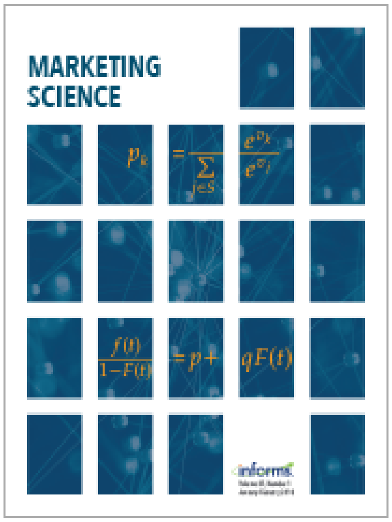

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Design Innovativeness and Product Sales' Evolution

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In the last decade, design innovation has gained increasing prominence in the marketplace, with a growing number of firms innovating not only through technology but also through novel product forms (i.e., design). However, while the effect of technological innovation on product sales is a heavily studied topic, a defining theory of how design innovation influences product sales is still missing. This paper provides demand- and supply-side theories to formulate a set of coherent hypotheses about the effect of design innovativeness, i.e., the degree of novelty in a product's design, on sales' evolution over time. The hypotheses are tested in two different samples. In the first, car models introduced in the United States from 1978 to 2006 (for a total of 2,757 model-year data) are analyzed. In the second, motorcycle models introduced in the United States from 1980 to 2008 (for a total of 2,847 model-year observations) are analyzed. I find that design innovativeness diminishes initial sales' status but increases sales' growth rates. Furthermore, design and technological innovativeness have a negative interaction effect on sales' initial status, but a positive effect on sales' growth rates. Finally, brand strength and brand advertising expenditures worsen the negative effect of design innovativeness on initial sales' status, but boost its positive effect on sales' growth rates.

Keywords: design innovativeness; technological innovativeness; individual growth curve analysis; car industry; motorcycle industry
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1. Introduction

In current competitive scenarios, technological advancements, albeit radical, are largely taken for granted, greatly limiting a firm's ability to drive sales through technological innovation alone. For instance, consumers take for granted that new cars will be more fuel efficient, and are unwilling to pay more for this feature.[1] While technology has lost relevance, design has gained prominence. For instance, design is now the second most relevant factor that consumers consider when buying cars[2] and motorcycles.[3] It should come as no surprise, therefore, that many companies are turning to design innovation, i.e., innovation in the external appearance of a product, to ward off commoditization and to stimulate demand (Hoegg and Alba 2011). As a testament to the growing strategic value of product design, the number of design patents worldwide has increased by 123% in the last 10 years, while the total number of patents has grown by 86% (WIPO Statistics Database).

In light of these trends, it is essential that we understand the effect of design innovativeness, i.e., *the degree of novelty in a product's external appearance*, on product sales. Prior literature has shown that product innovativeness has a crucial impact on sales (Szymanski et al. 2007), but has largely conceptualized it as technological in nature. Although design has emerged more recently as a fertile area of research in the marketing literature (Hoegg and Alba 2011, Chitturi et al. 2007, Landwehr et al. 2011, Talke et al. 2009), the following research questions remain unanswered.

First, how does design innovativeness influence product sales' evolution over time? This is a relevant managerial question, as introducing new designs requires significant investments. For instance, the redesign of a car model costs around $1.25 billion (Blonigen et al. 2013). The existing literature on technological innovativeness can only provide partial answers, as design and technology differ in critical ways: They satisfy different needs (Rubera et al. 2012), are evaluated in different ways (Noseworthy and Trudel 2011), and elicit different responses (Rindova and Petkova 2007). These dissimilarities highlight the importance of a large-scale, longitudinal analysis that accounts for the distinctive characteristics of design to shed light on whether substantial investments in design are well grounded or should be curtailed.

Second, what is the joint influence of design and technological innovativeness on sales? When introducing

[1] http://www.consumerreports.org/cro/news/2010/11/survey-americans-want-better-fuel-efficiency-but-don-t-want-to-pay-extra-for-it/index.htm.

[2] http://www.researchscape.com/leisure/car-truck-factor-preference-survey.

