel, 1999) and that these prototypes have an important influence on how people process and evaluate a stimulus (Landwehr, Labroo, & Herrmann, 2011; Loken, Barsalou, & Joiner, 2008; Veryzer & Hutchinson, 1998).

2.2. Why advertising up may or may not increase advertising effectiveness

Arguments embedded in the hedonic consumption literature support the notion that advertising up may positively impact the advertising elasticity of non-premium brands because it can increase the functional and symbolic value of the advertised product. The hedonic consumption principle states that consumers buy products not only for their functional attributes but also for their symbolic value (Bagwell & Bernheim, 1996; Hirschman & Holbrook, 1982). The functional value of the product is generally associated with its quality, whereas the symbolic value is related to social needs such as prestige, status, or uniqueness (Gierl & Huettl, 2010).

Ads can help brands to not only inform consumers about the true quality of a product but also enhance the prestige associated with it (Mehta, Chen, & Narasimhan, 2008). Producers of socially visible goods, such as cars, generally communicate in their ads the functional and symbolic meanings of their products because they recognize the functional and symbolic needs of consumers (Amaldoss & Jain, 2005). This is especially done by premium brands because their main differentiating characteristics are their superior quality and their social signaling ability. Therefore, premium-like ad claims (advertising up) may increase the effectiveness of non-premium brand's ads because these claims may help increase the perceived quality and symbolic value of the product. In line with these ideas, we postulate:

H1a. Advertising up increases advertising elasticity.

On the other hand, marketing applications of the functional theory of attitude (Katz, 1960; Kelman, 1958; Lutz, 1991) support the notion that advertising up can have a negative effect on the ad effectiveness of non-premium products. In line with this theory, consumers hold attitudes toward products because they can serve a utilitarian function of seeking tangible rewards and a symbolic function of self-expression and value-expression (LeBoeuf & Simmons, 2010; Park, Jaworski, & MacInnis, 1986; Shavitt, 1990; Shavitt, Lowrey, & Han, 1992). Utilitarian attitudes are related to consumers' expectations about the performance of the product, whereas symbolic attitudes are related to how well consumers expect the product to satisfy their symbolic needs.

Prior research in advertising suggests that “function-matching” messages are more persuasive than “function-mismatching” messages (Johar & Sirgy, 1991; Shavitt, 1990; Snyder & DeBono, 1985). Function-matching messages increase the strength of engagement in the message processing activity (Cesario, Higgins, & Scholer, 2008) and provide information that allows individuals to behave in a manner consistent with their own underlying attitudes (Snyder & DeBono, 1985). Since the types of appeals generally used in premium-like ads are less likely to match the attitudes that consumers hold regarding non-premium products, advertising up should decrease the persuasiveness of the ad.

In addition, the theory on persuasion knowledge (Darke & Ritchie, 2007; Johar, 1995; Kirmani & Zhu, 2007) also supports the idea that advertising up may have a negative impact on advertising effectiveness. Persuasion knowledge is a mechanism that allows consumers to realize when someone is trying to persuade them. It can be especially activated if consumers realize that a company is trying to persuade them with claims that do not match what the product represents to them. This may happen when non-premium products are advertised as if they were premium. Activation of persuasion knowledge usually leads to resistance to persuasion (Campbell & Kirmani, 2000) and to adopt a generally negative attitude toward persuasion attempts (Darke & Ritchie, 2007). In line with the previous arguments, we postulate:

H1b. Advertising up decreases advertising elasticity.

2.3. Product characteristics and the impact of advertising up on advertising elasticity

The product's price, quality ratings, and market share may influence the utilitarian and symbolic attitudes of consumers toward products. Product characteristics, thus, might determine the degree of fit between the ad statements and the product, influencing the likelihood of persuasion knowledge and the persuasiveness of the ad. Therefore, the impact of advertising up on advertising elasticity can be moderated by product characteristics.

2.3.1. The moderating impact of price and quality ratings

Price and quality ratings can help consumers form their utilitarian attitudes because they influence how consumers perceive the quality of a product. Consumers use price as a heuristic to assess a product's overall quality when objective quality is difficult to assess (Dawar & Parker, 1994; Kirmani & Rao, 2000; Milgrom & Roberts, 1986). Moreover, they use quality ratings to assess the real quality of a product (Basuroy, Chatterjee, & Ravid, 2003; Floyd, Freling, Alhoqail, Cho, & Freling, 2014).

Price and quality ratings can also affect the symbolic attitudes that consumers have toward products. Higher price products are more accessible for consumers with higher incomes, thus, these products are better able to communicate social status and prestige (Han, Nunes, & Dreze, 2010). Additionally, products with higher quality ratings are generally associated with higher prices, which again can lead to inferences about the status of the owner (Bagwell & Bernheim, 1996).

According to the previous arguments, advertising up should be more effective for products with a higher price and higher quality ratings. The reason is that a higher fit between the attitudes that consumers hold toward the product and the ad statements should increase the persuasion of the ad and decrease the likelihood of persuasion knowledge. Thus, we formally propose:

H2. The impact of advertising up on advertising elasticity will increase as (a) the price and (b) the quality rating of the product increases.

2.3.2. The moderating impact of market share

Prior research also suggests that scarcity (i.e., a lower market share) can be used as a heuristic to assess an unknown product's overall quality because consumers apply the logic that scarce products are of higher quality (Cialdini, 1993; Gierl & Huettl, 2010; Griskevicius et al., 2009). Additionally, scarcer products are more likely to be owned by fewer customers and, thus, are more successful at communicating uniqueness. Furthermore, they are better at signaling exclusivity because if too many people consume a good, its signaling value disappears (Amaldoss & Jain, 2005; Corneo & Jeanne, 1997). Thus, ads with a high level of advertising up should be more effective for low market share products because these ads are more likely to match the attitudes that consumers have about these products.

Moreover, consumers are likely to have well developed “non-premium” attitudes toward products with a high market share because consumers' knowledge about these products is higher. In this situation, advertising up would be more likely to conflict with consumers' attitudes, activate persuasion knowledge, and ultimately, decrease ad persuasiveness. The conflict between attitudes and advertising up is less likely to happen for products with a low market share because consumers are likely to have lower knowledge and less developed attitudes for these products.[4] Thus, we expect the following:

H2c. The impact of advertising up on advertising elasticity will decrease as the market share of the product increases.

2.4. Advertising up and its impact on brand equity

Brand equity is commonly understood in terms of the differential preference that a product obtains due to its brand identification (Datta, Ailawadi, & van Heerde, 2017; Keller, 1993) and it is a key strategic asset that can help products become more profitable (Erdem et al., 1999; Sriram et al., 2007). We propose that advertising up intensity (i.e., the average level of advertising up in a specific period) will have a positive impact on brand equity in the long run. Greater advertising up intensity signals a higher managerial effort at emphasizing superior functional and symbolic value. A higher emphasis in value should lead to long-term improvements in product attitudes, associations, and perceived quality, with the consequent increase in the product's brand equity. In line with this argument, we propose:

H3. The intensity of advertising up has a positive impact on brand equity in the long run.

Additionally, we propose that inconsistency (i.e., the variability in the levels of advertising up in a specific time period) will have a negative impact on brand equity because maintaining a brand's image is crucial to its long-term success (Park et al., 1986). Prior research suggests that consistency is key to manage brand equity over time because it helps strengthen brand associations (Aaker, 1996; Keller, 1998). Moreover, temporal consistency in claims about the product should help ensure the clarity of its positioning and enhance the credibility of the brand, thus, improving its equity (Erdem & Swait, 1998). Therefore, we hypothesize the following:

H4. The inconsistency in the use of advertising up over time has a negative impact on brand equity in the long run.

3. Operationalization of advertising up

3.1. Context

We test our hypotheses in the automotive industry. The industry is an appropriate setting to test our theories for two reasons. First, the industry is vertically differentiated and naturally distinguishes between premium and non-premium brands. For instance, brands such as BMW, Cadillac, and Lexus, are widely recognized as premium brands whereas brands such as Chevrolet, Hyundai, and Toyota, are recognized as non-premium brands. This characteristic allows us to operationalize advertising up as a function of the advertising content generally used by premium and non-premium brands. Second, the industry offers a broad range of products that are advertised using a large variety of ad copies. The variability in advertising content and product characteristics

[4] We thank an anonymous reviewer for suggesting this explanation.

allows us to study the impact of advertising up, and the heterogeneity of this impact, on advertising effectiveness and brand equity.

