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The Effects of Products' Aesthetic Design on Demand and Marketing-Mix Effectiveness: The Role of Segment Prototypicality and Brand Consistency

A product's physical appearance is difficult to quantify, and the impact of product appearance on demand has rarely been studied using market data. The authors adopt a recently developed morphing technique to measure a product's aesthetic design and investigate its effect on consumer preference. Drawing upon categorization theory, the authors consider the effects of three dimensions of aesthetic design—segment prototypicality (SP), brand consistency (BC), and cross-segment mimicry (CSM)—and their moderating effects on marketing mix effectiveness in a unified framework. The empirical analysis uses a unique, large data set consisting of 202 car models from 33 brands sold in the United States from 2003 to 2010. The authors find that consumer preference peaks at moderate levels of SP and BC and that economy-segment products benefit from CSM of luxury products. Moreover, SP intensifies price sensitivity, and BC muffles price sensitivity while increasing advertising effectiveness. Two what-if studies illustrate how managers can use the empirical model to evaluate alternative aesthetic design choices.

Keywords: product design, segment prototypicality, brand consistency, categorization, marketing-mix effects

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"The consumer is also sensitive to style, even in the laundry room, and we have hit that well."

—LG's Vice President of Sales, Digital Appliance Division (Wolf 2004)

As the above quote suggests, the aesthetic design of a product can be critical to consumer acceptance and market success (Bloch 1995). LG designed a front-loading washing machine that combined useful features, appealing electronics, and great looks to break into a very crowded U.S. market (Wolf 2004). Likewise, Apple had much success with its iMac, which had similar functional features as PCs but used its visual appearance as its principal means of differentiation (Talke et al. 2009). Conversely, poor aesthetic designs can lead to market failures. The unique-looking Edsel that Ford launched with great expectations in 1959 was seen as odd and was discontinued in the same year at a significant loss to Ford (Barron 2007). Given the importance of aesthetic design, firms are putting increasing emphasis on seeking the ideal product aesthetics (Orth and Malkewitz 2008; Veryzer and Hutchinson 1998).

Despite the critical role that a product's aesthetic design plays in consumers' purchase decisions, there has been relatively little academic research on this topic in the marketing literature. On the one hand, the impact of product aesthetics on consumer preference has been largely ignored in modeling of consumer choice, mainly because of the difficulty of quantifying the physical appearance of products. In recent work, Landwehr, Labroo, and Herrmann (2011) do present a morphing technique to quantify and incorporate aesthetic design in an empirical model of car sales, observed over a six-month period. Although their work is an important step in modeling the effect of aesthetic design on sales, their substantive findings that consumers favor prototypical designs appear to merit further research because they run counter to anecdotal evidence (as noted in the previous

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paragraph) that consumers respond favorably to attractive, differentiated product aesthetics. Moreover, their findings also run counter to experimental results in the categorization literature that support the notion that consumer evaluations would be highest for moderately prototypical products (Meyers-Levy and Tybout 1989). Detecting such nonlinear effects of prototypicality of aesthetic design on consumer evaluation may require a more extensive data set than what Landwehr, Labroo, and Herrmann (2011) use in their research. In our empirical study, we compile a large-scale, unique data set that includes aesthetic design features of 202 passenger car models from 33 brands sold in the U.S. market from 2003 to 2010, in order to be able to detect potential nonlinear effects of segment prototypicality (SP). On the other hand, while experimental work (Meyers-Levy and Tybout 1989) has demonstrated nonlinear effects of prototypicality on consumer evaluations, these effects have not been shown for elements of aesthetic design or in a field setting. Our research fills the gap on both of these counts.

While the novelty-versus-prototypicality debate is an important one, many design managers also believe that different products under the same brand should be somewhat consistent in their aesthetics, to aid brand recognition (Gibbs 2015). For example, Gibbs writes that Jaguar's sedans feature the "same wide-oval grille and narrowing headlights." In contrast, Audi has tried to move away from too much uniformity in its car models (Martin 2012). To the best of our knowledge, no previous research has considered the optimal level of brand consistency (BC) in the aesthetics of a product line. Moreover, in many categories from handbags to automobiles, products in lower-price-tier segments often try to mimic the aesthetics of luxury segments (Stoklosa 2013; The Fashion Law 2014). Research on such cross-segment mimicry (CSM) of aesthetic designs is also lacking in the literature.

Our research, therefore, focuses on the aforementioned critical research gaps in the area of product design aesthetics. The three dimensions of aesthetic design that we study—namely, SP, BC, and CSM—while managerially relevant, have also suggested by categorization theory to be influential in determining consumers' reactions to product aesthetics. We compute these three aesthetic design variables from 50 coordinate-point measures of a car's aesthetic design generated using the morphing technique proposed by Landwehr, Labroo, and Herrmann (2011). We then incorporate these variables in our empirical choice model, which is a random-coefficient logit model (Berry, Levinsohn, and Pakes 1995, henceforth BLP 1995). In addition to these aesthetic design variables, our choice model includes standard marketing-mix variables such as price and advertising, as well as the moderating effects of the aesthetic design variables on these marketing-mix effects, while controlling for endogenous price and advertising. In addition to estimating our empirical model, we present two what-if studies to illustrate the application of our model to evaluation of potential aesthetic design changes.

Table 1 summarizes the research gaps in the marketing literature on aesthetic design and shows how our research addresses the research gaps. Specifically, we contribute to this literature in the following ways. First, using an extensive data set, we empirically examine consumer preference implications of various aspects of a product's aesthetic design as suggested by categorization theory, such as SP, BC, and CSM, in a unified framework. Our substantive findings in this regard show that consumers prefer moderate levels of SP and BC in a product's aesthetic design and that products in the economy segment of a market can gain by mimicking the aesthetics of luxury products. While previous behavioral studies have used lab data to show the nonlinear effect of SP on consumer preference (Mandler 1982; Meyers-Levy and Tybout 1989), very few studies have investigated such effects with a consumer demand model and real-world sales data. The only exceptions are Landwehr, Labroo, and Hermann (2011) and Landwehr, Wentzel, and Herrmann (2013). Our results on SP in this article are in contrast to Landwehr, Labroo, and Hermann (2011), who find that prototypical products are most preferred. Moreover, in contrast to Landwehr, Wentzel, and Hermann (2013), who find that prototypical designs become less preferred by consumers over time, we find that prototypical designs may not be the most preferred even in the short run. The differences between our findings and those of Landwehr, Labroo, and Hermann (2011)

TABLE 1
Benchmarking the Current Study Against the Literature

Academic Studies	Study of Aesthetic Design?	Field Study?	Dimensions of Aesthetic Design Considered			Aesthetic Design × Other Marketing Mix?	Finding of Nonlinear Effects of Prototypicality?
			SP	BC	CSM		
Landwehr et al. (2011, 2013)	Yes	Yes	Yes	No	No	No	No
Meyers-Levy and Tybout (1989)	No	No	Yes	No	No	No	Yes
Veryzer and Hutchinson (1998)	Yes	No	Yes	No	No	No	No
Brand extension literature	No	Some	No	Yes	No	No	No
Choice/demand models (e.g., BLP 1995)	No	Yes	No	No	No	No	No
This study	Yes	Yes	Yes	Yes	Yes	Yes	Yes

and Landwehr, Wentzel, and Hermann (2013) are likely due to the fact that our study investigates a greater number of car models (202 vs. 28) over a much longer time period (8 years vs. 6 months), which may allow us to isolate nonlinear effects of SP.

Second, while there has been empirical work on brand extensions (Randall, Ulrich, and Reibstein 1998), to the best of our knowledge, our article is the first to look empirically at the implications of BC in aesthetic design across a brand portfolio. Furthermore, in contrast to the brand extension literature, which focuses on brand concept consistency in terms of similarity across brand extensions (e.g., Broniarczyk and Alba 1994; Park, Milberg, and Lawson 1991; Randall, Ulrich, and Reibstein 1998), the BC measure in this article addresses similarity in aesthetic designs across products that share a brand name. Third, we examine how aesthetic design moderates price sensitivity and advertising effectiveness and thus contribute to a better understanding of how aesthetic design interacts with traditional marketing-mix variables.

Finally, the empirical approach we adopt and the conclusions we draw using the large, unique data set hold the potential to help marketing managers make better decisions on products' aesthetic designs. In particular, we illustrate how our model may be used to inform managerial decision making on aesthetic design through illustrative what-if analyses. Although we apply our conceptual framework and empirical model in the automobile industry, our approach can be directly applied in a wide range of product categories, such as mobile devices, wearable technology (e.g., smart watches, fitness trackers), wearable accessories (e.g., handbags), and home appliances. For example, stylish design is among the top selection criteria for mobile devices and wearable technology (Nielsen 2013, 2015). Similarly, home appliances are no longer just functional products but need to have "decorative appeal" (Jean 2004). Moreover, all these categories have luxury and economy segments, similar to our automobile industry application. For example, as the leading smart watch brand, Apple offers both a lower-end sports watch and the luxury watch Hermès. Likewise, in the refrigerator category, there are economy refrigerators that retail for far less than luxury refrigerators like the Samsung's Chef Collection (Crist 2014). Our model can also be applied in categories in which product subcategories exist, such as cameras, with SLR and point-and-shoot subcategories.

Conceptual Framework

Figure 1 presents the conceptual framework underlying our empirical model. We posit that the aesthetic design of a product, other marketing-mix variables (e.g., price, advertising), and measurable product attributes (e.g., a car's horsepower) influence consumers' preferences for the product. Our conceptual framework also allows for interaction effects between aesthetic design and the other marketing-mix variables.

We use categorization theory to conceptualize the effect of a product's aesthetic design on consumer preference. Because some of the early applications of categorization theory involved human processing of visually presented objects such as chairs and birds (Rosch et al. 1976), it seems apt to use categorization theory to conceptualize consumer evaluation of aesthetic design. Moreover, studies show that visual appearance is a key determinant of category membership (Barsalou 1992, p. 602) and dominates other types of cues, such as semantic cues (Snodgrass and McCullough 1986).