[3] http://www.prnewswire.com/news-releases/consumer-reports-survey-harley-davidson-and-bmw-less-reliable-than-japanese-motorcycles-200004881.html.

new technologies, managers face the following dilemma: Should they use a familiar design to establish a link with existing products, thereby reducing the risk that consumers face (e.g., Tivo's resemblance to a VCR) or propose radically new forms to mark a clear contrast with existing technologies, such as the Toyota Prius? So far, empirical evidence has been limited to experimental studies (Hoegg and Alba 2011, Noseworthy and Trudel 2011) with (to my knowledge) no attention to how the joint influence of design and technological innovativeness on sales evolves over time.

Finally, how do brand strength *before* launch and brand advertising expenditures *after* launch shape the effect of design innovativeness on product sales over time? Theoretically, it is important to both identify the moderators of the sales impact of design innovativeness and understand the principles underlying these effects. Answers to these questions may enable managers to derive more accurate sales predictions and determine whether, in their particular circumstance, increasing sales through design innovativeness is more effective than other actions.

To answer these critical questions, I analyze the effects of design innovativeness in two different samples. In the first sample, I consider car models introduced in the United States from 1978 to 2006 (2,757 model-year data). In the second sample, I consider motorcycle models introduced in the United States from 1980 to 2008 (2,847 model-year data). In both samples, I control for several potential variables that might influence sales at the model level (i.e., price, technological innovativeness, number of prior models, and existence of future models) and at the brand level (i.e., quality and brand reputation with design). Despite the different industry settings, the results of the two samples are perfectly consistent, increasing confidence in the validity of the findings.

This paper contributes to the marketing literature in three critical ways. First, it explains how and why the effects of design innovativeness on product sales evolve over time. I find that design innovativeness diminishes initial sales' status but increases sales' growth rates. Second, it investigates the interaction between design and technological innovativeness. I find that this interaction decreases initial sales' status while increasing growth rates. Third, it shows how the effects of product design innovativeness on sales' evolution vary depending on the level of brand strength and brand advertising expenditures. I find that these two variables worsen the negative effect of design innovativeness on initial sales' status, but boost its positive effect on growth rates.

2. Theoretical Framework

In this section I define design innovativeness and present demand- and supply-side theories to formulate a set of coherent hypotheses about the effect of design innovativeness on sales.

2.1. Design Innovativeness: Definition and Role

Over the last few years, researchers have dedicated increasing attention to the role of design, i.e., the external appearance of a product. Chitturi et al. (2007) recognized the importance of product form as a critical element that consumers consider in their purchasing decisions. Even though the literature has primarily conceptualized innovativeness as technological in nature, product design is distinct and is not predetermined by technological changes (Rindova and Petkova 2007). Thus, I define design innovativeness as *the degree of novelty in a product's external appearance*.

The external appearance of a product is inherently intertwined with the meaning of a product; by changing a product's design, firms also change the product's meaning (Eisenman 2013, Rindova and Petkova 2007, Rubera and Droge 2013). Take the case of Vespa by Piaggio. The rounded shapes and bright colors were used to convey a meaning of enjoyment and vacation in an industry dominated by masculine-shaped motorcycles designed for high speed and racing.

2.2. Design Innovativeness: Theoretical Perspectives

2.2.1. Demand-Side Theories. Because design innovativeness changes the meaning of a product, I discuss the theory of collective selection (Blumer 1969), which explains how consumers develop preferences for products with new meaning, and the theory of symbolic value creation (Hirschman 1986), which explains how consumers attach meaning to objects. Furthermore, since design innovativeness changes the external appearance of a product, I discuss the theory of internal processing algorithms (Veryzer 1999), which addresses how consumers react to new product forms.

Theory of collective selection. This theory maintains that individuals express a common taste in their design preferences (Blumer 1969), which emerges from interactions among people that are immersed in the same social world, share the same cultural references, and collectively respond to the spirit of the times (Yoganarasimhan 2012). Consumers with common tastes share the same evaluation of the fit between a new design and the cultural norms. This shared evaluation leads to a collective selection of the same design. Thus, adoption of a certain design reflects a collectively endorsed standard that the individual perceives by interacting with others. Only those designs that reflect the milieu of a particular period of time are accepted and become successful (Miller et al. 1993, Sproles 1981). According to this theory, the success of a new design does not depend on its beauty, but only on the fit between the design and the cultural norms.