3.2. Data

We obtained information about the expenditures and the video copies for individual ads broadcast on television from January 2000 through September 2010 for all vehicles in the automotive industry. Due to financial constraints, we coded only a subset of the ads and used their content to operationalize advertising up. We selected ads belonging to sport utility (SUV) and sedan models broadcast from January 2007 through September 2010. We considered only the ads used by the top 10 brands in the premium and the top 10 brands in the non-premium segments (based on sales). The top 10 brands in each segment accounted for 96.6% and 79.7% of the sales in the premium and non-premium segments, respectively. Web Appendix A outlines the brands in each segment as defined by the data provider, an expert in the industry. Finally, we selected ads with a total expenditure of at least one million U.S. dollars during the period under study. The final sample contained 2317 ads (1646 from non-premium brands), representing a total expenditure of US$11.3B. Next, we explain the procedure we used to code the content of the ads.

3.3. Advertising content codification

We used the coding guide proposed by Stewart and Furse (1986), because it provides an exhaustive description of the messages and executional elements used in advertising. We adapted the content of the guide to match the context of the auto industry. The final version of the guide, which describes the content of an ad using 118 different items (i.e., ad characteristics), is available in the Web Appendix B.

Consistent with previous research we recruited university students to code the ads (MacInnis, Rao, & Weiss, 2002). The 12 coders were between 18 and 26 years old. Two coders coded each ad to estimate a measure of inter-coder agreement. We randomly assigned ads to coders and the order of coding, making sure that no coder was assigned the same ad twice. Random assignment circumvents biases that could be generated by the familiarity of coders with the coding guide over time. Finally, the average inter-coder agreement was 0.866 (s.d. 0.011).

Due to the large number of coded items, we could not solve disagreements by discussion. Instead, we obtained a single response about the presence of each ad characteristic with the assumption that it was present if any of the coders indicated as such. This rule is in line with the reasoning that the probability of missing the presence of an item is much higher than the probability of reporting an item as present when it is not.[5] We provide more details about the coding process in Web Appendix C.

3.4. Advertising up metric for individual ads

To operationalize advertising up, we used information about the 2317 selected ads; including their coded characteristics, and the products and brands they belong to. We operationalize advertising up as the probability that an ad n belongs to the premium segment (i.e., to a premium brand) given its k characteristics (f_{nk}). Formally, this probability is expressed as:

$$P_n(\text{Premium}|f_{nk}) = \frac{1}{1+\ \exp\left\{-\sum_{k=1}^{K}\beta_k f_{nk}\right\}}. \tag{1}$$

The dependent variable used in the estimation of Eq. 1 is a dummy variable indicating whether the ad belongs to a non-premium (premium = 0) or a premium brand (premium = 1). The probability P_n should also capture the similarity of ad n with respect to ads in the premium segment. Ad n will be more similar to typical ads in the premium segment the closer the probability is to 1. In contrast, the ad will be more similar to ads in the non-premium segment the closer the probability is to 0. Additionally, we can identify what elements are commonly found in campaigns of premium and non-premium brands by analyzing the sign and significance of the β's. A positive and significant value of β_k implies that the k characteristic is commonly used in ads of premium brands. In contrast, a negative and significant value of β_k implies that the k characteristic is commonly used in ads of non-premium brands. An advantage of this operationalization over directly asking coders to assess advertising up is that it allows us to provide insights regarding which characteristics determine whether an ad looks similar to non-premium or premium ads.

3.5. Calculating advertising up

To calculate advertising up, we first estimated the logistic regression in Eq. 1. To facilitate the interpretation of the results, we considered only ad characteristics that appeared in more than 5% and less than 95% of the ads.[6] The model correctly classified 82.4% of the observations, which indicates that ad characteristics help in discriminating whether an ad belongs to a premium or a non-premium brand. Table 1 presents a summary with the effects of the different items that were significant in the logistic

[5] The robustness checks show that our results also hold when we use other rules.
[6] The robustness checks show that our results do not change when we include all the characteristics.

Table 1
Results from the logistic regression: Items making an ad similar to the typical ads in the standard and premium segments.

Item code	Item name	Coefficient	S.E.
Standard items			
Information			
V2	Rebate/cash back	−0.744***	0.224
V5	Value	−0.558**	0.266
V6	Superiority claim	−0.388**	0.198
V8	Independent research	−0.606***	0.194
V10	Savings	−1.007***	0.173
V13	Warranty	−0.520*	0.277
V14	Reliability	−0.386*	0.227
V19	User satisfaction	−0.789**	0.316
V22	Availability	−0.804***	0.221
Auditory devices			
V28	Rhymes/slogans	−0.409***	0.142
Settings/scenery and visual devices			
V32	Performance setting	−0.443**	0.189
V40	Substantive super	−0.600***	0.211
Selling proposition, appeals, and tone			
V44	Attributes main message	−0.464***	0.178
V49	Comfort appeal	−0.602***	0.222
V60	Modern/contemporary	−0.357**	0.156
V66	Cool/laid-back	−1.042***	0.236
V68	Uneasy/tense/irritated	−0.933***	0.304
V71	Humorous	−1.044***	0.291
V73	Rough/rugged	−0.392*	0.214
Comparisons			
V76	Substantiated comparison	−1.032***	0.350
Structure, format, cast, and music			
V80	Humorous closing	−0.888***	0.330
V85	Comedy	−0.586*	0.355
V100	Ethnic	−0.457*	0.264
V104	Background cast	−0.409***	0.153
Premium items			
Information			
V4	Quality	0.505***	0.159
V16	Sensory information	0.432***	0.161
V25	Sales event	0.711***	0.190
Settings/scenery and visual devices			
V34	Indoors	0.418***	0.154
V35	Outdoors	0.639***	0.216
V36	Scenic beauty	0.647***	0.229
V41	Visual memory device	0.262*	0.143
V45	Product performance main message	0.313**	0.143
Selling proposition, appeals, and tone			
V52	Excitement appeal	0.517***	0.181
V61	Wholesome/healthy	0.411*	0.228
V62	Technological/futuristic	1.023***	0.156
V63	Conservative/traditional	0.993***	0.183
V67	Somber/serious	0.614***	0.206
V70	Glamorous	1.747***	0.235
Comparisons			
V74	Comparison	0.81**	0.349
Structure, format, cast, and music			
V81	Blind lead-in	0.571***	0.201
V99	Child	0.643**	0.314
V112	Created mood	0.328**	0.139

Note. Only significant items are displayed. Full results are given in Web Appendix D.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

regression.[7] We interpret the sign of the coefficients as the contribution of the item toward the similarity with the prototypical ad in the non-premium (negative sign) and premium (positive sign) segments. Because all the items are binary, the size of the coefficient indicates the relevance of an ad characteristic in the advertising up metric.

We find that several items determine the degree of similarity between an ad and the prototypical ad in the premium segment. For example, some informational cues (e.g., savings, availability, user satisfaction) appear to be more typical in non-

[7] Full results are reported in Web Appendix D.

premium brand ads, whereas others (e.g., quality, sensory information) seem to be more typical in premium brand ads. The type of selling propositions used in non-premium and premium ads also seems to differ. The central message of ads for non-premium brands focuses more on attributes whereas for premium brands it focuses more on product performance. In terms of appeals, non-premium brand ads appear to use more humor and informal appeals, whereas premium brand ads emphasize more sophistication, glamour, and technology. Finally, ads for non-premium brands appear to rely more on comedy and ethnic characters to build their plots, whereas ads for premium brands seem to use deeper plots that only show the product at the end.

Using the estimated coefficients from Eq. 1, we calculate the *predicted* probability that an ad belongs to a premium brand given its ad characteristics. This probability represents the advertising up metric for an individual ad.

3.6. Validation of the advertising up metric

To confirm that the advertising up metric represents the proposed construct, we asked two coders to answer how similar an ad was with respect to the prototype in the premium segment (1 = the ad looks like the typical ad of a non-premium brand; 7 = the ad looks like the typical ad of a premium brand). The coders had previously participated in the coding process so they had been exposed to a significant number of car ads. Therefore, they could accurately assess the similarity between each ad and the prototype in each segment. They coded a total of 252 ads (47.6% from premium brands). As expected, our metric significantly correlated with the coders' answers ($r = 0.51$; $p < 0.01$). Additionally, we asked the coders to rate the creativity of the ads to confirm that creativity does not drive our results. Advertising up did not correlate with creativity ($r = 0.02$; $p = 0.73$).[8]

4. Study 1. Advertising up and advertising elasticity

To assess the impact of advertising up on the advertising elasticity of non-premium cars, we specify a sales model such that the advertising elasticity is a function of advertising up and product characteristics. Our methodology: (1) accounts for the dynamic impact of advertising by including advertising stock variables, (2) accounts for unobserved heterogeneity in the level of sales, (3) includes the impact of competitive advertising and sales, and (4) accounts for the endogeneity of price, advertising expenditure, and the advertising up metric. Next, we explain the data used to calibrate the sales model and, subsequently, we provide more details on the model specification and estimation.

4.1. Sales

The focus of our paper concerns the consequences of advertising up for non-premium products. Thus, in our demand model we only consider registrations for products belonging to non-premium brands (85 different car models). We obtained registrations from R. L. Polk Company. We identify a *car model* as the unique combination of parent brand (e.g., Toyota), model name (e.g., Camry), and engine type (hybrid/gasoline). This definition of car model implies that product upgrades are part of the same car model.