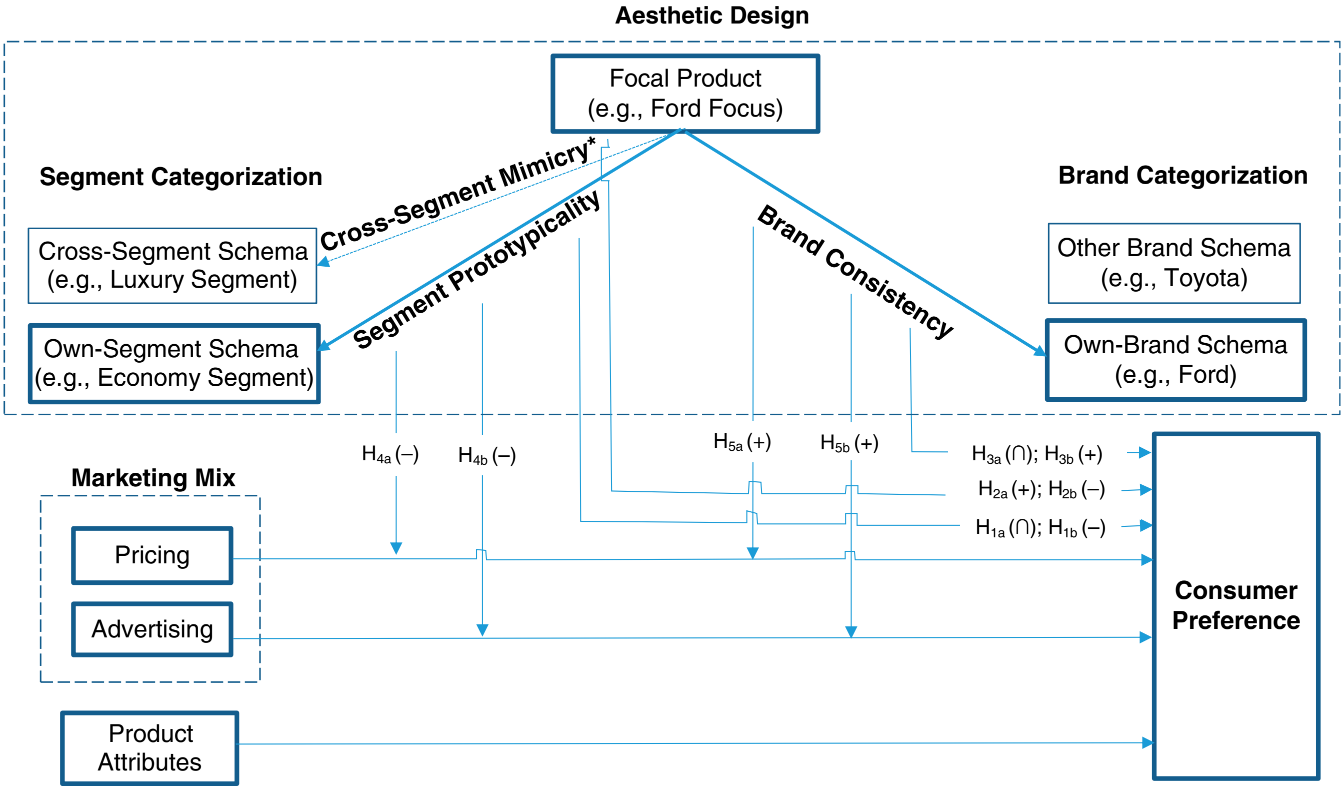
Both the psychology and marketing literature streams widely recognize categorization as a fundamental activity for human cognition, memory, and learning (e.g., Rosch et al. 1976; Sujan 1985). The basic premise of categorization is that individuals group objects into categories according to their similarities and differences, and over time, they develop a set of expectations about each category, or the category "schema." When a new object can be categorized as a member of a previously defined category, consumers can quickly retrieve their evaluations associated with the category and apply them to the new object, resulting in efficient understanding and processing (Rosch et al. 1976; Sujan 1985).

We now discuss the category schemata in Figure 1 that consumers may use to compare and classify a specific product presentation. According to categorization theory, the most useful categories for consumers in the categorization process are "basic" categories, in which members of a category have many attributes in common, while sharing few attributes with other categories (Rosch et al. 1976). Thus, classifying a product into a basic category enables a consumer to make maximal inferences about the product without cognitive overload, because of the high discrimination ability of basic category schema.[1] Past studies in marketing have used product type (or product segment) schema and brand schema in studying consumer information processing involving categorization (e.g., Boush and Loken 1991; Broniarczyk and Alba 1994; Park, Milberg, and Lawson 1991), suggesting that these schemata may play the role of basic categories in consumer categorization processes. We follow a similar approach by considering product segment schema and brand schema in understanding consumer response to product design aesthetics (see Figure 1).

Because many product categories have both a premium, or luxury, segment and an economy, or low-price, segment, with distinct product attributes (including aesthetics), we posit that schemata related to these product segments influence consumer response to design aesthetics (see Figure 1). For example, the car market has luxury and economy segments. Similarly, there are high-end designer refrigerators, such as the Samsung Chef Collection, that sell for upward of \$5,000, while more common, everyday refrigerators may sell for \$1,000–\$2,000. Likewise, Blattberg and Wisniewski (1989) note that price tiers in product categories are common. Moreover, luxury and economy product segments are likely to be meaningful categories to consumers, as much categorization may be "goal derived" (Barsalou 1985; Loken and Ward 1987), meaning the price or budget requirement could be a relevant attribute for the category. Landwehr, Labroo, and Hermann (2011) also employ this product segment classification in their study of product design aesthetics. While luxury- and economy-segment schemata may be relevant in many categories, other types of segments may be possible in other categories (e.g., riding lawn mowers vs. push lawn mowers).

[1]For example, classifying an object as a bird as opposed to a mammal enables the consumer to deduce much more information about the object for the cognitive effort involved than a more fine-grained classification of an object as a species of bird, such as an eagle.

FIGURE 1
Conceptual Framework



Notes: The CSM arrow in this diagram points to the luxury-segment schema because Ford Focus, used as the example, has an economy price. For a luxury product, the CSM and SP arrows would point to the economy and luxury schemata, respectively. Note also that we operationalize CSM as a function of both cross-segment prototypicality and SP (Equation 3).

Next, we examine the implication of categorization by consumers who are using segment and brand schemata for their evaluation of product design aesthetics.

Product Segment Schema and Aesthetic Design: Segment Prototypicality

With respect to the luxury or economy product segment schemata in Figure 1, the product's price will trigger comparison with the appropriate schema, with a premium-priced product being compared with the premium or luxury-segment schema and an economy-priced product being compared with the economy-segment schema (the solid lines leading from the focal product to own-segment schema in Figure 1). Because product segment schema may represent the central tendency (i.e., the average look of the category) or the prototypical product in that segment (Barsalou 1985; Rosch et al. 1976; Sujan 1985), a natural measure that arises out of this comparison is how closely the product in question resembles the segment schema, or, in other words, the product's SP. Thus, the Ford Focus's economy price triggers consumers to compare it with the economy-segment schema (its own-segment schema in Figure 1), and this comparison results in an assessment of its SP. Likewise, a product with a luxury price, such as Toyota's Lexus brand, would trigger comparison with the luxury-segment schema, leading to an evaluation of its SP.

Typicality has long been studied as a predictor variable in the categorization literature (e.g., Loken and Ward 1987; Rosch et al. 1976). Several articles in this literature suggest that a product that is more prototypical of a category is more quickly classified by the consumer, leading to a positive evaluation of the product (Barsalou, 1985, 1983; Nedungadi and Hutchinson 1985; Sujan 1985). These arguments are consistent with findings that prototypical or average looks are perceived to be beautiful (e.g., Valentine, Darling, and Donnelly 2004), and this "beauty in averageness" phenomenon goes beyond human faces to animals and products (Veryzer and Hutchinson 1998). A related argument that favors a higher evaluation of prototypical products is that such products can be processed more fluently (Veryzer and Hutchinson 1998; Winkielman et al. 2006) than atypical products. A similar argument has long been made in marketing studies that have shown repeated exposure increases liking (Sawyer 1973; Zajonc 1968). A third argument that supports the idea that consumers prefer prototypical products is that such products are more likely to resemble market share leaders, which enjoy a strong preference among consumers (Loken and Ward 1987). Consistent with these arguments, Landwehr, Labroo, and Hermann (2011) present evidence that SP positively affects automobile sales in the German market.

However, counterarguments in the categorization literature have suggested that the relationship between ease of categorization and consumer preferences may not be linear. Mandler (1982) suggests that an increase in ease of categorization may enhance preferences, but only to a certain extent. This is because while ease of categorization leads to fluency and a mild level of preference, a moderate level of difficulty in categorization could lead to perceptions of novelty and increased arousal (Berlyne 1970). Consistent with this argument, Meyers-Levy and Tybout (1989) demonstrate that products that are moderately incongruent with a category schema, which evoke a moderate level of categorization difficulty, are preferred over both (1) products that are either entirely congruent, which can be too easily categorized and are thus perceived as boring, and (2) extremely incongruent products, which are very difficult to categorize and thus may lead to frustration. Likewise, Schoormans and Robben (1977) find that a moderate level of deviation from a typical package design increases attention compared with no deviation, without hurting consumer evaluation as extreme deviation would do. Many examples in the commercial world likewise suggest that products with more unique designs are more successful. Examples of such products include the Volkswagen Beetle in cars (Stenquist 2012), Apple products in technology (Talke et al. 2009), and Pottery Barn products in home decor (Lloyd 2007). Thus, we make the following hypothesis:

> H_{1a}: Consumer preference for an aesthetic design is highest at a moderate (vs. high or low) level of SP.

Building further on H_{1a}, one might expect consumer preferences for the level of prototypicality in a design to vary across segments. We propose that consumers have lower preferences for a segment-prototypical design when a product is categorized as luxury (vs. economy). The rationale is that consumers may purchase luxury products to help them stand out from the crowd and signal their social status (Grossman and Shapiro 1988; Han, Nunes, and Dreze 2010). When prestige and exclusivity are desired, the preference for SP should be diminished or even reversed because of the enhanced need for uniqueness (Loken and Ward 1987). Similarly, Pocheptsova, Labroo, and Dhar (2010) observe that while fluency may enhance the liking of ordinary products, consumers might like special-occasion products better when fluency is low, due to their lay theory that such products should be unusual and thus harder to process. For these reasons, we make the following hypothesis:

> H_{1b}: The level of SP at which consumer preference for an aesthetic design is highest is lower for the luxury than the economy segment.

When separate aesthetic schemata exist for the economy and luxury segments, it is possible that visual processing of the aesthetics of a product leads to a segment categorization that conflicts with the product's segment membership derived from price. For example, a Ford Focus would belong to the economy segment, according to its price. However, if its aesthetic design shows significant similarities to the luxury-segment schema, consumer categorization processes may evoke evaluations associated with the luxury category for a Ford Focus (Rosch et al. 1976). Thus, in addition to own-segment prototypicality (i.e., SP), cross-segment similarity, as discussed earlier, can influence consumer preference for a product. This cross-segment similarity, which we term "cross-segment mimicry" (CSM), is represented by the dotted line leading from the focal product to "Cross-Segment Schema" in Figure 1.[2] Likewise, CSM can occur if a product with a luxury price, such as the Lexus, has aesthetic similarity to the economy-segment schema.