Even though this theory was originally proposed to explain fashion, two elements support its use to explain the effect of design innovativeness on product sales. First, Miller et al. (1993) argue that a fashion process approach must be used to explain the diffusion of products that are not demonstrably superior to one another, as is the case with design (Cappetta et al. 2006). Second, the impossibility of objectively evaluating a design (for an extensive review refer to Charters 2006) forces consumers to rely on collective, rather than individual, judgment (Midgley 1983).

Theory of symbolic value creation. According to this theory, the value of a design is the outcome of a cultural production process that involves firms, institutional intermediaries (i.e., media and critics), and consumers (Ravasi and Rindova 2004). Designers originate new designs by "encoding in their creations a meaning, which they intend the consumer to extract" (Bloch 1995, p. 22). Then, institutional intermediaries make information available about the design's meaning, so that consumers can understand its cultural significance (McCracken 1986). The meaning of a design emerges from the complex interplay of social interactions among peer consumers who are not simply recipients, but active contributors to the creation of symbolic meaning (Hirschman 1986).

The theories of collective selection and symbolic value creation contend that social context determines the value of a particular design. Also, they both affirm that the success of a design is the outcome of a collective process. Finally, these theories suggest that a design can be successful *regardless of its beauty*, as long as consumers can collectively attach meaning to it.

Theory of internal processing algorithms. This perspective analyzes how consumers react to the physical product form, leaving any meaning or symbolic value out of the picture. Responses to a design are greatly determined by internalized preexisting rules, namely nonconsciously acquired internal processing algorithms (Bloch 1995, Veryzer 1999). When exposed to a new design, individuals evaluate its consistency with rules that have been developed over time. Individuals prefer objects that conform to these rules so that prototypicality, not beauty, determines how they respond to design innovativeness (Veryzer 1999, Landwehr et al. 2011).

Two forces might lead to changes in internal processing algorithms. First, repeated exposure to the same design creates a new set of algorithms that help consumers to like the new design (Veryzer 1999). Second, internal processing rules can change as the context changes: "Influences such as mass exposure to significant events, assimilation of new ideas or tastes into a culture, and so on, can introduce new elements and associations that may be incorporated into existing internal processing algorithms or give rise to new ones" (p. 509). Hence, the social context indirectly influences response to design by shaping the internal algorithms that regulate design evaluations.

2.2.2. Comparison with the Traditional Diffusion Theory. I now outline the similarities of and differences between the diffusion process described in the Bass model (1969) and the two-segment mixture model (Van den Bulte and Joshi 2007).

Social contagion is central to the theory of processing algorithms, as it triggers and hastens the creation of algorithms that make a novel design acceptable. The other two theories also identify social contagion as the primary mechanism through which preferences for a design emerge, but the nature of the contagion process is different. In the theory of collective selection, the social contagion process involves the definition of a collectively endorsed standard. The development of homogenous preferences about a specific design is simply a part of this broader contagion process. Thus, consumers influence each other when defining a collective standard, but do not imitate when adopting a specific design. In the theory of symbolic value, however, the social contagion is unique to a particular design, whereby consumers discuss and learn about the meaning of a certain novel form.

The different nature of the social contagion process has implications for the distinction between innovators and late adopters, as well as between influentials and imitators. In the collective selection theory, there is only room for innovators and late adopters. Consumers are said to have heterogeneous alertness to the emergence of an incipient, collective taste, which arises from different education or vocation. Consumers with high alertness play the role of innovators in Bass, as they are the first to adopt a new design, but cannot be considered influentials because consumers make their decisions independently (Blumer 1969). Consumers react alike, not out of imitation, but because they have developed homogeneous preferences through social contagion. Conversely, the theory of symbolic value creation maintains that through the practice of consumption, some consumers make the meaning of a design available to others (Ravasi and Rindova 2004). Thus, in this theory, there is room for both influentials and imitators (Van den Bulte and Joshi 2007).

2.2.3. Supply-Side Theories. The innovation diffusion literature has shown two supply-side elements that influence the sales evolution of new products, i.e., supply restrictions (Jain et al. 1991) and salespeople's commitment to sell new products (Ahearne et al. 2010).

Supply restrictions. Supply restrictions cause initial sales to be lower than demand, as consumers cannot buy the desired product. These restrictions are particularly harmful for novel designs. First, even if institutional intermediaries could convey the social meaning of a design to consumers, this would not generate sales. Second, by reducing the number of times consumers are exposed to a design, supply restrictions delay the creation of the new algorithms necessary to accept it.