To synchronize registration data with other variables we define our dependent variable in month t as the registrations of a car in month t + 1. The current legislation in the U.S. dictates that cars must be registered within 15 to 30 days after purchase (variability is due to differences across states). The legislation ensures that the sale of a car occurred at most one month earlier than its registration. One advantage of using this operationalization is that we reduce the risk of endogeneity of marketing-mix variables because only part of the registrations in month t actually correspond to sales occurring in t. For simplicity, from now on we refer to registrations in month t + 1 as sales in t.

4.2. Advertising stock

We obtained monthly advertising expenditures per car model from Kantar media. This dataset details expenditures for different advertising media (newspaper, radio, internet, outdoor), including television, which represents 98.5% of the total expenditure for the products considered in the analysis. To account for the fact that the effect of advertising expenditure could be realized over time, we assume that advertising forms a stock variable. The stock of advertising depreciates over time, and it accumulates as the firm advertises. We operationalize product p's advertising stock in month t as the discounted sum of the monthly expenditure in logs (Burmester, Becker, van Heerde, & Clement, 2015; Luan & Sudhir, 2010):

$$AS_{pt} = \sum_{\tau=1}^{t} \lambda^{t-\tau} \ln\left(1 + ADV_{p\tau}\right), \tag{2}$$

where the parameter λ ($0 \le \lambda \le 1$) represents the carryover parameter and $ADV_{p\tau}$ is the total advertising expenditure for product p in month τ, which includes expenditures of coded and non-coded ads and expenditures on television and other media.[9]

[8] We also generated advertising up metrics based on the Euclidean and the Manhattan distances (UP = 1/distance), considering only the significant attributes from Eq. 1. However, we discarded these metrics because the answers of the coders correlated stronger with the logistic regression-based UP metric (Euclidean distance: $r = 0.25$, $p < 0.01$; Manhattan distance: $r = 0.26$, $p < 0.01$).

[9] Our advertising spending data starts in January 1996. Thus, we initialized the AdStock variable considering the focal product's ad spending during its introduction month. For products that were in the market before 1996, we initialized the AdStock using the ad spending in January 1996.

4.3. Advertising up for individual products over time

The advertising up metric calculated in Eq. 1 is specific to an individual ad. However, a product p can be advertised in more than one ad during the same month. Because our dependent variable (sales) is measured monthly, we calculate our advertising up metric for product p in month t (UP_{pt}) as the expenditure-weighted average of the predicted probabilities for all the ads of product p that were broadcast in month t. Mathematically:

$$UP_{pt} = \frac{\sum_{n=1}^{N_{pt}} \widehat{P_n}(\text{Premium}|f_{nk}) AE_{nt}}{\sum_{n=1}^{N_p} AE_{nt}}, \tag{3}$$

where N_{pt} is the total number of ads for product p in month t, $\widehat{P_n}(\text{Premium}|f_{nk})$ is the predicted probability that ad n belongs to the premium segment given its f_{nk} characteristics (Eq. 1), and AE_{nt} is the advertising expenditure in ad n in month t. Note that UP_{pt} is undefined for months where the total expenditure in coded ads is zero. To avoid having missing data, we coded undefined values of UP_{pt} as zero and created a dummy variable ($NOCONT_{pt}$) indicating when this happened. We included the dummy in the model to capture differences in sales for periods when we had and did not have ad content data. We also added the interaction between the dummy and advertising stock to capture potential differences in advertising elasticity.

Fig. 1 illustrates the evolution of advertising up for different products. There is substantial variation in the content used by products. Most of the advertising campaigns for the products in Fig. 1 have low levels of advertising up. Moreover, campaigns with high levels of advertising up seem to occur sporadically and only for a few consecutive months. The plots are consistent with prior research documenting that the ad campaigns for some products might exhibit important changes in attributes and appeals over time (Pauwels, Sud, Fisher, & Antia, 2016). These changes can occur because brands broadcast different ads within the same campaign, change campaigns during the year, and insert extraordinary ads for especial events (Super Bowl, Black Friday, etc.).

Although we did not code the totality of ads for the considered brands, we believe that the advertising up metric accurately represents the population of ads in a given month for two reasons: First, coded ads represent the large majority of expenditures for the considered non-premium products (87.7%). Second, due to the principle of integrated marketing communications, different ads belonging to the same advertising campaign generally communicate the same message. Thus, the content of non-coded ads should not drastically differ from the content of coded ads.

4.4. Moderators of advertising up

As explained in the theory section, we considered price, market share, and quality ratings as moderators of the impact of advertising up. We obtained *price* data from Wards Auto. As in prior research, we used yearly MSRP (manufacturer suggested retail price) instead of transaction prices because these were not available to us (Balachander, Liu, & Stock, 2009). To obtain the market share of a car, we first calculated the monthly shares of the focal car and, subsequently, averaged them over the period of analysis to obtain a *share* variable for each car model.[10] Finally, to operationalize quality, we collected data from J.D. Power's Initial Quality Study (IQS)[11] and Vehicle Dependability Study (VDS)[12] and the U.S. News' Reliability Study for 2008 car models.[13] We operationalized *quality* as the average among the different ratings (a factor analysis indicates that all the ratings can be summarized by one dimension).

Table 2 shows summary statistics and the correlations among advertising up and its moderators.[14] The correlations indicate that non-premium car models with higher quality ($r = 0.49$) are more likely to be advertised using ad characteristics that are commonly used by premium brands. This could indicate that brands that have worked their way out into providing better quality may use advertising up to strengthen their positioning. The smaller correlations between advertising up and market share ($r = 0.26$) and price ($r = 0.06$) suggest that advertising up is not necessarily used more to advertise more popular or expensive non-premium car models.

4.5. Other variables

Additionally, we included several variables that can affect the car sales in the specification of our sales model. We calculated competitive advertising stock (AS^{comp}) for a focal car model considering the formula in Eq. 2 and the sum of the advertising expenditures of all other brands in the competitive segment (either sedan or SUV). We also created the variable $SALES^{comp}$ (competitive sales) as the sum of sales for all the car models in the same competitive segment.

To account for changes in sales during the introduction period, we created I^{intro}, a dummy variable indicating the first six months after the introduction of a new car model. Similarly, we created I^{exit}, a dummy variable identifying the years in which a model was not manufactured to account for lower sales due to possible supply constraints. We also included the variable MPD

[10] The market share was calculated dividing the sales of a focal car by the total number of sales in the SUV and sedan categories combined.
[11] The IQS measures car quality by analyzing problems reported by owners in the first 90 days of ownership.
[12] The VDS examines issues reported by original owners of 3-year-old vehicles, analyzing problems experienced over the past 12 months of ownership.
[13] We used earlier ratings when this information was not available for the 2008 models.
[14] We show a full correlation table in Web Appendix E.