These two types of CSM—an economy-segment product mimicking the luxury-segment schema and a luxury-segment product mimicking the economy-segment schema—may have different effects. It is likely that CSM of luxury products by an economy product increases preference for the economy product because consumers may react favorably to a product with luxury aesthetics at a bargain price. A corollary to this effect is that consumer preference for luxury products becomes correspondingly lower in the presence of such mimicry by an economy product because these luxury products face substitution by the mimicking economy-segment product. There are many examples of economy-segment products trying to mimic the aesthetics of luxury products. Michael Kors has subtly imitated the design of luxury brands such as Louis Vuitton, Chanel, and Gucci to increase its sales at the expense of these luxury brands (The Fashion Law 2014). Likewise, Kia has tried to gain an edge for its K900 sedan by designing headlights and taillights whose aesthetics mimic those of BMW's 5- and 7-series (Stoklosa 2013) cars. Conversely, reverse CSM (i.e., a luxury product mimicking the economy-segment schema) may reduce consumer preference for the luxury product. The rationale is that luxury products with an "economy" look may fail to signal the status of the owner and thus may not fit the luxury positioning of those products (Hagtvedt and Patrick 2009). The Lexus car has suffered from such concerns in consumer reviews because of a lack of sufficient differentiation from its economy sibling, the Toyota Camry. Therefore, we predict the following:

> H_{2a}: Consumer preference for an aesthetic design in an economy-segment product increases with CSM of the luxury-segment schema.
>
> H_{2b}: Consumer preference for an aesthetic design in a luxury-segment product decreases with CSM of the economy-segment schema.

Brand Schema and Aesthetic Design: Brand Consistency

As Figure 1 illustrates, we posit that consumers compare the aesthetic design of a product carrying a given brand name (a branded product variant) with the schema of that brand (or brand concept) to form their evaluation of the product. Such an evaluation process, wherein the brand is viewed as a "category," is consistent with that proposed in the brand extension literature (Boush and Loken 1991; Broniarczyk and Alba 1994; Park, Milberg, and Lawson 1991). Whereas the aforementioned brand extension studies focus on the similarity in associations between the brand extension product and the brand schema (brand concept), we focus on the similarity in aesthetics

[2]Note that increasing CSM is likely to make a product less prototypical of its own segment. However, having a lower SP does not imply a greater level of CSM because a product can be atypical of both the luxury and economy segments.

between the focal product with a given brand name and the corresponding brand schema. We use the term "brand consistency" (BC) to denote this latter measure of aesthetic similarity, although prior brand extension research (Park, Milberg, and Lawson 1991) has used the term "brand concept consistency" to denote the similarity in associations between the brand extension and the brand concept. In other words, BC in this article measures how similar a product's aesthetic design is to the average aesthetics of its brand. Thus, the BC of a Ford Focus measures the similarity of the Focus's aesthetics to the schema for the Ford brand name in the consumer's mind.

There are several theoretical arguments that suggest that a high level of BC in aesthetic design will lead to higher preference. Drawing from categorization theory, a higher level of BC in aesthetic design may result in an easier transfer of brand-related affect to the focal product (Boush and Loken 1991; Park, Milberg, and Lawson 1991; Randall, Ulrich, and Reibstein 1998; Sujan 1985). Moreover, BC in aesthetic design may facilitate brand recognition because of the closeness of the product's aesthetics to the typical aesthetics of its brand (Creusen and Schoormans 2005). These reasons may explain why commercial products of the same brand often share many aesthetic design features that make them "not only technically but also visibly members of one family" (Weber 2009, p. 5). For example, all of Kia's latest designs feature a consistent front shape with the "tiger-nose" grille (LeBlanc 2012).

While the above arguments point to the desirability of brand-consistent designs, we also propose that too much consistency can hurt a product. Past research has suggested that if a product looks too similar to the average look of its brand, it may become less noteworthy and thus may be perceived as boring (Berlyne 1970; Meyers-Levy and Tybout 1989). Moreover, some level of variety in aesthetic design can facilitate product customization to better match the preferences of a specific group of customers. Thus, customers seeking a car with a sportier feel may be offered a branded variant with a spoiler attached to the body; this notion is consistent with past research linking product features to consumer perception of product performance (Hauser and Simmie 1981). Engineering constraints may also require differences in aesthetic design to provide different functionalities as demanded by different customers.

Consistent with these arguments, Audi promised to move away from its practice of having a common style across its models by introducing more cross-model differentiation (Martin 2012). As a reporter noted, "It's just that with such a huge breadth of models, there's a danger that less far-sighted neighbors might think your new A8 was actually a humble A3" (Gibbs 2015). Audi aimed to have exterior styling and interior design that "further accentuates the unique character of each model" (Martin 2012). Likewise, in rejuvenating the Chevrolet Impala in 2000, General Motors redesigned the model with large, round taillights to be more distinctive from its Chevrolet sibling the Malibu. An Impala executive noted, "I think we learned our lesson on the look-alike cars. People see through that. Yeah, maybe a chassis or a powertrain, but especially with these cars, you've got to be true to the heritage" (Vaughn 1999). Similarly, in refrigerators, General Electric sells the Artistry line to offer a distinctive, retro styling not available elsewhere in the General Electric refrigerator lineup (Crist 2016).

To summarize, a product with an aesthetic design that is not overly consistent with its brand schema may enjoy higher consumer preference because of greater interest or customization benefits; however, if a product is too inconsistent with the brand schema, it may fail to tap into brand equity. Therefore, we predict the following:

> H_{3a}: Consumer preference for the aesthetic design of a brand variant is highest at a moderate (vs. high or low) level of BC.

Similar to hypothesized differential effects of SP across segments (H_{1b}), we propose that consumers should have stronger preferences for a brand-consistent design when a product is a luxury (vs. economy) product. The brand names and associated aesthetic designs of luxury products serve as vehicles for consumers' self-expression (Park, Milberg, and Lawson 1991) and as signaling devices to other users (Grossman and Shapiro 1988; Han, Nunes, and Dreze 2010; Pesendorfer 1995). A brand-consistent aesthetic design facilitates clear signaling by the buyer and may thus be preferred by luxury-product consumers. In this vein, Gibbs (2015) notes that among automobiles, "premium brands have some of the narrowest design differentiation between their models." A Jaguar design executive notes that such BC aids recognition, "allowing neighbors to see it (the brand) too" (Gibbs 2015). In contrast, economy products are more likely to be evaluated on the basis of functionality (Park, Milberg, and Lawson 1991), making BC in aesthetic design less critical. Therefore, we hypothesize the following:

> H_{3b}: The level of BC that maximizes consumer preference for the aesthetic design of a brand variant is higher for luxury than for economy products.

Aesthetic Design Categorization and Marketing-Mix Effectiveness

In addition to the direct effects already discussed, aesthetic design may interact with marketing-mix elements to moderate their effectiveness in influencing preference. When consumers can easily categorize a product into a segment due to its typical design, the product becomes more substitutable with products in the same segment (Creusen and Schoormans 2005). Indeed, Anderson, Green, and McCulloch (2000) demonstrate that when a consumer recalls a target product, if the target–competitor similarity is high, features shared between the target and the competitor are strengthened, and recall of the competitor is enhanced. Translated into our setting, when SP is high, similarity among the competing products increases the likelihood of the competitors being recalled and compared during the purchase process. As a result, consumers may become more price sensitive, relying more on prices to choose among products (Nagle and Holden 2002, p. 119).

By the same token, similarity among products may make it difficult for consumers to recall the particular product promoted in advertisements. Such confusion may increase the recall of the competing products in the same category, and as a result, the impact of advertising may spill over to competing products (Burke and Srull 1988; Janakiraman, Sismeiro, and Dutta 2009). When competitors also benefit from a firm's advertising, consumers may switch to other brands, leading to smaller market share and reduced advertising effectiveness for the firm that advertised. Therefore, we predict the following:

H_4: Segment prototypicality in aesthetic design (a) increases consumers' price sensitivity and (b) decreases advertising effectiveness.

Similarly, BC in aesthetic design may interact with pricing and advertising to affect demand. High BC in aesthetic design facilitates the categorization of a product as belonging to its brand and thus enhances the product's brand identity. A strong brand identity can make products less substitutable with competing products (Mela, Gupta, and Lehmann 1997), increasing the price premiums that the product can command (Ailawadi, Lehmann, and Neslin 2003) and lowering consumers' price sensitivity in comparison with unbranded generic products (Kaul and Wittink 1995; Sethuraman and Tellis 1991). Therefore, price sensitivity should be lessened when a product carries a brand-consistent design. In addition, a product with a brand-consistent design that communicates a clear brand identity can easily leverage the brand equity built by advertisements (Keller 2013, p. 221). Therefore, for products with brand-consistent designs, advertising may increase consumer demand to a greater degree (vs. products with less brand-consistent designs).

H_5: Brand consistency in aesthetic design (a) decreases price sensitivity and (b) increases advertising effectiveness.

Data

Our conceptual framework and empirical model incorporating aesthetic design can be applied in various product categories, as discussed earlier. In the current research, we focus on the U.S. passenger car market.

Data on Car Attributes, Price, Advertising, and Sales

Our data set consists of 33 brands (e.g., Toyota), 202 car models (e.g., Toyota Camry), and 1,192 model-year cars (e.g., 2010 Toyota Camry) sold in the U.S. passenger car market from 2003 to 2010. We exclude cars priced over $110,000 because these are unlikely to be in the consideration set of mainstream car shoppers. Because automakers make changes to their cars annually, revisions of automobiles are commonly identified by "model year." We obtain car model-specific attributes, such as horsepower (HP), miles per dollar (MP$), weight, product classification (i.e., regular vs. sporty/specialty), and product segment (i.e., luxury vs. economy), from *Ward's Automotive Yearbook* (wardsauto.com/wards-automotive-yearbook). Out of the 202 car models in the data set, 124 are economy models and 78 are luxury models. We obtain data on size classification (i.e., full-size vs. midsize vs. compact) from Cars.com, car safety ratings from the Insurance Institute for Highway Safety (www.iihs.org), and annual data on predicted reliability ratings from *Consumer Reports* (www.consumerreports.org).

The data on manufacturer-suggested retail price (MSRP) and cash rebate programs are obtained from Automotive News (www.autonews.com). The cash rebates are provided directly to consumers by manufacturers or dealers. We obtain detailed information about each cash rebate program, including the associated car models, start and end dates of the promotion, and the amount of the rebate. We use monthly advertising expenditure data from Ad$pender, a web-based database that provides advertising expenditure data on many product categories across all major media (www.kantarmedia.com). Monthly sales data for each car model come from the Automotive News Market Data book (www.autonews.com/section/datalist11).