Salespeople's commitment. Salespeople's commitment to sell new products is fundamental to a product's success, as it reduces the information asymmetry that consumers face when evaluating the value of a novel product (Ahearne et al. 2010). The role of salespeople is critical in the case of design for three reasons. First, adoption by salespeople signal that the design fits the collective taste. Second, salespersons play the role of institutional intermediaries that make the value of a new design available to customers. Third, by repeatedly showing the new design, committed salespeople assist in the development of new algorithms that make the design acceptable.

3. Hypotheses

In this section I hypothesize about the effect of design innovativeness on initial sales' status and growth rates, its interaction effect with technological innovativeness (i.e., the degree of novelty in a product's functions), and the moderating effects of brand strength and advertising expenditures.

3.1. Effects of Design Innovativeness

Initial sales' status. First, the theory of collective selection indicates that, as innovativeness increases, consumers become more reluctant to adopt new designs, preferring to wait for the emergence of collective tastes that declare the innovation acceptable (Sproles 1981). Declaring radical designs acceptable requires substantial shifts in collective tastes. Blumer (1969) notes that collective tastes and norms change slowly, and that sudden, dramatic shifts are quite rare. Thus, as design innovativeness increases, consumers will be more reluctant, initially, to buy. Second, the theory of symbolic value creation suggests that the social construction process through which the value of a design becomes accessible to consumers takes longer as design innovativeness increases. Hence, consumers will initially refrain from buying a radical design, as they are skeptical about its value. Third, the theory of internal processing algorithms argues that products that deviate from the typical form of a certain product category initially evoke negative reactions (Veryzer 1999). Thus, the three demand-side theories consistently suggest that initial sales will be lower as design innovativeness increases.

As for supply-side effects, products with higher design innovativeness are more likely to experience supply restrictions because they have a longer ramp-up time (i.e., the time necessary to reach the planned production volume). In fact, novel designs may require a change in the layout of a company's assembly line, machinery, tools, and/or material flow (Pufall et al. 2007). Thus, higher supply restrictions would lower initial sales' status as design innovativeness increases. As for salespeople's commitment, I contend that it is also lower with more radical designs. Even though salespeople are more informed than consumers, the effort necessary to convey the value of a design is higher at higher levels of innovativeness. As effort reduces commitment (Ahearne et al. 2010), initial sales should be lower for products with higher design innovativeness. Combining demand-side and supply-side theories, I hypothesize that:

Hypothesis 1A (H1A). *The greater the product design innovativeness, the* lower *the initial product sales' status.*

Sales' growth rates. According to the theory of collective selection and the theory of symbolic value creation, products have higher sales' growth when consumers are involved in a deeper sense-making process. This process becomes more intense at increasing levels of innovativeness because consumers and producers are more engaged when they have to understand novel products (Rosa et al. 1999). Thus, sales for products with low design innovativeness are likely to reach their plateau shortly after introduction, as the number of consumers to which they appeal does not vary over time. Conversely, products with higher design innovativeness have the potential to reach a larger group of consumers and experience higher sales growth.

The algorithms used to evaluate a design are likely to remain the same over time when design innovativeness is low because consumers can rely on pre-existing algorithms with no need to create new ones. Hence, consumer evaluations of products with low design innovativeness remain stable (whether positive or negative) throughout the product life cycle. Conversely, repeated exposure to more radical designs triggers the creation of new algorithms that make the innovations valuable (Veryzer 1999). Because consumers are increasingly exposed to new designs, the evaluation of products with radical designs should become more positive over time. Thus, product sales' growth would be greater at increasing levels of design innovativeness.

As for the supply-side effects, customers who face supply restrictions have two options, i.e., wait for future delivery or switch to substitutable products. Backlogging increases sales' growth rates: Initial demand that cannot be satisfied by initial supply is met only when the firm reaches full production. Conversely, customer migration to substitutable products reduces sales' growth: Customers forgo the purchase of the product when it is finally available because they have already been satisfied by other products. Thus, the effect of supply constraints on sales' growth rates depends on whether consumers perceive a product to be substitutable. The fact that a design is completely different from other products should cause consumers to consider products with radical designs to be non-substitutable. Thus, supply restrictions should cause higher sales' growth rates as design innovativeness increases.