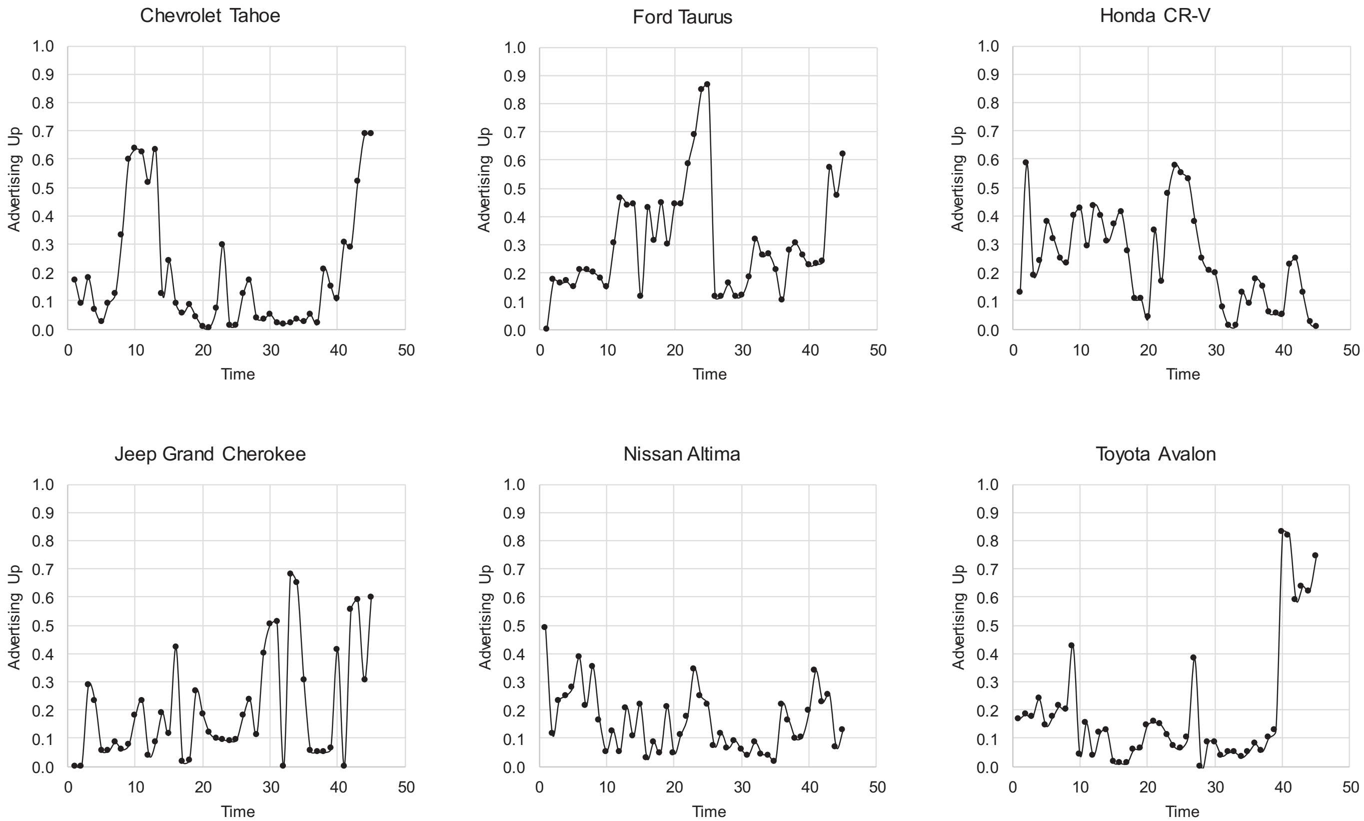

Fig. 1. Advertising up over time for different car models.

Table 2
Correlations and summary statistics for advertising up and its moderators.

	Up	Price	Share	Quality
Up	1.00			
Price	0.06	1.00		
Share	0.26	−0.21	1.00	
Quality	0.49	0.07	0.17	1.00
Mean	0.151	25011	1.55%	3.368
Std. dev.	0.160	8023	1.50%	0.743
Min.	0.000	12505	0.02%	2.000
Max.	0.866	54530	8.02%	5.000
Observations	3544	3544	3544	3544

(miles per dollar), defined as the ratio between a product's combined fuel efficiency and the fuel price per gallon obtained from Wards Auto and the U.S. Energy Information Administration, respectively. Finally, we used the University of Michigan's consumer sentiment index (CSI) to control for consumers' attitudes and their expectations about the economy.

4.6. Model specification

We model the sales of product p in time t using a panel data model (Binken & Stremersch, 2009; Luan & Sudhir, 2010). We assume that advertising up has an influence on the sales of product p by changing the elasticity of advertising expenditure. We model this moderation effect by interacting the advertising stock variable and the advertising up metric. We add the three-way interactions with price, share, and quality rating to describe the heterogeneity in the impact of advertising up on advertising elasticity. Formally, the sales equation is specified as

$$\begin{aligned}
\ln\left(\mathrm{SALES}_{pt}\right) = {} & \mu_p + \alpha_0 \mathrm{AS}_{pt} + \alpha_1 \mathrm{AS}_{pt}\mathrm{UP}_{pt} + \alpha_2 \mathrm{AS}_{pt}\mathrm{UP}_{pt} \ln\left(\mathrm{PRICE}_{pt}\right) + \alpha_3 \mathrm{AS}_{pt}\mathrm{UP}_{pt}\mathrm{QUALITY}_p \\
& + \alpha_4 \mathrm{AS}_{pt}\mathrm{UP}_{pt}\mathrm{SHARE}_p + \alpha_5 \mathrm{AS}_{pt} \ln\left(\mathrm{PRICE}_{pt}\right) + \alpha_6 \mathrm{AS}_{pt}\mathrm{QUALITY}_p + \alpha_7 \mathrm{AS}_{pt}\mathrm{SHARE}_p \\
& + \alpha_8 \mathrm{AS}_{pt}\mathrm{NOCONT}_{pt} + \alpha_9 \mathrm{UP}_{pt} \ln\left(\mathrm{PRICE}_{pt}\right) + \alpha_{10}\mathrm{UP}_{pt}\mathrm{QUALITY}_p + \alpha_{11}\mathrm{UP}_{pt}\mathrm{SHARE}_p \\
& + \alpha_{12}\mathrm{UP}_{pt} + \alpha_{13}\mathrm{NOCONT}_{pt} + \delta_1 \ln\left(\mathrm{PRICE}_{pt}\right) + \delta_2 \mathrm{AS}_{pt}^{comp} + \delta_3 \ln\left(\mathrm{SALES}_{pt}^{comp}\right) \\
& + \delta_4 I_{pt}^{intro} + \delta_5 I_{pt}^{exit} + \delta_6 \ln\left(\mathrm{MPD}_{pt}\right) + \delta_7 \ln\left(\mathrm{CSI}_t\right) + \gamma_p \mathrm{TIME} + \delta_t + \varepsilon_{pt}.
\end{aligned} \tag{4}$$

In the model specification, we also include month-of-the-year specific fixed effects (δ_t) to account for seasonality and a deterministic time trend specific to each product (γ_p). Finally, the terms μ_p are fixed effects that control for product-specific unobserved factors that are constant over time. We mean-center all the variables used to calculate the interaction terms to facilitate the interpretation of the results. Note that Eq. 4 includes the two-way interactions between UP_{pt} and product characteristics. These terms must be included in the model in order to perform statistical inference for the three-way interaction coefficients (Ghosh, Dutta, & Stremersch, 2006).

To estimate the carryover parameters for own and competitive advertising, we perform a grid search from 0 to 0.95, with steps of 0.05, and select the λs that minimize the sum of squared residuals. In the estimation of the models we use Driscoll-Kraay standard errors, which are consistent in the presence of serial correlation, cross-sectional heteroscedasticity, and cross-sectional dependence (Driscoll & Kraay, 1998; Hoechle, 2007). If these issues are not accounted for, the ordinary least squares (OLS) estimates will be consistent but inefficient, and the standard errors may be biased (Beck, 2001; Beck & Katz, 1995).

Finally, according to the specification of Eq. 4, the advertising elasticity for product p is given by:

$$\begin{aligned}
\frac{\partial \ln\left(\mathrm{SALES}_{pt}\right)}{\partial \mathrm{AS}_{pt}} = {} & \alpha_0 + \alpha_1 \mathrm{UP}_{pt} + \alpha_2 \mathrm{UP}_{pt} \ln\left(\mathrm{PRICE}_{pt}\right) + \alpha_3 \mathrm{UP}_{pt}\mathrm{QUALITY}_p + \alpha_4 \mathrm{UP}_{pt}\mathrm{SHARE}_p \\
& + \alpha_5 \ln\left(\mathrm{PRICE}_{pt}\right) + \alpha_6 \mathrm{QUALITY}_p + \alpha_7 \mathrm{SHARE}_p.
\end{aligned} \tag{5}$$

Given Eq. 5, we can directly test hypotheses H_{1a} and H_{1b} by assessing the sign and significance of α_1, and hypotheses H_{2a}, H_{2b}, and H_{2c} by looking at the sign and significance of α_2, α_3, and α_4. Additionally, we can examine how the advertising elasticity changes across products with different characteristics by looking at the coefficients α_5, α_6, and α_7.

4.7. Endogeneity

Endogeneity concerns could arise for two reasons. First, there can be product-specific time-invariant variables that are unobserved to us (e.g., design, style) that can simultaneously affect sales and managerial decisions regarding advertising expenditures, advertising content, and price. The inclusion of product-specific fixed effects should account for this omitted variable problem (Papies, Ebbes, & van Heerde, 2017).

Second, managers may set advertising expenditures, generate advertising content, and estimate prices based on expected sales. We tackle this reverse causality problem using the Gaussian copula approach (Park & Gupta, 2012). The approach accounts for endogeneity by explicitly modeling the correlations between the endogenous variables and the error term in the sales equation through a copula structure. The copulas are included as covariates in the sales equation and they "control" for the parts of the endogenous variables that are correlated with the error term. The remaining variation in the endogenous variables is independent of the error in the sales equation and, therefore, the estimation is consistent.

An advantage of the Gaussian copula method is that it does not require the use of instrumental variables for identification.[15] This is useful in our case because it is difficult to obtain variables that are uncorrelated with sales but correlated with the endogenous variables. The condition for identification is that the endogenous variables should be non-normality distributed. The Shapiro-Wilk test rejects the null hypotheses that the endogenous variables are normally distributed ($\ln(\mathrm{ADV}_{pt}+1)$: $W = 0.95$, $p < 0.01$; UP_{pt}: $W = 0.84$, $p < 0.01$; $\ln(\mathrm{PRICE}_{pt})$: $W = 0.99$; $p < 0.01$).[16] The Gaussian copulas we include in the sales equations are calculated as:

$$\text{Copula } X_{jt} = \Phi^{-1}\left(H_X\left(X_{jt}\right)\right), \tag{6}$$

where Φ^{-1} is the inverse of the cumulative function of the normal distribution and H_X is the empirical cumulative function of the focal endogenous variable X (X: $\ln(\mathrm{ADV}+1)$, UP, $\ln(\mathrm{PRICE})$).