Aesthetic Design Data

We include information on aesthetic design as it pertains to the appearance or styling of a car. Landwehr, Labroo, and Hermann (2011) use morphing technology to quantify a product's aesthetic design. We follow their approach and obtain aesthetic design data as follows. We first obtain standard frontal pictures of all car models in the sample period from Edmunds.com, an online resource for automotive information. We focus on the front view of car models because, just as human beings are most recognizable by their faces, the most recognizable design feature of a car is its front view (Ranscombe et al. 2012). We then use morphing software to analyze the car pictures and create morphs for each segment and each brand. This process involves four steps. First, we set the lowest point on the central line of the car face as the origin of the Cartesian coordinate system. We then standardize the width of the car to be 1 and decide on the height of the car according to the actual height/width ratio in the car specification data set. Second, we identify 50 feature points (e.g., grill, headlights, side mirrors, windshield) that represent the key components of each design (for details, see Figure 2; see also Landwehr, Labroo, and Hermann 2011). Third, on the basis of the positions of the 50 feature points, we compute the mean position of each feature point across all car models within a segment and across all car models within a brand in each year. The last step is to create morphs by warping images, according to the defined feature points, and cross-dissolving the color values of all individual cars within a segment or a brand. The position of each feature point of the morphed car is the mean position of the corresponding feature point across all car models, calculated in step 3. Figure 2 illustrates the 50 feature points of two luxury car models (2010 Lexus LS and 2010 Acura RL) and two economy car models (2010 Scion TC and 2010 Ford Fusion), as well as the comparison between the design of the selected cars with the design of the morphed cars of their segment and the morphed cars of their brand. In the next section, we describe how we use the car image data to create the aesthetic design measures of SP, BC, and CSM, as motivated by our conceptual framework, shown in Figure 1.

Model and Estimation

Empirical Model

We estimate a random coefficient logit model on the sales data to uncover consumer preferences for a car's aesthetic design, marketing-mix variables, and other car attributes (BLP 1995; Sudhir 2001). We consider a market with utility-maximizing households who shop for passenger cars. We assume that each household chooses from a set of $M_t = \{1, 2, \ldots, J_t\}$ car models offered by a group of brands indexed by i in month t. A household also has the option of not buying any of the car

FIGURE 2
Brand Morph and Segment Morph of Selected 2010 Car Models

Notes: The values in parentheses indicate the values of BC and SP of the car in the middle of each row, compared with the average design of its brand (on the left) and the average design of its segment (on the right). A higher value indicates a higher degree of similarity to the brand or segment morph. Relative to the average design, Lexus LS looks more like its brand as well as its segment, Acura RL looks more like its brand but less like its segment, Scion TC looks like its segment but not its brand, and Ford Fusion does not look like either its segment or its brand.

models, in which case it is considered to purchase an outside good denoted by j = 0. Household h maximizes its utility by making the optimal purchase decision:

$$\text{(1)}\qquad \max_j u_{hsijt} = \gamma_{hi}^0 + \gamma_{hs}^1 SP_{ijt} + \gamma_{hs}^2 SP_{ijt}^2 + \gamma_{hs}^3 BC_{ijt} + \gamma_{hs}^4 BC_{ijt}^2 + \gamma_{hs}^5 CSM_{ijt} + \gamma_{hs}^6 Mkt_{ijt} + \alpha_h^1 SP_{ijt} Mkt_{ijt} + \alpha_h^2 BC_{ijt} Mkt_{ijt} + \beta_{hs} X_{ijt} + \xi_{ijt} + \varepsilon_{ijt}.$$

In Equation 1, u_{hsijt} is the indirect utility that household h derives from buying car model j (e.g., Camry) of brand i (e.g., Toyota) and segment s (e.g., economy segment) in month t. The variables SP_{ijt}, BC_{ijt}, and CSM_{ijt} are, respectively, the SP, BC, and CSM of car model j of brand i in month t. The variable Mkt_{ijt} is a vector of other marketing-mix variables, including Pr_{ijt} and Ad_{it}, where Pr_{ijt} is price of model j of brand i in month t and Ad_{it} is advertising spending of brand i in month t. We mean-centered the aesthetic design variables to reduce multicollinearity. Other variables in Equation 1 include X_{ijt}, which is a vector of car attributes (i.e., horsepower-to-weight ratio [HPWT], MP$, reliability rating, safety rating, size classification, regular car indicator, and country of origin) and seasonality. The term ξ_{ijt} is an error term that is observed by consumers but not recorded in the data, and ε_{ijt} is a mean-zero extreme-value-distributed error. Finally, γ_{hi}^0 is household h's intrinsic preference for brand I; γ_{hs}^1 and γ_{hs}^2 (γ_{hs}^3 and γ_{hs}^4) capture the nonlinear effects of SP_{ijt} (BC_{ijt}) on indirect utility; γ_{hs}^5 captures the effect of CSM of products belonging to segment s[3]; γ_{hs}^6 is a vector of marketing-mix parameters; α_h^1 and α_h^2 are parameter vectors that capture the moderating effect of SP and BC on the effectiveness of marketing-mix variables (i.e., prices and advertising)[4]; and β_{hs} is a vector of car attribute parameters.

Note that Equation 1 allows a product's aesthetic design to have a nonlinear effect on consumer's utility. For example, if $\gamma_{hs}^1 > 0$ and $\gamma_{hs}^2 < 0$, household h's utility first increases and then decreases as the aesthetic design becomes more typical relative to that of the product's segment s. Such a result would support our prediction that the effect of SP_{ijt} on preference is highest at a moderate level of SP. Moreover, a product's aesthetic design not only has a direct effect on a household's mean utility (as captured by the parameters γ_{hs}^1 through γ_{hs}^4) but also has an indirect effect on the household's mean utility through influencing the effectiveness of the marketing-mix variables (captured by α_h^1 and α_h^2). Furthermore, Equation 1 shows that the effectiveness of marketing-mix variables is $\gamma_{hs}^6 + \alpha_h^1 SP_{ijt} + \alpha_h^2 BC_{ijt}$ and thus varies across different designs. For example, positive moderating effects of BC on the effectiveness of marketing-mix variables (both elements of α_h^2 are positive) should lend support to our prediction that consumers are less sensitive to price and more responsive to advertising when a design has a higher BC.

Assuming ε_{ijt} in Equation 1 to be extreme value distributed, we derive a logit model of consumer choice. Moreover, to account for household heterogeneity, we assume that the coefficients $\{\gamma_h, \alpha_h, \beta_h\}$ in Equation 1 are normally distributed. By integrating out over the distribution of consumer's heterogeneous coefficients, we obtain the market shares conditional on aesthetic design variables. Thus, household utility determines market shares of the car models. We provide additional details of the random coefficient model in the Web Appendix. Note that we do not model firms' decisions with a supply-side model. This is because there is a possibility of obtaining biased estimates for the demand-side parameters if the supply-side model is incorrect. Moreover, not having to impose equilibrium conditions implied by the supply-side model when estimating the parameters of the demand function allows us to investigate a larger set of behaviors (Chintagunta et al. 2006).

Variables in Empirical Model

Market share. Because consumers are allowed to not purchase any car according to our model specification in Equation 1, we need to compute a product's market share among all consumers who are potentially considering a car purchase, including those who do not make a purchase. Thus, our total market size for market share calculation is the number of consumers considering a car purchase in a particular time period. Following prior research (Sudhir 2001), we calculate the monthly market size for each year (MS_t) as follows: MS_t = [number of households(t) × number of cars per household(t)]/[average age of car in years × 12]. We obtain annual data on the number of households during 2003–2010 from the Statistical Abstract of the United States. According to the Simmons database, the average U.S. household owned 1.66 passenger cars in the sample period. The average age of a car in the United States was 10.70 years during the same period, according to *Ward's Automotive Yearbook*. Using the MS_t estimated above along with sales data, we calculate a car model's monthly market share, which serves as our observed dependent variable.

Product attributes and seasonality (X_{ijt}). For car model j of brand i in month t, we incorporate the following attributes of car models, similar to those used in BLP (1995) and Sudhir (2001): (1) HPWT, as a measure of the car's power; (2) MP$, measuring fuel efficiency; (3) a regular car indicator according to Ward's classification; and (4) dummy variables for size classifications, including full-size and midsize (compact is the base).[5] Moreover, we include two third-party ratings of product quality and safety: (1) the *Consumer Reports* reliability, measured on a five-point scale, and (2) the Insurance Institute

[3]Given the structure of the choice model, an increase (decrease) in consumer utility of consuming an economy (luxury) product mimicking luxury (economy) products would positively (negatively) affect consumers' likelihood of choosing the focal economy (luxury) product and, at the same time, reduce consumers' likelihood of choosing all other products.

[4]Note that we do not allow α_h^1 and α_h^2 to vary across product segments. This is because the issue of multicollinearity arises when such three-way interactions (i.e., aesthetic design × marketing mix × segment indicator) are included in the model because the variance inflation factor of design variables exceeds the common standard tolerance level (i.e., 4).

[5]Because our model does not explicitly control for the ergonomic implication of an aesthetic design, there is the possibility of bias in our parameter estimates. To explore this issue further, we obtain ratings on comfort/convenience from *Consumer Reports*, although these data cover only car models after 2006. We then estimate a model with the comfort ratings, using data from 2006 to 2010. The results are consistent with the proposed model and are available in the Web Appendix.

for Highway Safety rating, measured on a four-point scale according to performance in a moderate overlap frontal crash test.[6] We also include seasonality indicator variables (Q2, Q3, and Q4) for different quarters of a year (Q1 is the base).

Price and advertising variables (Mkt_{ijt}). We follow the previous literature (Zettelmeyer, Morton, and Silva-Risso 2006) and use the MSRP minus cash rebate as a proxy for the transaction price.[7] The advertising variable is operationalized as the total amount an automaker spends on a car brand (e.g., Toyota) each month.

Aesthetic design variables (SP_{ijt}, BC_{ijt}, and CSM_{ijt}). According to our conceptual framework (Figure 1), SP_{ijt} should represent the aesthetic similarity of a car model to the schema of its own segment. In our empirical application, the aesthetics of the car model and the segment schema are captured by the coordinates of the 50 feature points on the car's frontal image and the segment morph, respectively. Using the coordinates of the 50 feature points, we operationalize SP_{ijt} following the method of Landwehr, Labroo, and Hermann (2011). We first sum the Euclidean distances of each of the 50 feature points of the car model (model j of brand i) from the corresponding feature point in its segment morph at time t, and then take the reciprocal of the summation.[8] More formally,

$$SP_{ijt} = 1\Big/\sum_{p=1}^{50}\sqrt{\left(y_{ijt}^{1p} - y_{st}^{1p}\right)^2 + \left(y_{ijt}^{2p} - y_{st}^{2p}\right)^2}. \quad (2)$$

In Equation 2, y_{ijt}^{1p} and y_{ijt}^{2p} are the two-dimensional coordinates of feature point p of car model j and brand i; y_{st}^{1p} and y_{st}^{2p} are the corresponding coordinates of the morph of the segment s to which product j belongs. For instance, SP_{ijt} for the 2003 Ford Focus, which falls in the economy segment, is computed using the coordinates of the 50 feature points in its frontal image, as well as those for the economy-segment (own-segment) morph in 2003. Note that the aesthetic design variables are at the annual level because automakers introduce new models annually. The value of SP_{ijt}, as computed above, can theoretically range from 0 to ∞, with a higher score indicating that the car model is more prototypical of its segment in its aesthetics. To compute BC_{ijt}, we follow a similar procedure except that the Euclidean distances of the car model's (e.g., Ford Focus's) frontal image are computed with respect to the morph for its brand (e.g., Ford), representing the brand's schema. Thus, a higher BC_{ijt}, which can range from 0 to ∞, suggests that the car model's aesthetic design is closer to the average look of all car models offered by the same brand.