As for salespeople, I maintain that, like consumers, they become, over time, more engaged with products with higher design innovativeness (see Rosa et al. 1999). Thus, I contend that salespeople's commitment to lead consumers into the social sense-making process that generates sales' growth is higher for products with higher design innovativeness. In sum, demand-side and supply-side effects lead us to hypothesize that:

Hypothesis 1B (H1B). *The greater the product design innovativeness*, *the* higher *the product sales' growth rate*.

3.2. Interaction Effects Between Design Innovativeness and Technological Innovativeness

Product design influences the way consumers evaluate product function. This influence is *independent of the aesthetic appeal* of the design (Hoegg and Alba 2011, Noseworthy and Trudel 2011). The existence of such an influence suggests that design innovativeness interacts with technological innovativeness to shape the sales evolution of a product.

Initial sales' status. Products with high technological innovativeness are initially characterized by high levels of risk and uncertainty (Chandy and Tellis 2000). The categorization-based knowledge transfer paradigm suggests that firms can use a familiar product form to facilitate transfer of knowledge from a known product to a new one (Gregan-Paxton and John 1997). Thus, initial sales' status should be lower when high technological innovativeness is coupled with high design innovativeness because a high degree of design innovativeness delays the transfer of knowledge by making it difficult to establish a connection between new technology and an existing product.

On the supply side, the development of products with high levels of both design and technological innovativeness should cause higher supply restrictions than products with low levels of either or both types of innovativeness; these extremely radical products would require a significant change in the firm's production facilities. Also, the complexity of products that couple design and technological innovativeness should reduce salespeople's commitment. Thus:

Hypothesis 2A (H2A). *There is a* negative *interaction effect between technological innovativeness and design innovativeness on initial sales' status*.

Sales' growth rates. Low design innovativeness prompts consumers to activate certain preexisting schema to understand technological innovations. This schema might dominate consumer understanding of a new technology in such a way that "the new possibilities and solutions generated by the technological novelty may remain unnoticed, uncomprehended, and underappreciated" (Rindova and Petkova 2007, p. 224). This may hurt sales' growth rates, as consumers might not fully appreciate the relative advantage of a new technology. On the other hand, by providing a visual cue for new functionalities, design innovativeness may make the advantages of new technology more evident to consumers. Rindova and Petkova (2007) provide the example of TiVo cable box, which was designed to externally resemble a VCR. The visual similarity helped boost initial sales. Still, after a while, consumers perceived TiVo as merely an improved VCR, which dampened long-term sales. Also, design innovativeness can keep the interest in a product alive over time, even past the initial excitement for novel technology, keeping salespeople committed to promoting the product. Hence, I hypothesize that:

Hypothesis 2B (H2B). *There is a* positive *interaction effect between technological innovativeness and design innovativeness on sales' growth rates*.

3.3. Moderating Effects of Brand Strength

Initial sales' status. At the brand level, a distinctive characteristic of design is its potential to change the meaning and image of the brand (Karjalainen and Snelders 2009, Srinivasan et al. 2012). Radical changes in the external appearance might compromise the brand image in the marketplace (Kreuzbauer and Malter 2005). Thus, before buying products with high design innovativeness, consumers must overcome the deviation from brand image and its associations. Because strong brands have better established associations than weak brands, I argue that brand strength exacerbates the negative effect of design innovativeness on the initial product sales' status. Hence:

Hypothesis 3A (H3A). *The effect of design innovativeness on initial sales' status becomes more negative as brand strength increases*.

Sales' growth rates. I have discussed how sales grow more as consumers are further exposed to a new design. Here, strong brands have an advantage over weak brands because consumers pay more attention to the innovation introduced by strong brands. This increased attention subtly increases the frequency at which consumers are exposed to the innovation, thus facilitating the creation of new internal algorithms that make novel design acceptable. Thus:

Hypothesis 3B (H3B). *The effect of design innovativeness on sales' growth rates becomes more positive as brand strength increases*.

3.4. Moderating Effects of Brand Advertising Expenditures

Brand advertising expenditures have a spillover effect on products sales; information about a brand is transferred to its products (Sullivan 1990). I investigate how brand advertising expenditures, starting at the year of launch of a new product, interact with design innovativeness to influence a product's sales evolution. Because information provided by advertising accumulates over time, I investigate cumulative brand advertising expenditures.