4.8. The impact of advertising up on advertising elasticity

We estimated different model specifications considering all the possible combinations of advertising up moderators to test the stability of the estimated coefficients. The results in Table 3 show that the estimated coefficients for the advertising stock and advertising up variables are quite stable across the different model specifications. Remarkably, the only moderator of advertising up that is consistently significant across model specifications is market share. The optimal carryover effects are 0.45 for own advertising stock and 0.35 for competitive advertising stock.[17] Additionally, the Akaike Information Criterion (AIC) suggests that the explanatory power and parsimony of the model increase with the inclusion of advertising up and its moderators. The condition index for the full model is 27.4, below the recommended threshold of 30, suggesting that multicollinearity is not a major concern (Belsley, Kuh, & Welsch, 1980). Next, we focus our discussion on the results of the full model (in the last column).

4.8.1. Advertising elasticity and its moderators

The short-term advertising elasticity for a car model with average characteristics using an average level of advertising up (all the moderators are mean-centered) is 0.052 ($p < 0.01$). This value is between the empirical generalization of 0.12 reported by Hanssens (2015) and the average short-term advertising elasticity of 0.038 reported by Hu, Du, and Damangir (2014) who also used monthly data from the automobile industry.

The interaction between advertising stock and advertising up is positive and significant ($\alpha_1 = 0.037$, $p < 0.05$). Thus, in support of H1a, our results indicate that advertising up appears to have a positive impact on the advertising elasticity, at least for an average car model. Regarding the moderators of the impact of advertising up on the advertising elasticity (i.e., the three-way interactions), we find that the impact does not appear to be moderated by the price of the product ($\alpha_2 = 0.114$, $p > 0.1$). Thus, our analysis fails to support H2a. Additionally, our results suggest that the impact of advertising up on the advertising elasticity does not depend on the quality rating of the product ($\alpha_3 = -0.023$, $p > 0.1$) and, thus, the analysis fails to support H2b. Finally, in favor of H2c, we find that the impact of advertising up on the advertising elasticity decreases as the market share of the product increases ($\alpha_4 = -0.034$, $p < 0.05$).

We now turn our attention to the two-way interactions between advertising stock and product characteristics, which model the heterogeneity of the advertising elasticity across products. Our results show that the interaction between advertising stock and price is non-significant ($\alpha_5 = 0.011$, $p > 0.1$). Thus, after controlling for market share and quality, the price of the product does not appear to play a role in the magnitude of the advertising elasticity. Additionally, the advertising elasticity does not appear to vary across products with different quality ratings because the interaction between advertising stock and quality is non-significant ($\alpha_7 = 0.008$, $p > 0.1$). Finally, we find that the interaction between advertising stock and market share is negative and significant ($\alpha_6 = -0.013$, $p < 0.01$), meaning that car models with a higher market share have a lower advertising elasticity. This is consistent with the notion that attracting additional customers gets more difficult as the customer base increases.

[15] Park and Gupta (2012) show that the copula approach leads to similar results than instrument-based 2SLS estimation, and that the approach is robust to mispecifications of the distribution of the error term and of the dependence structure between the endogenous variables and the error term. Papies et al. (2017) show that the copula method resolves the endogeneity bias and is almost as efficient as the instrumental variable approach.

[16] We included the copula for ad spending rather than for ad stock because the correlation between ad stock and the error term of the sales equation is through ad spending. As a robustness check, we added the copula for ad stock and our main results did not change (Shapiro-Wilk AS_{pt}: $W = 0.96$; $p < 0.01$).

[17] We use the same carryovers across models for maximum comparability.

Table 3
Parameter estimates for different specifications of the sales model.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Full model
AdStock	0.062***	0.059***	0.063***	0.052***	0.051***	0.060***	0.053***	0.052***
	(0.011)	(0.011)	(0.011)	(0.009)	(0.010)	(0.011)	(0.009)	(0.010)
AdStock × UP	0.055**	0.047**	0.059**	0.038**	0.036**	0.052***	0.038**	0.037**
	(0.027)	(0.019)	(0.027)	(0.019)	(0.018)	(0.019)	(0.019)	(0.017)
AdStock × UP × ln(Price)		0.159*			0.117	0.159*		0.114
		(0.089)			(0.087)	(0.093)		(0.093)
AdStock × UP × Quality			−0.026			−0.030	−0.020	−0.023
			(0.026)			(0.030)	(0.022)	(0.030)
AdStock × UP × Share				−0.039***	−0.032**		−0.041***	−0.034**
				(0.013)	(0.014)		(0.014)	(0.016)
AdStock × ln(Price)		0.026*			0.016	0.022		0.011
		(0.016)			(0.016)	(0.017)		(0.016)
AdStock × Quality			0.007			0.006	0.008	0.008
			(0.007)			(0.007)	(0.005)	(0.007)
AdStock × Share				−0.014***	−0.013***		−0.014***	−0.013***
				(0.003)	(0.003)		(0.003)	(0.003)
AdStock × NoContent dummy	−0.014**	−0.012*	−0.010	−0.016**	−0.015**	−0.009	−0.013	−0.012
	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)
UP × ln(Price)		0.271			0.255	0.282		0.284
		(0.268)			(0.272)	(0.287)		(0.290)
UP × Quality			−0.150			−0.137	−0.158*	−0.153
			(0.092)			(0.103)	(0.084)	(0.112)
UP × Share				0.058	0.052		0.078	0.073
				(0.050)	(0.057)		(0.051)	(0.062)
UP	0.181	0.164	0.267	0.256*	0.220	0.245	0.350*	0.309
	(0.191)	(0.169)	(0.217)	(0.149)	(0.162)	(0.192)	(0.177)	(0.196)
NoContent dummy	0.169**	0.167**	0.123*	0.202***	0.201***	0.124*	0.158**	0.158**
	(0.067)	(0.068)	(0.067)	(0.075)	(0.074)	(0.069)	(0.077)	(0.077)
ln(Price)	0.001	0.037	−0.103	−0.008	0.012	−0.065	−0.108	−0.096
	(0.443)	(0.467)	(0.431)	(0.375)	(0.449)	(0.456)	(0.368)	(0.440)
AdStockComp	0.081**	0.081**	0.083**	0.086***	0.085**	0.083**	0.087***	0.087**
	(0.035)	(0.034)	(0.035)	(0.031)	(0.034)	(0.035)	(0.031)	(0.035)
ln(Competitive Sales)	0.824***	0.821***	0.825***	0.839***	0.834***	0.822***	0.839***	0.832***
	(0.053)	(0.050)	(0.051)	(0.043)	(0.048)	(0.048)	(0.041)	(0.046)
Intro dummy	−0.309***	−0.307***	−0.311***	−0.295***	−0.295***	−0.308***	−0.297***	−0.296***
	(0.061)	(0.060)	(0.061)	(0.048)	(0.058)	(0.060)	(0.047)	(0.058)
Exit dummy	−1.441***	−1.422***	−1.437***	−1.444***	−1.432***	−1.416***	−1.443***	−1.430***
	(0.398)	(0.388)	(0.393)	(0.316)	(0.388)	(0.383)	(0.313)	(0.384)
ln(Miles per Dollar)	0.096***	0.098***	0.093**	0.099***	0.100***	0.095**	0.094***	0.096***
	(0.035)	(0.035)	(0.037)	(0.033)	(0.034)	(0.037)	(0.035)	(0.036)
ln(Customer Sentiment Index)	−0.385***	−0.386***	−0.380***	−0.394***	−0.392***	−0.380***	−0.385***	−0.382***
	(0.074)	(0.074)	(0.074)	(0.060)	(0.075)	(0.075)	(0.061)	(0.076)
Copula advertising	−0.000	0.001	−0.002	0.015	0.014	−0.000	0.013	0.012
	(0.025)	(0.025)	(0.025)	(0.023)	(0.024)	(0.025)	(0.024)	(0.025)
Copula UP	−0.050	−0.041	−0.061*	−0.047*	−0.040	−0.050	−0.059*	−0.050
	(0.032)	(0.031)	(0.036)	(0.027)	(0.031)	(0.036)	(0.030)	(0.035)
Copula price	−0.073	−0.102	−0.050	−0.077	−0.096	−0.076	−0.052	−0.068
	(0.104)	(0.104)	(0.103)	(0.090)	(0.107)	(0.104)	(0.090)	(0.106)
Constant	−1.430	−1.726	−0.404	−1.470	−1.608	−0.725	−0.474	−0.537
	(4.106)	(4.375)	(4.001)	(3.516)	(4.212)	(4.259)	(3.468)	(4.126)
Observations	3544	3544	3544	3544	3544	3544	3544	3544
Number of car models	85	85	85	85	85	85	85	85
R^2	0.766	0.768	0.767	0.769	0.770	0.768	0.770	0.770
AIC	2874.9	2856.6	2868.8	2838.3	2832.0	2852.3	2831.8	2826.5