Next, to compute CSM_{ijt}, we first compute cross-segment prototypicality (CSP_{ijt}) in the same fashion as SP_{ijt} except that the Euclidean distances for a car model are computed with respect to the morph of the segment to which it does *not* belong, that is, the cross-segment. For example, CSP_{ijt} for the Ford Focus is computed with reference to the luxury-segment morph. The value of CSP_{ijt} can also range from 0 to ∞, with a higher CSP_{ijt} indicating that the car model's design is increasingly prototypical of the other (cross-) segment. Using SP_{ijt} and CSP_{ijt}, we compute the CSM variable ($CSM_{ijt,}$) as

$$CSM_{ijt} = CSP_{ijt}\big/\left(CSP_{ijt} + SP_{ijt}\right) = 1\big/\left(1 + SP_{ijt}/CSP_{ijt}\right). \quad (3)$$

Therefore, CSM depends on the ratio of SP to cross-segment prototypicality (i.e., SP_{ijt}/CSP_{ijt}); it increases with cross-segment prototypicality (CSP_{ijt}) and decreases with own-segment prototypicality (SP_{ijt}). That is, the more a design resembles the typical look of the other segment, or the less it resembles the typical look of its own segment, the greater is the SCM. Note that $CSM_{ijt,}$ ranges from 0 to 1. The value of $CSM_{ijt,}$ is close to 1 (0) when a design greatly mimics (bears little resemblance to) the average look of the other segment but has little (great) similarity to the average look of its own segment. This operationalization is consistent with the argument that a category member is the easiest to categorize if it is maximally similar to other members of its category and maximally dissimilar to members of a different category (Alba and Hutchinson 1987). Table 2 shows the descriptive statistics of all the key variables.

We now discuss the relationships among the aesthetic design variables (Table 3). First, SP and BC are weakly correlated. This is because the categorizations at the product segment and brand levels are related by class inclusion (e.g., all BMW cars are in the luxury segment). Since we have sufficient number of brands in each segment, these two measures are positively, but weakly, correlated. Second, CSM is negatively correlated with SP. This is because a segment-prototypical design is less likely to be miscategorized as the other segment (Equation 3). Third, since CSM is a function of SP and CSP, a strong relationship between CSM and BC is not expected. Table 3 shows a very small positive correlation between CSM and BC.

We assessed the reliability of our design data to ensure that these measures are repeatable and stable. Three coders independently collected the Cartesian coordinates of the car design features that were used to compute the design variables. The data obtained by these three coders were highly correlated (correlation coefficients ranged from .88 to .98), testifying to the reliability of our measures. To verify the validity of our design variables in capturing consumer perceptions of car design, we recruited 195 subjects (average age = 33, 53% male) from MTurk, an online labor outsourcing platform, to rate car designs in the sample. We presented each subject with frontal photos of 40 randomly selected cars (with brand logo removed), shown one at a time, and asked subjects to rate the typicality of the car design relative to its segment and brand. The correlations

[6]The Insurance Institute for Highway Safety provides crashworthiness ratings on five types of tests: moderate overlap front, small overlap front, side, roof strength, and head restraints. We include rating on only moderate overlap frontal crash test in this study because it is the most common test, and the other four tests either cover only a small proportion of car models or are available only after the beginning of our sample.

[7]We estimated our model with the average of consumer-level transaction prices in Texas, obtained from Polk. The results are consistent with the proposed model and are available in the Web Appendix. However, these data cover only 50% of the transactions that occurred in Texas, whereas our sales are at the national level. Therefore, we operationalize price as described.

[8]To empirically check the validity of equal weighting of the design feature, we categorized the 50 feature points into five groups (i.e., overall body shape of the car, windshield, headlights, grille, and bumper) and designed a questionnaire to measure the perceived weights of these five groups by consumers. Our test suggests that consumer perceived weights are not significantly different from equal weights. Furthermore, we ran a model using design variables derived from the perceived weights and the estimation results are consistent with those with equal weights. Details of this analysis are provided in the Web Appendix.

TABLE 2
Descriptive Statistics

	M	Min	Max	Total Variation	Variation Breakdown: Within Car	Variation Breakdown: Between Car
Dependent Variable						
Market share (%)	.32	6.35×10^{-6}	6.51	.25	19.26%	80.74%
Independent Variables						
Aesthetic Design						
SP	.59	.13	1.26	49.70	10.64%	89.36%
BC	.81	.28	1.98	134.79	14.97%	85.03%
CSM	.40	.14	.67	26.02	12.65%	87.35%
Marketing Activities						
MSRP (in thousands of dollars)	32.88	8.23	99.13	3.37×10^5	3.12%	96.88%
Cash rebate (in thousands of dollars)	.62	0	8.50	3,145.31	31.64%	68.36%
Advertising (in millions of dollars)	8.30	0	78.83	1.52×10^6	34.35%	65.65%
Car Attributes						
HPWT	6.81	41.43	3.45	6,293.34	30.81%	69.19%
MP$	1.11	4.28	.37	198.99	46.97%	53.03%
Reliability	3.32	1	5	1,310.03	35.35%	64.65%
Safety	3.18	1	4	1,082.97	1.35%	98.65%
Regular	.76	0	1	193.45	0%	100%

Notes: Market share is computed as the estimated share among all consumers shopping for a car, including those who do not purchase.

between the subjective ratings of design variables and our objective measures of these variables are significant (R(SP) = .46, $p < .01$; R(BC) = .45, $p < .01$). In an additional MTurk study to validate our objective measure of CSM, a total of 254 respondents (average age = 34, 45% male) were asked to rate the degree to which car designs mimicked the other segment relative to their own segment. The correlation between the subjective rating of CSM and our objective measure is significant (R(CSM) = .45, $p < .01$). These results are in line with those reported in extant research (e.g., Landwehr, Labroo, and Hermann [2011] reported a correlation coefficient of .42 in validating the SP measure) and show that our design variables satisfactorily capture the perceived design attributes by consumers. We present additional details of these validation studies in the Web Appendix.

Estimation

Our estimation procedure uses the generalized method of moments (GMM) combined with a contraction mapping technique, similar to BLP (1995). Additional details of this estimation procedure can be found in Nevo (2000). We check for possible multicollinearity in the proposed model. The variance inflation

TABLE 3
Correlations Among Market Share, Aesthetic Design Variables, Marketing-Mix Variables, and Car Attributes

	Market Share	BC	SP	CSM	Price	Advertising	HPWT	MP$	Reliability	Safety	Regular
Market Share	1	.23 (7.84)***	.18 (6.15)***	.02 (.71)	−.29 (10.06)***	.27 (9.30)***	−.15 (4.89)***	.03 (1.16)	.15 (5.20)***	.32 (11.24)***	.25 (8.71)***
BC		1	.15 (4.89)***	.07 (2.38)**	−.03 (.91)	−.14 (4.60)***	−.01 (.32)	.04 (1.31)	.03 (.96)	.22 (7.43)***	.14 (4.58)***
SP			1	−.05 (1.50)	−.10 (3.16)***	.04 (1.12)	−.04 (1.31)	.03 (.85)	.04 (1.12)	.20 (6.78)***	.18 (6.06)***
CSM				1	.02 (.56)	−.03 (.89)	.02 (.50)	−.05 (1.51)	.01 (.43)	.00 (.03)	−.01 (.94)
Price					1	−.07 (2.21)***	.30 (10.03)***	−.29 (9.65)***	.09 (3.01)***	.15 (4.94)***	−.26 (8.49)***
Advertising						1	−.01 (.30)	−.11 (3.54)***	.07 (2.14) **	.21 (6.95)***	.12 (3.72)***
HPWT							1	−.38 (13.41)***	.07 (2.16) ***	−.21 (6.63)***	−.28 (9.38)***
MP$								1	.06 (2.05)**	−.20 (6.63)***	.06 (1.90)*
Reliability									1	.07 (2.17)**	.04 (1.25)
Safety										1	.33 (11.53)***
Regular											1

*$p < .10$.
**$p < .05$.
***$p < .01$.

factors of all independent variables are smaller than 4; thus, our model does not have serious multicollinearity problems.

To check the effects of incorporating the main effects of SP and BC on consumer utility, the moderating effects of aesthetic design on marketing-mix effects, and the impact of CSM, we compare our proposed model with four nested models: (1) Model 1, a model with only the linear effect of SP, based on Landwehr, Labroo, and Hermann (2011); (2) Model 2, which is Model 1 plus the nonlinear effects of both SP and BC; (3) Model 3, which is Model 2 plus the moderating effects of SP and BC on marketing-mix effects, and the main effect of CSM; (4) Model 4 (the full model), which includes segment-specific effects of aesthetic design variables, marketing-mix elements, and car attributes. We use selection criteria for nested or nonnested GMM model selection (Andrews and Lu 2001), including the model and moment selection criteria–Bayesian information criteria (MMSC-BIC) and model and moment selection criteria–Akaike information criteria (MMSC-AIC), to compare the fit of these four models.

Technical Estimation Issues

Endogeneity. In the automotive industry, the appearance of a car and/or its technical attributes, such as horsepower or gas mileage, are redesigned when a new car model is introduced. For example, there are 202 car models in our sample, and a typical car model has changed its design every three to four years during our sample period (2003–2010). Since our data are at the monthly level, we assume that neither aesthetic design nor car attributes is correlated with the short-run demand shocks, as do previous articles (BLP 1995; Sudhir 2001). Thus, both aesthetic design and car attributes are assumed to be exogenous in our study. We have performed a robustness check of possible endogeneity in the aesthetic design variables. Details of this analysis are reported in the Web Appendix.

However, also similar to previous articles, we account for the endogeneity of price and advertising. The potential endogeneity arises because econometrically unobserved factors (ξ_{jt} in Equation 1) may affect a firm's decisions on price and advertising spending. We follow BLP (1995) and use functions of car attributes as instruments for endogenous short-run pricing and advertising activities (see also Liu and Shankar 2015; Sudhir 2001). Moreover, we follow prior research and use advertising cost as an additional instrument for advertising (Luan and Sudhir 2010). Advertising cost is likely negatively correlated with advertising spending and is reasonably exogenous because it is common across brands and does not change in anticipation of demand shocks. We use the average unit cost across media (from Ad$pender) in nonpassenger car categories (e.g., SUV, minivan, light truck) as a proxy for the advertising cost in the passenger car market. We provide additional details of the instruments in the Web Appendix. The results of the first-stage regression show that the instruments explain the variation in price and advertising well (results are available in the Web Appendix).

Identification of aesthetic design effects. Table 2 shows both cross-sectional (i.e., between-car) and cross-time (i.e., within-car) variations in SP, BC, and CSM, although such variations arise mostly from between-car differences (85%–89%). A typical car model has changed its design every three to four years during the eight-year sample period (2003–2010). Thus, the time covered in our study is greater than the length of the design cycle for the typical model. Although the data period may not capture the full cycle of design changes of all cars in some competitive sets, the considerable variation in the aesthetic design variables help us identify their effects. One may be concerned that aesthetic design variables may simply be proxies for the unobserved differences between cars. In particular, each car brand may have a unique positioning that is unobserved to researchers but that may affect its design decisions. For example, to leverage its premium brand image, a well-established brand may have a consistent design across its product line. Without accounting for the unobserved brand image, we may overestimate the importance of BC in affecting household utility. To address this concern, we include brand-level fixed effects in the utility function (γ_i^0 in Equation 1) to control for any unobserved brand-specific attributes that correlate with both household utility and aesthetic design.

Results

Model Comparison

The values of MMSC-BIC and MMSC-AIC in Table 4 show that the model fit is significantly improved from Model 1 to Model 4, indicating the importance of considering (1) the nonlinear effects of SP and BC on utility, rather than just the linear effect of SP (Model 2 vs. Model 1); (2) the moderating effects of SP and BC on price sensitivity and advertising effectiveness and the effect of CSM (Model 3 vs. Model 2); and (3) segment-specific effects of aesthetic design, marketing-mix elements, and car attributes (Model 4 vs. Model 3). Moreover, the results of Model 1 show a positive linear impact of SP on utility, consistent with Landwehr, Labroo, and Hermann (2011). Next, we discuss estimation results of the full model. The Appendix details several robustness checks of the results that we performed.

Full Model Estimation Results

Coefficients of product attributes and heterogeneity. The mean coefficients of product attributes are largely consistent with prior studies (BLP 1995; Sudhir 2001), except that these prior studies find no significant effect of MP$. Given that those studies use pre-1990 data, the different results suggest greater consumer sensitivity to fuel efficiency in recent years. The heterogeneity coefficients for MP$, reliability, price, advertising, BC, and SP are significant ($p < .01$).

Main effects of aesthetic design variables and marketing-mix elements. Table 4 shows that the linear and quadratic coefficients of SP and BC are significant in economy and luxury segments ($p < .05$ or better), indicating nonlinear effects of aesthetic design variables on utility in both segments. Moreover, all these coefficients are significantly different across product segments ($p < .10$ or better). In Figure 3, we plot such nonlinear effects of aesthetic design within the range of our data (i.e., $\gamma_s^1 SP_{ijt} + \gamma_s^2 SP_{ijt}^2$ for SP and $\gamma_s^3 BC_{ijt} + \gamma_s^4 BC_{ijt}^2$ for BC). Figure 3, Panel A, shows that SP has the strongest effects in both segments when it is at a moderate level, supporting H_{1a}. Thus, a design that is either too similar to or too different from the segment-typical look is not ideal. Rather, consumers prefer a design with a moderate level of resemblance to the average look

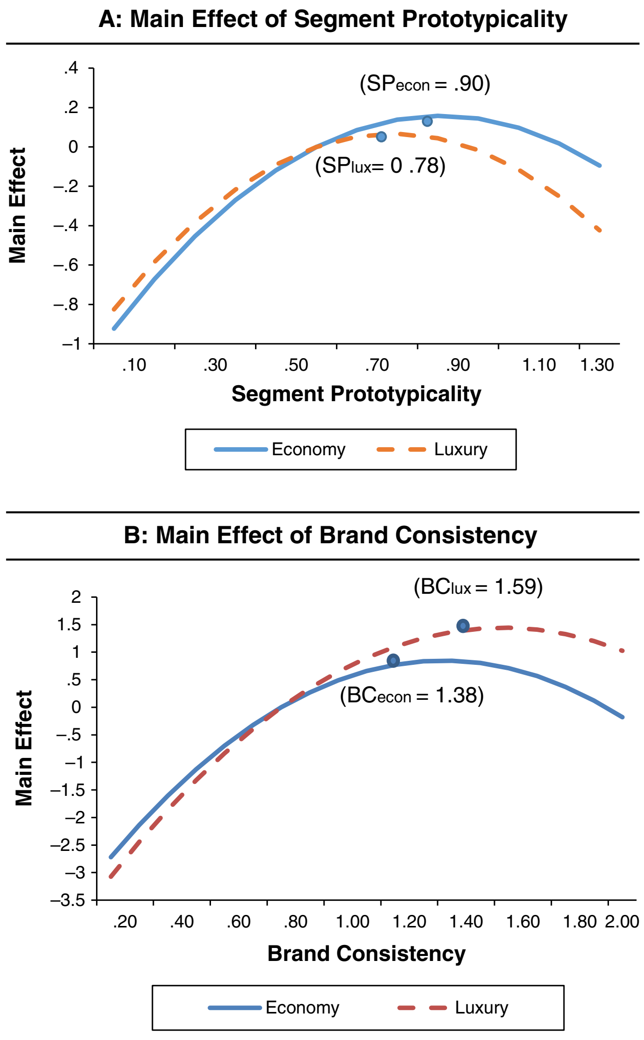
TABLE 4
Model Comparisons and Full Model Estimates

	Model 1	Model 2	Model 3	Model 4: Economy	Model 4: Luxury
Aesthetic Design Main Effects					
SP	.29 (.05)***	1.21 (.29)***	1.90 (.14)***	1.02 (.11)***	.71 (.08)***,††
SP^2		–1.13 (.13)***	–1.42 (.08)***	–1.65 (.06)***	–1.88 (.13)***,††
BC		1.58 (.08)***	2.18 (.19)***	2.97 (.29)***	3.70 (.35)***,†††
BC^2		–1.32 (.41)***	–2.97 (.33)***	–2.60 (.20)***	–2.37 (.06)***,†
CSM			.03 (1.49)	.06 (.03)**	–.01 (.59)
Marketing-Mix Effects					
Price	–4.02 (.02)***	–3.64 (.20)***	–8.81 (.52)***	–9.87 (.48)***	–7.94 (.50)***,†††
Advertising	4.31 (.23)***	4.81 (.23)***	5.37 (.23)***	4.99 (.27)***	6.40 (.49)***,†††
Moderating Effects of Aesthetic Design					
SP × Price			–2.77 (.52)***	–2.17 (.45)***	
SP × Advertising			–1.21 (4.43)	1.37 (6.02)	
BC × Price			.73 (.34)**	.73 (.12)***	
BC × Advertising			3. 68 (.59)***	2.26 (.92)**	
Car Attributes					
MP$	1.04 (.00)***	1.08 (.04)***	.87 (.10)***	1.33 (.02)***	.64 (.09)***,†††
Reliability	.15 (.09)**	.25 (1.46)	–.44 (2.07)	.01 (1.02)	.00 (2.14)
HPWT	.09 (1.05)	–.09 (1.07)	–.38 (1.18)	.19 (.59)	–.05 (1.91)
Safety	.90 (.30)***	.25 (.06)***	.16 (.08)**	.24 (.02)***	.50 (.10)***,†††
Regular	–1.72 (4.60)	–1.46 (9.36)	–1.36 (24.18)	–2.40 (.70)***	–4.11 (13.42)
Full size	.59 (.04)***	.88 (.41)**	.50 (.23)**	2.01 (1.24)*	4.32 (1.41)***,††
Midsize	.11 (1.94)	–.70 (1.08)	–.61 (1.35)	–.31 (.22)	3.61 (2.08)**
Q2	–.39 (.11)***	–.06 (.02)***	–.30 (.15)**	–.21 (.02)***	
Q3	–.71 (.20)***	–.42 (1.07)	–.92 (.98)	–.45 (.02)***	
Q4	–.83 (.52)*	–.79 (.11)***	–.95 (.45)**	–.74 (.01)***	
Heterogeneity Coefficients					
Constant	–.06 (.12)	.03 (.32)	.11 (.42)	.05 (.96)	
MP$	5.30 (.14)***	5.38 (.48)***	.50 (.13)***	.38 (.09)***	
Reliability	.04 (.01)***	.02 (.01)**	.03 (.01)***	.02 (.00)***	
HPWT	.05 (.14)	.12 (.40)	.11 (.91)	.10 (.61)	
Safety	.04 (.09)	.02 (.37)	.01 (.51)	.01 (.38)	
Regular	.15 (.18)	.03 (.43)	.02 (.64)	.06 (.52)	
Price	1.520 (.13)***	1.58 (.46)***	1.44 (.48)***	1.61 (.40)***	
Advertising	3.47 (.16)***	7.02 (.81)***	6.50 (.57)***	2.18 (.71)***	
SP	.52 (.11)***	.60 (.32)**	.44 (.05)***	1.12 (.08)***	
BC		.02 (.01)**	.30 (.08)***	.51 (.06)***	
Objective Function	1,435.16	366.97	265.95	111.97	
MMSC-BIC (MMSC-AIC)[a]	1,928.86 (1,539.16)	908.13 (480.97)	854.23 (389.59)	824.03 (261.97)	

*$p < .10$.
**$p < .05$.
***$p < .01$.
†Significantly different from the economy segment at $p < .10$.
††Significantly different from the economy segment at $p < .05$.
†††Significantly different from the economy segment at $p < .01$.
[a]MMSC-BIC = Y – ln(n) × (k_m – k_b), and MMSC-AIC = Y – 2 × (k_m – k_b), where Y is the value of the GMM objective function, n is the number of data points, k_m is the number of moments, and k_b is the number of parameters.
Notes: Standard errors are in parentheses. Advertising, price, and MP$ are multiplied by .00001, .00001, and .01, respectively. The brand preference parameters γ_i^0 are not shown, to save space. They range from –2.54. (Porsche) to 1.61 (Hyundai).

of the segment. This finding is different from that of Landwehr, Labroo, and Hermann (2011), who find the coefficient of the quadratic term of SP to be insignificant. This may be because the standard errors of the estimates in the current study are significantly reduced, with a greater number of car models (202 vs. 28) over a much longer time period (8 years vs. 6 months). Moreover, Figure 3, Panel A, shows that SP's effect peaks at lower levels of prototypicality for the luxury segment (i.e., $SP_{lux} = .78$ and $SP_{econ} = .90$). We use bootstrapping to compute the standard error of the difference between the peak points across segments (Efron and Tibshirani 1993, p. 88). The difference is significant ($p < .05$), indicating that consumers prefer a more unique design when shopping for a luxury car than when shopping for an economy car, supporting H_{1b}.

FIGURE 3
Main Effect of SP and BC



Notes: The difference between the peak points of SP_{econ} and SP_{lux} and the difference between the peak points of BC_{econ} and BC_{lux} are both significant at $p = .05$.