Note 1. All regressions include product-specific fixed effects, their interaction with a linear trend, and month-specific fixed effects.
Note 2. Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

To graphically explore how the impact of advertising up and the magnitude of the advertising elasticity depend on the characteristics of the product, we use Eq. 5 to calculate the advertising elasticity at different levels of advertising up and product characteristics. Panel A in Fig. 2 confirms that the positive effect of advertising up on the advertising elasticity does not depend on the price of the product (i.e., α_2 non-significant). Additionally, for a given level of advertising up, the advertising elasticity does not change with the price of the product (α_5 non-significant). Panel B shows that advertising up has the same positive effect across products with different quality ratings (α_3 non-significant) and that, for a specific level of advertising up, the advertising elasticity does not change across products with different quality ratings (α_6 non-significant). Finally, Panel C shows the moderating effect of

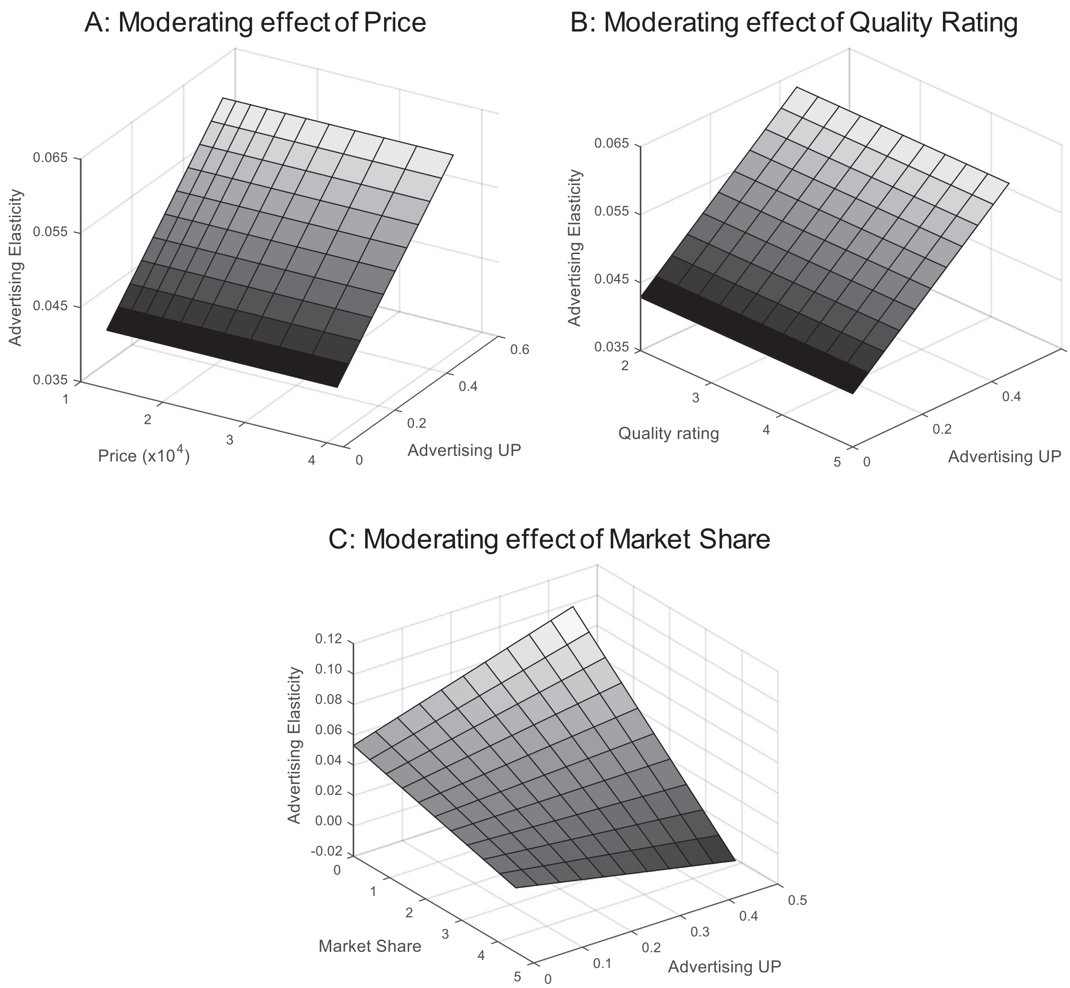

Fig. 2. Effects of advertising up on the advertising elasticity at different levels of price, quality ratings, and market share.

market share. The figure indicates that adverting up increases the advertising elasticity for products with a low market share but decreases the elasticity for products with a high market share (α_4 negative and significant). Moreover, keeping advertising up constant, the advertising elasticity is higher for products with a lower market share (α_7 negative and significant).

4.8.2. Additional drivers of car sales

According to our expectations, the price coefficient is negative although non-significant ($\delta_1 = -0.096$, $p > 0.1$). Due to the inclusion of fixed effects, the identification of the price coefficient is driven by the longitudinal variation of price within products. Because the price variable is measured yearly, the non-significance of the coefficient may be due to limited longitudinal variation in this variable.

For an average car, competitive advertising has a positive and significant impact ($\delta_2 = 0.087$, $p < 0.05$), consistent with the idea that competitive advertising expands sales for products in the same competitive segment. This could happen because higher advertising levels in the competitive group might attract consumers from other categories (e.g., pickup trucks, vans, or even premium products). This finding is in line with prior studies that have also reported positive competitive advertising effects in diverse product categories (Danaher, Bonfrer, & Dhar, 2008; Steenkamp, Nijs, Hanssens, & Dekimpe, 2005; Van Heerde, Gijsenberg, Dekimpe, & Steenkamp, 2013).

The coefficient of competitive sales is positive and significant ($\delta_3 = 0.832$, $p < 0.01$), consistent with the notion that the sales of a car model are in-sync with sales in the competitive segment. The intro and exit dummies are both negative and significant ($\delta_4 = -0.296$, $p < 0.01$; $\delta_5 = -1.430$, $p < 0.01$) consistent with the ideas that sales are lower during the introduction phase of a new car model and that the sales of a car decrease when it is not being manufactured due to supply constraints. Miles per dollar is positive and significant, consistent with the idea that fuel efficient cars are preferable ($\delta_6 = 0.096$, $p < 0.01$). The consumer sentiment index has a negative and significant effect on car sales ($\delta_7 = -0.382$, $p <$

0.01). A reason for this could be that consumers substitute non-premium cars with more expensive cars when the economic outlook is better. Finally, the copulas' coefficients for advertising up, advertising spending, and price are non-significant.

4.9. Robustness checks

We run several robustness checks to ensure the reliability of our results. Specifically, our results are robust to different specifications of the advertising up metric and of the advertising stock variable, and hold for the sedan and SUV categories separately. We report the details of the additional analyses in Web Appendix F.

5. Study 2. Advertising up and brand equity

To investigate the impact of the use of advertising up on brand equity, we implement a two-stage procedure. In the first stage, we calculate brand equity for different time periods. In the second stage, we examine the association between changes in brand equity and two measures that summarize the use of advertising up over time: intensity and inconsistency.

5.1. Data and variable operationalization

We complemented the data used in Study 1 with data between October 2010 and September 2011. The new data included all the variables used in Study 1 except advertising content. We identify three periods in the data: A first period spanning from January 2007 to December 2007; a second period going from January 2008 to September 2010; and a third period spanning from October 2010 to September 2011. The objective of the study is to relate changes in brand equity between periods 1 and 3 with the use of advertising up during period 2.

We calculate the *intensity* of advertising up for product p in period 2 ($UP_{p2}^{intensity}$) as the average level of adverting up used by the product during the second period. Additionally, we operationalize the *inconsistency* in the use of advertising up ($UP_{p2}^{inconsistency}$) as the variability of advertising up during the second period. Next, we explain how we recover changes in brand equity and how we relate them with the use of advertising up.