The coefficient of CSM is significant and positive for the economy segment ($p < .05$), consistent with H_{2a}. For the luxury segment, the coefficient of CSM is negative, directionally consistent with H_{2b}, although this effect is not significant. Similar to SP, BC's effect on preference is also the highest in both product segments when BC is at a moderate level (Figure 3, Panel B), supporting H_{3a}. This suggests that a design that is neither too similar to nor too different from the average look of a brand is ideal. Moreover, Figure 3, Panel B, shows that BC's effect peaks at higher levels of BC for the luxury segment (i.e., BC = 1.38 for the economy segment and BC = 1.59 for the luxury segment, $p < .05$). This result indicates that consumers prefer a car's design to carry a greater resemblance to its brand when the car is a luxury car versus an economy car. Therefore, H_{3b} is supported.

Marketing-mix effects. Both price and advertising coefficients are significant, with expected signs in both product segments ($p < .01$). Consumers are significantly more price sensitive to economy cars than to luxury cars ($p < .01$), which is not surprising. Moreover, the advertising effectiveness is greater in the luxury segment.

Moderating effects of aesthetic design on the marketing-mix effectiveness. The coefficient of the interaction term between SP and price is negative and significant ($\gamma = -2.17$, $p < .01$), suggesting increased price sensitivity for cars with a segment-typical design, supporting H_{4a}. The coefficient of the interaction term between BC and price is positive and significant ($\gamma = .73$, $p < .01$), indicating reduced price sensitivity for cars with greater resemblance to their brand average, supporting H_{5a}. The coefficient of the interaction term between SP and advertising is not significant, so H_{4b} is not supported. The coefficient of the interaction term between BC and advertising is positive and significant ($\gamma = 2.26$, $p < .05$), suggesting that consumers are more responsive to the advertising of car models with greater BC, supporting H_{5b}.Table 5 shows a summary of the hypotheses and results.

Willingness to pay for aesthetic design. To better understand the importance of the aesthetic design measures, we compute the consumer's willingness to pay (WTP) for their most preferred levels of all design measures. We calculate WTP as the income that would compensate for the loss of utility if the given design measure were moved to a less preferred benchmark level (cf. Allenby et al. 2014). These benchmark levels are set to values of SP = 0 (a very atypical design) and BC = 0 (a very brand-inconsistent design) for the calculation of WTP for SP and BC, respectively. Details of the WTP computation are provided in the Web Appendix. We find that an average consumer's WTP for SP is $670 for an average car in the luxury segment and $648 for an average car in the economy segment at the optimal SP level (i.e., $SP_{lux} = .78$ and $SP_{econ} = .90$ in Figure 3). Moreover, an average consumer's WTP for BC is even higher, at approximately $3,255 and $2,090 at the optimal BC levels (i.e., $BC_{lux} = 1.59$ and $BC_{econ} = 1.38$ in Figure 3) for an average car in the luxury and economy segments, respectively. The higher WTP for BC may reflect the important role that branding plays in the U.S. passenger car market. The WTP for CSM (comparing CSM = 1 with CSM = 0) is approximately $200 for an average car in the economy segment.

Conclusions and Managerial Implications

Summary of Findings

Our empirical results from the U.S. passenger car market establish that the aesthetic design of a product can have a significant effect on consumer preference. Beyond statistical significance, our results show that changes in aesthetic designs can add several hundred to a few thousand dollars to the WTP of consumers for the average car. The nature of the effect of product aesthetics on consumer preference is consistent with theoretical arguments presented in the categorization literature. Specifically, we find that consumer preference is the highest at a moderate level of SP, consistent with arguments and findings in the

TABLE 5
Summary of Hypotheses and Results

Effects/Variables	Hypothesis	Description	Result
Main effect of SP	H_{1a}	Highest at the moderate level of SP	Supported
Optimal level of SP across segments	H_{1b}	Lower for luxury segment	Supported
CSM for economy products	H_{2a}	+	Supported
CSM for luxury products	H_{2b}	–	Not significant
Main effect of BC	H_{3a}	Highest at the moderate level of BC	Supported
Optimal level of BC across segments	H_{3b}	Higher for luxury segment	Supported
SP × Price	H_{4a}	–	Supported
SP × Advertising	H_{4b}	–	Not significant
BC × Price	H_{5a}	+	Supported
BC × Advertising	H_{5b}	+	Supported

categorization literature (Mandler 1982; Meyers-Levy and Tybout 1989).

Also consistent with the categorization arguments related to branding (Boush and Loken 1991; Broniarczyk and Alba 1994; Park et al. 1991), we find a significant effect of BC on consumer preference. Interestingly, we find that consumer preference for aesthetic design of a product is the highest at a moderate level of BC, which balances brand recognition and product differentiation. Moreover, we find that economy cars benefit from CSM, that is, mimicking the aesthetics of the luxury segment.

Notably, the optimal level of SP and BC depends on whether the product is an economy or a luxury product. Thus, we find that relative to an economy product, a luxury product benefits when it looks more similar to its brand (optimal level of BC is higher) but less similar to its segment (optimal level of SP is lower). These results appear to be consistent with the buying motivation for luxury products, which are sought for their signaling value (Grossman and Shapiro 1988; Park et al. 1991). We also find that aesthetic design influences the effectiveness of other marketing-mix variables. Specifically, we find that price sensitivity increases for a product that has a high SP but decreases for a product with high BC, while advertising effectiveness increases for a product with high BC.

Managerial Implications and What-If Analyses

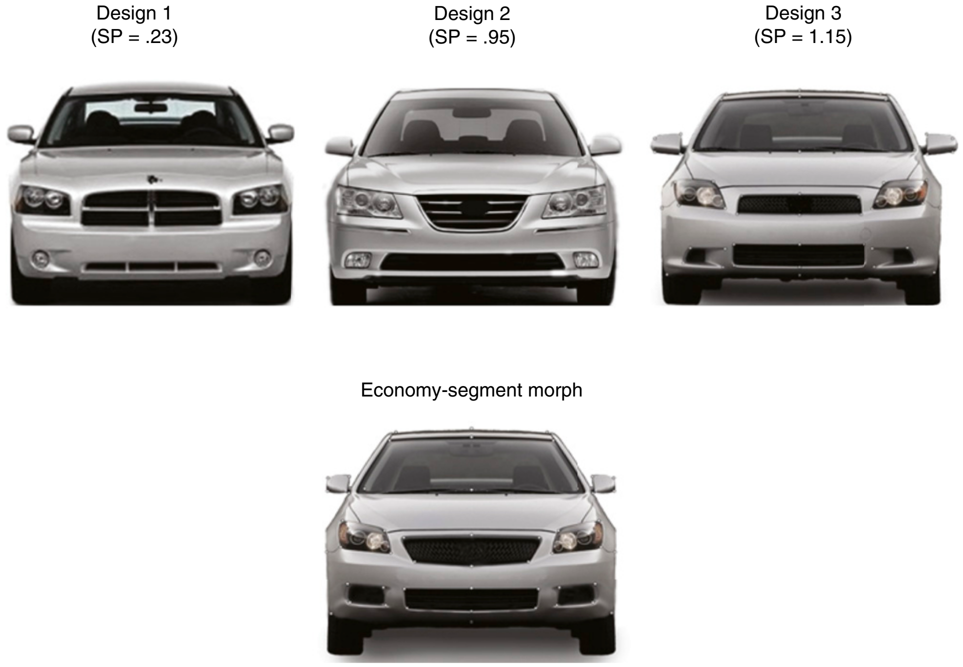
Marketing managers often look for analysis-driven guidance on difficult-to-quantify decisions about factors such as product aesthetics. In that regard, our model and methodology can inform firms' aesthetic design decisions. In this subsection, we conduct two what-if analyses from a manager's point of view to evaluate proposed design changes. We assume that these analyses are conducted in 2010 using data available up to 2010. For both what-if analyses, we consider the implication of design change for SP, BC, CSM, and marketing effectiveness in arriving at estimates for market share and profitability for each design, taking the estimates from the full model as given. When evaluating the profitability of the decision change, we assume a 15% profit margin (http://www.rmi.org/RFGraph-Automotive_and_oil_industry_profits).

What-If Analysis 1: choosing from alternative looks for a major redesign. In the automotive industry, the designs of car models are refreshed every three to four years. To understand the possible market outcome of design changes, in the first what-if analysis we assume that a selected car model, the Ford Fusion, is considering a new look for its 2011 model year. The current design of Ford Fusion (i.e., the 2010 model) is moderately atypical (SP_0 = .57) with low BC (BC_0 = .67) and moderately high CSM (CSM_0 = .50). We assume that the aesthetic design team has proposed three alternative new designs, as shown in Figure 4. Of these designs, Design 1 is a boxy muscular look that would make the car quite atypical and stand out from other cars in the economy segment (SP_1 = .23). Design 2 presents a sleek look, which is distinctive but is less atypical of the economy segment than Design 1 (SP_2 = .95). Design 3 presents a look that is close to the average look (segment morph) of a car in the economy segment in 2010 (also shown in Figure 4) and has an SP value of 1.15. Moreover, the new designs have slightly different BC and CSM values than the current design (Table 6, Panel A). Note that the mapping between our aesthetic design variables and the design choices are not unique. Thus, other car body designs may also lead to same values of the aesthetic design variables. After obtaining the SP, BC, and CSM values for the three new designs, we simulate the market share and profit, using the estimated parameters of our model as input. In performing this simulation, we assume that the competing models offer designs similar to those offered in 2010. This assumes a one-year lead time to implement the design, which may not be realistic for the auto industry. Therefore, the analysis presented here should be considered illustrative. Managers can refine this analysis further to adequately account for the lead time to implement a design and to account for uncertainties about future designs of competitor models.

Table 6, Panel A, reports the observed and projected SP, BC, CMS, market share, and profit for the Ford Fusion before and after the three alternative design changes. The simulation reveals that Design 2 yields the highest market share and profit. Note that Design 2 is moderately atypical (SP = .95), as compared with Design 3, which is very typical (SP = 1.15), and Design 1, which is very atypical (SP = .23). Thus, the simulation results appear to be consistent with our expectation, based on the categorization literature (hypothesis H_{1a}), that designs with a moderate level of SP, such as Design 2, would be preferred by consumers.

Because all three design variables, SP, BC, and CSM, change for the Ford Fusion with the new designs, we decompose the total profit gain/loss into seven components: (1) the main effect of SP on household utility, (2) the moderating effect of SP on price sensitivity, (3) the moderating effect of SP on advertising

FIGURE 4
What-If Analysis I: Different Looks for a Major Redesign



effectiveness, (4) the main effect of BC on household utility, (5) the moderating effect of BC on price sensitivity, (6) the moderating effect of BC on advertising effectiveness, and (7) CSM. Table 6, Panel A, shows that the main effect of SP contributes the most to the profit gain/loss. This is expected because there is a significant change in SP with all three new designs. The "winning" design, namely, Design 2, benefits greatly from a movement toward the optimum level of SP. However, the higher SP of the design leads to increased price sensitivity, which hurts profit, but it has no effect on advertising effectiveness, given our empirical results. Furthermore, the profits of all the new designs are lowered slightly because their CSM values are smaller than that of the current design. Moreover, BC decreases for all the new designs except Design 3. This decline in BC results in a loss of profit for Designs 1 and 2, while the increase in BC toward the optimum level benefits Design 3. Our analysis suggests that modifying the other Ford-branded car models to a design similar to that of the winning design, Design 2, may increase market share and profit further for the Ford Fusion through improvement in BC. Overall, this what-if analysis shows that our model incorporating SP, BC, and CSM can help managers choose the optimal design for their car models.

What-If Analysis 2: impact of adopting a common front grille for a brand. In the automotive industry, many brands use the grille, a key component of the frontal design, as a brand identifier. Automakers adopt a similar grille style for the majority, if not all, of their car models. For example, all models of BMW share a kidney-shaped grille, a defining characteristic of BMW styling (Lutz 2012). In the second what-if analysis, we assume that managers, in 2011, replace the grille of all models of a particular car brand with a common design. This common grille is identical to the grille of the morphed car of this brand before the design change. Such a design change thus leads to a higher value of BC for all car models of this brand. Thus, this analysis is performed at the brand level. We note that, given the design change of one brand, we need to update the segment morph and recompute the SP and CSM values for all cars. Again, we simulate the market share and profit, using the estimated parameters of our model as input. We assume that the designs of all other brands are unchanged for 2011 in this simulation. We perform this analysis for two economy brands, Chevrolet and Subaru, and two luxury brands, Lexus and Mercedes-Benz.

The observed values of BC on the left side of Table 6, Panel B, show that these four brands have different levels of mean BC (across all car models of the same brand), with Chevrolet having the lowest (.70), followed by Subaru (.87), Lexus (.90), and Mercedes-Benz (.97). The right side of Table 6, Panel B, reports the projected SP, BC, CSM, market share, and profit for the four brands after the brand-wide front grille change. Note that the projected values in Table 6, Panel B, are computed assuming that only the focal brand (e.g., Chevrolet) makes the grille change, while all other brands maintain the current designs. As expected, the mean BC values increase after the brand-wide grille change for every brand in the analysis. The change in SP because of the grille change is positive for all four brands, suggesting that the grille change makes all the brands more prototypical in their respective segments. However, the change in SP is consistently much smaller than the change in BC across all four brands. The simulation reveals that all four brands gain in both market share and profit. This result is understandable because the mean BC of each brand under consideration is smaller than the value at which consumer preference for the given brand is the highest. Recall that BC has a nonlinear relationship with consumer utility, with the peak preference occurring at BC values of approximately 1.38 and 1.59 for

TABLE 6
What-If Analyses

A: What-If Analysis 1

					Profit (M$)							
						Profit Gain (Loss) Breakdown (%)						
						SP			BC			
							Moderating Effect On			Moderating Effect On		
	SP	BC	CSM	Product-Market Share	Total	Main Effect	Price	Advertising	Main Effect	Price	Advertising	CSM
Observed	.57	.67	.50	3.93%	402.27							
Projected												
Design 1	.23	.64	.47	3.16% (–19.52%)	323.72 (–19.52%)	–81.33%	1.18%	0	–16.45%	–.03%	–3.12%	–.26%
Design 2	.95	.66	.36	4.22% (7.41%)	432.06 (7.41%)	145.63%	–7.58%	0	–25.02%	–.06%	–5.96%	–7.01%
Design 3	1.15	.69	.28	4.19% (6.58%)	428.71 (6.58%)	71.70%	–13.28%	0	43.52%	.11%	10.61%	–12.65%

B: What-If Analysis 2

					Profit (M$)							
						Profit Gain Breakdown (%)						
						BC			SP			
							Moderating Effect On			Moderating Effect On		
Brand	Mean BC	Mean SP	Mean CSM	Product-Market Share	Total	Main Effect	Price	Advertising	Main Effect	Price	Advertising	CSM
Observed												
Chevrolet	.70	.60	.39	11.39%	2,516.17							
Subaru	.87	.67	.33	2.98%	678.50							
Lexus	.90	.68	.41	2.03%	818.74							
Mercedes-Benz	.97	.67	.43	2.54%	1.162.37							
Projected												
Chevrolet	.73	.60	.39	12.85% (12.86%)	2,854.38 (13.44%)	80.23%	12.05%	6.43%	2.68%	–1.42%	0	.03%
Subaru	.90	.68	.34	3.25% (9.08%)	743.83 (9.63%)	70.08%	12.81%	4.87%	23.69%	–11.50%	0	.05%
Lexus	.93	.68	.41	2.24% (10.40%)	911.45 (11.29%)	70.74%	13.25%	4.87%	23.74%	–12.60%	0	0
Mercedes-Benz	1.00	.67	.42	2.75% (8.53%)	1,262.18 (8.59%)	74.14%	13.99%	4.69%	14.35%	–7.17%	0	0

Notes: Percentage differences from observed values are given in parentheses. Product-market share is computed as a product's share of the combined sales of all car models. In Panel B, the 95% confidence intervals of the projected profit are (2,854.38 ± 356.41), (743.83 ± 110.48), (911.45 ± 93.14), and (1,262.125 ± 146.07) for Chevrolet, Subaru, Lexus, and Mercedes-Benz, respectively (computed using bootstrapping; Efron and Tibshirani 1993).

economy and luxury cars respectively (Panel B of Figure 3). Thus, an increase in BC results in increased preference for all four brands under consideration. Moreover, the brand with the smaller mean BC in its segment (i.e., Chevrolet in the economy segment and Lexus in the luxury segment) has bigger gains in market share and profit because of the diminishing returns to BC arising out of the nonlinear response curve. However, note that the profit increase reported does not factor in the cost of the design change.

Similar to the first what-if analysis, we decompose the total profit gain into the component effects of BC, SP, and their interaction with the marketing mix, as well as the effect of CSM. Table 6, Panel B, shows that the main effect of BC contributes the most (70.08%–80.23%) to the gain for all four brands. The decreased price sensitivity due to increased BC accounts for 12.05%–13.99% of the gain, and the increased advertising effectiveness accounts for 4.69%–6.43% of the gain for these four brands. Because the increase in SP greatly varies across brands, there is a large variation in the contribution of SP's main effect to the total gain (2.68%–23.74%). There is also a small loss in profit (1.42%–12.60%) because consumers become more price sensitive as SP increases. Furthermore, CSM affects only the profits of the economy car brands, given our empirical estimation results—it contributes .03% and .05% to the gain of Chevrolet and Subaru, respectively. Overall, our second what-if analysis suggests that it can be profitable for the brands under consideration to adopt a common grille, as they would benefit from the positive effects of BC in aesthetic design.

Limitations

Our study has several limitations that can be fruitfully addressed in future research. First, we do not model other aspects of aesthetic design, such as complexity of car design (Landwehr et al. 2011). Complexity can be operationalized as the size of a compressed photograph of a car, using photographs of all car models with the same colors taken in a professional studio under standardized conditions (e.g., Landwehr et al. 2011). It is difficult to obtain such photographs in our case because we have a large number of car models (202) and a long period of historical data (2003–2010). Because Landwehr et al. (2011) find that complexity is not correlated with design variables such as SP in the automotive industry, excluding complexity in the model should have little impact on the estimated effect of aesthetic design variables. Second, we segment cars on the basis of price (economy vs. luxury); future research could explore other segmentation bases, such as size group (compact, midsize, and full size). Finally, in the what-if analyses, we assume that the strategy of other brands (car models) does not change when a selected brand (model) adopts a new policy. It would be helpful to compute equilibrium design strategies of brands. This problem is a complicated one that we leave for future research.

Appendix: Robustness Checks

To demonstrate the robustness of our findings, we performed the following additional analyses. Estimation results are shown in Table A1.

Model with Car-Model Fixed Effects

While we control for brand level fixed effects in the main model, we have also performed a robustness check and estimated a model with car model fixed effects. The results are qualitatively consistent.

Model with Within-Firm CSM

An economy (luxury) car model may resemble the average look of the luxury (economy) products offered by the same company, resulting in within-firm CSM (e.g. Toyota Camry mimics the appearance of Lexus). We find that the effect of within-firm CSM is not significant in our data.

Model with SP × BC Interaction

We find that the SP × BC interaction is not significant.

Split-Design Study

We performed a robustness check with a split-design study (i.e., analyzing data with economy car models only separately from data with luxury car models only). We find that the results are consistent with those of a fully mixed sample.

Table A1
Estimation Results of Robustness Checks

	Car Model Fixed Effects		Within-Firm CSM		Interaction Between SP and BC		Split Design	
	Economy	Luxury	Economy	Luxury	Economy	Luxury	Economy	Luxury
SP	1.27 (.66)**	.82 (.40)**	1.02 (.11)***	1.24 (.11)***	1.12 (.09)***	.79 (.09)***	1.32 (.24)***	.79 (.15)***
SP^2	–1.12 (.35)***	–1.33 (.32)***	–1.66 (.06)***	–1.14 (.05)***	–1.57 (.11)***	–1.92 (.12)***	–1.96 (.16)***	–1.83 (.49)***
BC	1.62 (.22)***	1.73 (1.03)*	2.97 (.28)***	2.59 (.23)***	3.02 (.39)***	3.59 (.37)***	2.79 (.73)***	3.11 (.90)***
BC^2	–3.27 (1.82)**	–2.14 (.47)***	–2.60 (.20)**	–2.70 (.36)**	–2.67 (.17)***	–2.21 (.09)***	–2.45 (.62)***	–2.69 (.10)***
SP × BC					.64 (.41)	.03 (.09)		
CSM	.05 (.03)*	–.22 (.37)	.04 (.04)	.06 (.04)*	.06 (.03)**	–.00 (.51)	–12.28 (.84)***	–8.87 (1.23)***
Price	–7.16 (1.02)***	–4.32 (.07)***	–9.89 (.48)***	–10.58 (.62)***	–9.66 (.52)***	–7.93 (.50)***	5.25 (.67)***	6.77 (.54)***
Advertising	3.88 (1.22)***	4.74 (1.47)***	4.92 (.27)***	5.89 (1.29)***	4.90 (.21)***	6.41 (.42)***	5.21 (1.82)***	7.32 (.13)***
SP × Price	–3.86 (1.77)**		–2.17 (.45)***		–2.22 (.42)***		–1.41 (.37)***	9.21 (7.38)
SP × Advertising	1.33 (1.86)		1.38 (6.02)		1.41 (6.19)		2.84 (7.39)	3.19 (2.07)*
BC × Price	.72 (.37)**		.70 (.11)***		.81 (.15)***		.26 (.72)	1.35 (.20)***
BC × Advertising	3.33 (1.47)**		2.26 (.93)**		2.20 (1.05)**		2.27 (1.46)**	–.38 (.37)

*$p < .10$.
**$p < .05$.
***$p < .01$.
Notes: Standard errors in parentheses. Advertising and price are multiplied by .00001 and .00001, respectively. Only key parameters are shown, to save space. Full results of these analysis are reported in the Web Appendix.

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