5.2. Model

In the first stage of the methodology, we measure brand equity as the intercept in a market share model, as is commonly done in the literature (Datta et al., 2017; Kamakura & Russell, 1993; Sriram et al., 2007). The intercept captures the part of the utility that is not explained by situational factors or by the marketing mix of the product (Kamakura & Russell, 1993). Following Berry (1994), we estimate the following market share model[18]:

$$SHARE_{pt} = \frac{\exp\left\{U_{pt}\right\}}{1+\sum_{k=1}^{K}\exp\{U_{kt}\}}, \tag{7}$$

where K is the total number of products in the SUV and sedan categories, and U_{pt} represents the mean utility for product p in time t, and it is given by:

$$\begin{aligned} U_{pt} = {} & \beta_{p1}\mu_p + \beta_{p2}\mu_p I_2 + \beta_{p3}\mu_p I_3 + \delta_1 AS_{pt} + \delta_2 \ln\left(PRICE_{pt}\right) + \delta_3 AS_{pt}^{comp} + \delta_4 \ln\left(SALES_{pt}^{comp}\right) + \delta_5 I_{pt}^{intro} + \delta_6 I_{pt}^{exit} \\ & + \delta_7 \ln\left(MPD_{pt}\right) + \delta_8 \ln(CSI_t) + \gamma_p TIME + \delta_t + \varepsilon_{pt}. \end{aligned} \tag{8}$$

The term μ_p is a product-specific dummy variable (i.e., a fixed effect), I_τ denotes a dummy equal to 1 if month t is part of period τ ($\tau = 1, 2, 3$) and 0 otherwise, β_{p1} is the coefficient that captures the brand equity for product p in period 1, and $\beta_{p\tau}$ ($\tau = 2, 3$) is the coefficient capturing the difference in product p's brand equity between period τ and period 1. We include competitive advertising and competitive sales in the utility function to capture changes in utility for a car due to product comparisons and social contagion effects respectively (people may be more likely to buy cars when people around them are buying cars).[19] We assume that ε_{pt} follows the Type I extreme-value distribution and, thus, the model in Eqs. 7 and 8 represents the multinomial logit model. We estimate the model using the reduced-form proposed by Berry (1994, pp. 205). Additionally, we account for the potential endogeneity of price and advertising using the copula approach explained in Section 4.7.[20]

[18] As is standard in discrete choice models for aggregate data, the market share of the car is calculated as a fraction of the market size. Following Balachander et al. (2009), we calculated the market size as: (number of households × average number of cars per household)/(average age of cars in years ×12). Additionally, we normalized the utility of the outside good to one for identification purposes.

[19] Robustness checks in Web Appendix F show that our main results are not sensitive to this choice.

[20] We report the results in Web Appendix G.

Table 4
Effect of the use of advertising up on changes in brand equity.

	Main effects model	Full model
$UP^{intensity}$	−0.140	1.210
	(1.121)	(1.327)
$UP^{intensity} \times \ln(PRICE)$		15.202***
		(4.709)
$UP^{intensity} \times$ Quality		−0.304
		(1.572)
$UP^{intensity} \times$ Share		1.099
		(0.813)
$UP^{inconsistency}$	−12.088***	−16.416***
	(3.890)	(4.688)
$UP^{inconsistency} \times \ln(PRICE)$		−40.478**
		(18.794)
$UP^{inconsistency} \times$ Quality		12.158*
		(7.232)
$UP^{inconsistency} \times$ Share		8.286**
		(3.417)
Ln(Advertising)	0.062**	0.107***
	(0.025)	(0.030)
ln(PRICE)	0.060	1.094**
	(0.137)	(0.491)
Quality	0.052	−0.174
	(0.059)	(0.167)
Share	−0.075**	−0.303***
	(0.032)	(0.073)
Copula advertising	−0.120	−0.261**
	(0.093)	(0.109)
Constant	0.282	0.013
	(0.210)	(0.231)
Observations	70	70
Chi^2	35.19***	94.63***

Note. Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In the second stage, we assess the relationship between the variables that summarize the use of advertising up over time during period 2 and the difference in brand equity between period 1 and period 3 using the following equation:

$$\begin{aligned}\beta_{p3} = {} & \alpha_0 + \alpha_1 UP_{p2}^{intensity} + \alpha_{11} UP_{p2}^{intensity} \ln\left(PRICE_p\right) + \alpha_{12} UP_{p2}^{intensity} QUALITY_p + \alpha_{13} UP_{p2}^{intensity} SHARE_p + \alpha_2 UP_{p2}^{inconsistency} \\ & + \alpha_{21} UP_{p2}^{inconsistency} \ln\left(PRICE_p\right) + \alpha_{22} UP_{p2}^{inconsistency} QUALITY_p + \alpha_{23} UP_{p2}^{inconsistency} SHARE_p + \alpha_3 \ln\left(ADV_{p3}\right) \\ & + \alpha_4 \ln\left(PRICE_p\right) + \alpha_5 QUALITY_p + \alpha_6 SHARE_p + \varepsilon_p. \end{aligned} \tag{9}$$

We include the interaction between intensity/inconsistency and mean-centered product characteristics to explore whether the impact of advertising up changes across products with different characteristics. Additionally, we include the sum of advertising expenditures in the third period to account for the impact of advertising spending on brand equity (Sriram et al., 2007). Finally, we estimate Eq. 9 using Weighted Least Squares to account for the uncertainty associated with the estimated dependent variable (Datta et al., 2017; Nijs, Dekimpe, Steenkamp, & Hanssens, 2001; Sriram et al., 2007), and include the copula of advertising spending to account for potential endogeneity.

5.3. The consequences of advertising up for brand equity

The first and second columns in Table 4 show the results of Eq. 9 for a main effects-only and a full model respectively.[21] According to the main effects model, increases in intensity do not lead to changes in brand equity for a car with average price, quality, and market share ($\alpha_1 = -0.14$, $p > 0.1$). However, for an average product, inconsistency leads to reductions in brand equity ($\alpha_2 = -12.01$, $p < 0.01$). To explore the heterogeneity in the effect of intensity and inconsistency, we now turn to the full model. We complement this analysis using floodlights (Spiller, Fitzsimons, Lynch, & McClelland, 2013), which are useful to visually assess the size and significance of the impact of intensity at different levels of product characteristics.[22]

[21] The condition index of the full model is 16.9 indicating that multicollinearity is not a concern.
[22] To calculate 95% confidence intervals, we use simulation methods based on the estimated coefficients, their variance-covariance matrix, and 50,000 draws (Krinsky & Robb, 1986).

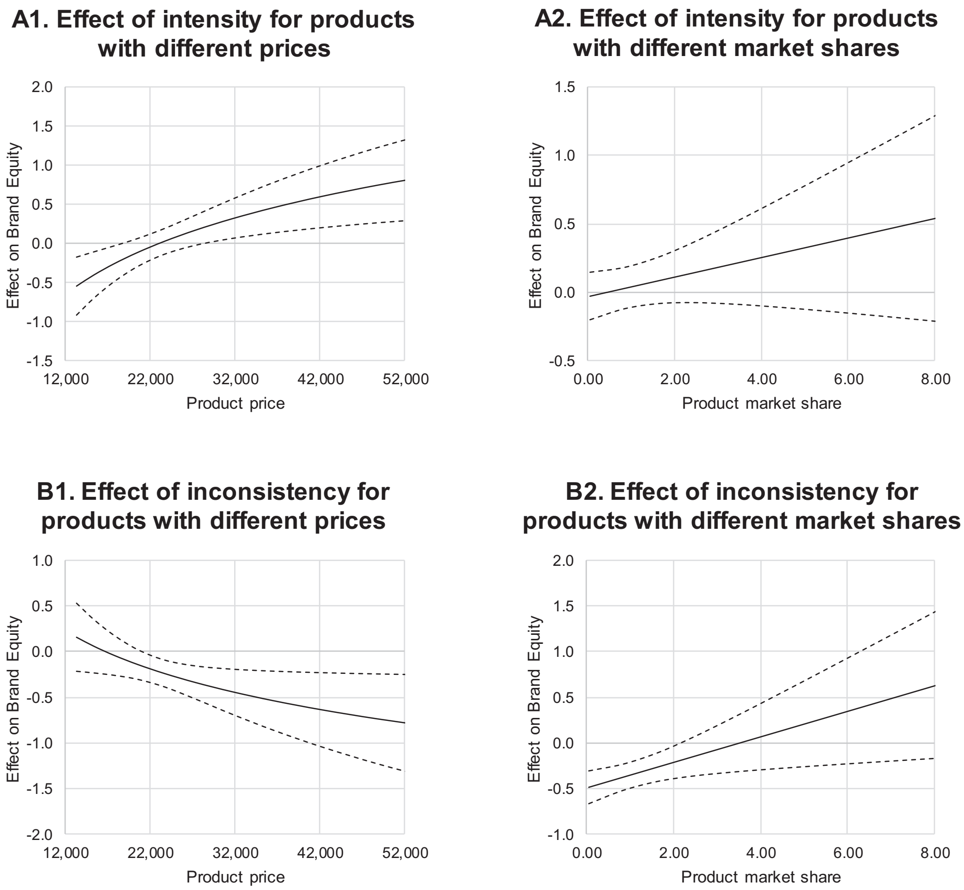

Fig. 3. Effect of the use of advertising up on brand equity for products with different prices and market shares. Note. Dotted lines represent 95% confidence intervals.

According to the full model, intensity is not associated with changes in brand equity for an average product ($\alpha_1 = 1.21$, $p > 0.1$). However, the interaction between intensity and price is positive and significant ($\alpha_{11} = 15.2$, $p < 0.01$), implying that the effect of intensity is stronger for products with a higher price. Panel A1, in Fig. 3, shows that a one standard deviation increase in the intensity of advertising up leads to a significant decrease in brand equity for products with a price smaller than $17,000. However, the same increase in intensity leads to a significant increase in brand equity for products with a price higher than $30,000. These findings are in line with the idea that, in the long-term, advertising up is credible for high-price products but not for low-price products. Additionally, we find that the impact of advertising up intensity does not depend on the product's quality or market share ($\alpha_{12} = -0.30$, $p > 0.1$ and $\alpha_{13} = 1.1$, $p > 0.1$, respectively). Panel A2 graphically confirms these results for the case of market share, showing that the impact of intensity is non-significant regardless of the product's market share. In summary, these results provide partial support for H3: advertising up intensity has a positive impact on brand equity, but only for products with a high price.

Additionally, the full model confirms that inconsistency has a negative effect on brand equity for an average product ($\alpha_2 = -16.42$, $p < 0.01$), providing support for H4. The interaction between inconsistency and price is negative and significant ($\alpha_{21} = -40.48$, $p < 0.05$), implying that the negative effects of inconsistency is stronger for products with a higher price. Panel B1 shows that the negative impact of one standard deviation in advertising up inconsistency is significant for products with a price higher than $20.000. We also find that the interaction between inconsistency and quality is positive and marginally significant ($\alpha_{22} = 12.16$, $p < 0.1$), in line with the idea that quality protects against the harming effects of inconsistency. Finally, the interaction between inconsistency and market share is positive and significant ($\alpha_{23} = 8.29$, $p < 0.01$), meaning that inconsistency is more harmful for products with a small market share. Furthermore, Panel B2 shows that the effect is negative only for products with a market share smaller than 2%. In general, the previous results imply that inconsistency in the use of advertising up damages more the brand equity of more exclusive products (i.e., higher price and lower market share) possibly because consumers get confused by discrepancies between the long-term marketing communication strategy and the perceived positioning of the product.

Finally, and in agreement with prior literature (Buil et al., 2013; Sriram et al., 2007), we find that advertising spending leads to increases in brand equity ($\alpha_3 = 0.11$, $p < 0.01$).

5.4. Robustness checks

In Web Appendix F, we show several robustness checks to ensure the reliability of our results. All the analyses support our main findings: (a) There is partial support for H3, meaning that advertising up intensity has a positive impact on brand equity only for non-premium products with a high price, and (b) there is full support for H4, meaning that inconsistency has a negative impact on brand equity.

6. Discussion

The marketing literature generally stresses the need to design the marketing mix in a way that supports the desired positioning of products. For instance, a premium product should have a high price, superior quality, and more limited distribution than a non-premium product. However, little is known regarding the short- and long-term consequences for non-premium brands of emulating the strategies used by premium brands. This research explores how using advertising elements that are commonly used by premium brands (i.e., advertising up) affects the advertising elasticity and the brand equity of non-premium products in the short and the long run respectively. Next, we discuss the implications of our results for managerial practice as well as the limitations and opportunities for future research.

6.1. Managerial implications

Our results are useful for advertisers interested in improving the effectiveness of their advertising campaigns in the short run. We found evidence that using ads that resemble the ads of premium products has a positive effect on the advertising elasticity of an average non-premium product. However, advertising up appears to decrease the advertising elasticity for non-premium products with a high market share. Given these results, we recommend advertisers of non-premium high-share products to be especially wary of the negative effects that this practice can have on the effectiveness of their ads.

To understand the short-term impact of advertising up on advertising elasticity and sales, we conducted a post-hoc analysis using the parameter estimates from Table 3. We show the results of this analysis in Table 5. The advertising elasticity of a car with a low market share (e.g., Hyundai Azera), using an average level of advertising up (0.15), is 0.072, meaning that doubling the monthly ad spending leads to an increase of 143 units sold. When we apply the same increase in ad spending to an ad campaign scoring 0.6 in advertising up, the increase in sales equals 222 units, generating a 55.4% increase in revenues (compared to the case with an advertising up score of 0.15). For a product with an average market share (e.g., Mazda 3), an increase of 0.45 in advertising up would lead to an extra 83 units sold, generating a 32% increase in revenues. Finally, for a product with a high market share (e.g., Nissan Altima), an increase of 0.45 in advertising up would lead to a reduction in advertising elasticity and, consequently, in the number of units sold. This product would see a sales decrease of 76 units, leading to a reduction of 19.4% in revenues. This analysis suggests that changing the level of advertising up of an advertising campaign can have an important short-term impact in the revenue performance of the campaign, and that this short-term impact depends on the product's market share.

Our results also indicate that advertising elasticity is higher for products with a lower market share. This finding is particularly relevant for marketing managers interested in allocating their advertising budgets across products. Prior research has shown that an optimal allocation policy distributes the budget proportionally to the advertising elasticity (Doyle & Saunders, 1990; Fischer, Albers, Wagner, & Frie, 2011). Thus, our results suggest that managers using simple heuristic rules, such as the percentage-of-sales, would benefit from increasing (decreasing) the advertising spending for products with a low (high) market share.

Additionally, our results are useful for managers interested in improving the brand equity of their products. In agreement with prior literature (Buil et al., 2013; Sriram et al., 2007), our results suggest that advertising spending helps lifting the brand equity of products. However, the effects on brand equity do not only depend on the amount spent on advertising but also on how the content of that advertising is used over time. Specifically, we find that the managers of expensive non-premium products would benefit by using high levels of advertising up *intensity* to improve brand equity in the long run. However, the managers of cheap non-premium products should refrain from using advertising up because increases in its intensity of use can lead to long-term reductions in brand equity.

Furthermore, we found that the inconsistency in the use of advertising up over time leads to reductions in brand equity for most products. This finding suggests that using advertising up opportunistically rather than consistently (Fig. 1 suggests that

Table 5
Short-term impact of an increase in advertising up.

	Monthly unit sales	Advertising elasticity		Extra units due to:		% revenue increase due to 0.45 increase in UP metric
		UP: 0.15	UP: 0.6	Doubling monthly ad spending (UP: 0.15)	Doubling monthly ad spending (UP: 0.6)	
Low-share car	2000	0.072	0.111	143	222	55.4%
Average car	5000	0.052	0.069	260	343	32.0%
High-share car	12000	0.033	0.026	390	314	−19.4%

Note. The analysis assumes an average price of $25000; the low and high market share conditions represent a market share of 0.5% and 3% respectively.

this seems to be the case for several products in our empirical application), to increase advertising effectiveness in the short run, could lead to reductions in brand equity in the long run. Additionally, our result empirically demonstrates theoretical arguments stating that consistency in marketing communications is essential to strengthen brand associations and improving the equity of the brand in the long run. Therefore, we recommend managers to strive for consistency in the level of advertising up used in their ads because failing to do so could confuse consumers and harm future sales.

6.2. Limitations and future research

Our study has some limitations. First, we used car registrations rather than car sales as a dependent variable. The use of registration may lead to problems with data synchronization (e.g., matching registrations and advertising expenditures). However, we attempted to solve this problem by lagging all the independent variables. In this way, we ensured that advertising occurred before or at the same time as the sales of a vehicle. We believe that our empirical implementation is appropriate because sales should be highly correlated with registrations. Therefore, it is very likely that our same results would hold when using sales data.

Second, our study is based on the automobile industry. However, our findings could also apply to other vertically differentiated markets where products have functional and symbolic value (e.g., watches, perfumes, luggage, whisky, mobile phones). In these markets, consumers should hold different attitudes toward premium and non-premium products. Moreover, consumers should be able to notice whether a non-premium brand is using advertising up. The match (or mismatch) between attitudes and ad content should lead to the results we find in our analysis. Although the theoretical mechanisms identified in the paper should hold for other product categories, it would be useful to empirically examine whether our results indeed generalize to other product categories.

Finally, our advertising up metric is descriptive rather than normative in that it is based on the ad content that premium and non-premium brands actually used rather than on the content they should have used to stay positioned as either premium or non-premium. Our metric thus is sensitive to the fact that premium brands also use non-premium ad elements. Future operationalizations of advertising up could be purely normative and be generated based on the elements that premium and non-premium brands *should* use to be perceived by customers as such. Future research could also study what type of consumers are more/less persuaded by advertising up. For instance, does advertising up convince customers of premium products to buy non-premium products? Or it is just the consumers of competing non-premium products that get persuaded by advertising up?

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijresmar.2018.03.004.

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