Initial sales' status. Advertising is a means for brands to convey the meaning of an innovation and to increase consumers' exposure to it. Thus, the social exchange between consumers and producers that culminates with the acceptance of a design should start earlier for products made by brands that heavily invest in advertising. Similarly, consumers should be more exposed to novel designs introduced by brands that heavily invest in advertising, leading to a more rapid acceptance of the novel design. On the supply-side, recent research has shown that salespeople have higher commitment toward products introduced by brands with high advertising expenditures (Hughes 2013) because they are more confident that their efforts will generate results. Hence:

Hypothesis 4A (H4A). *The effect of design innovativeness on initial sales' status becomes more positive as brand advertising expenditures increase.*

Sales' growth rates. Brand advertising expenditures positively influence the mechanisms that cause sales' growth for products with high design innovativeness. First, brand advertising expenditures can facilitate the social construction process by making the meaning of a product's design more easily available to consumers (Ravasi and Rindova 2004). Second, brand advertising expenditures increase the number of times a consumer is exposed to the design innovation, making consumers more prone to adapt their internal algorithms and accept design innovations from brands with higher advertising expenditures. Hence, for the same level of design innovativeness, sales should grow more for products introduced by brands with higher advertising expenditures. Formally:

Hypothesis 4B (H4B). *The effect of design innovativeness on sales' growth rates becomes more positive as brand advertising expenditures increase.*

4. Method

This section describes the data collection and measures.

4.1. Data Collection

I test the hypotheses with two product categories, i.e., cars and motorcycles. In these industries, the typical design process extends over a period of a few years. It starts with a characterizing brief that provides designers with a context for the model they are about to create. For example, the brief for the new Fiat 500 was "To create the heir to a veritable icon of our times." Then, designers begin sketching the basic layout and lines of the incipient vehicle. The numerous solutions are gradually whittled down on the basis of considerations related to technological feasibility, cost, and consistency with the meaning outlined in the original briefing. After selecting a solution, digital renderings and clay prototypes are used to modify the styling until the model is finalized. New models debut at motor shows, which are the principal means by which journalists, dealers, and consumers are informed of a brand's innovation. Journalists are also invited to test drive the new models and provide their opinions to consumers in specialized magazines.

For cars, I analyze models introduced in the United States from 1978 to 2006. Every time a new generation of a model is introduced, I count it as a new model. This is necessary to account for the common automobile industry practice of updating existing models, while keeping the nameplate constant. For instance, Dodge introduced two different generations of the Intrepid in the period under study. I consider these two generations as two different models. A total of 502 models introduced by 37 brands from 1978 to 2006 have been identified (2,757 model-year observations).

For motorcycles, I analyze models introduced in the United States from 1980 to 2006. Also in this case, every time a new generation of a nameplate is introduced, I count it as a new model. A total of 574 models introduced by 20 brands have been identified (2,847 model-year observations).

4.2. Measures

Model sales. For cars, I collect yearly sales data from Ward's Auto Yearbook. For motorcycles, I use Polk, the leading provider of marketing information for the motorcycle industry. Polk provides a database based on the registration data in the National Vehicle Population Profile database and the Vehicle Identification Number codes used to track makes and models. This database provides information about the number of models sold every year in the U.S. market. I had many discussions with the Polk managers who explained that only motorcycles that are bought to be kept in a garage (i.e., collectors) can be sold without being registered. Hence, I am confident that my database contains accurate information about every motorcycle sold in the United States during the period of study.

Model design innovativeness. I adopt a historical analysis to measure design innovativeness (Golder and Tellis 1993). This technique relies on the use of past records from publicly available, published sources of information. Because designs are centered in a social milieu and may be considered differently in retrospect, a historical method is particularly well suited because it provides information collected at the time a design was introduced. Because expert evaluations are made when a new model is introduced in the market, the historical method eliminates the concern that today's experts may find older innovations harder to evaluate than more recent ones.

As for the car industry, I reviewed the following magazines that provide detailed reviews of new cars: Road and Track, Automotive News, Car and Driver, and Autoweek. I studied 80 car reviews and created a dictionary of phrases that capture the extent of design innovativeness, ranging from no innovation (1) to radical innovation (5) (see Appendix A). Consistent with prior research (e.g., Pauwels et al. 2004) I use a multilevel categorization to build my measure of design innovativeness. Two research assistants then rated the design innovativeness of all car models. I met with the research assistants to resolve discrepancies between the raters. Following the meeting, the inter-rater reliability of the measure of design innovativeness was 85%. The measure of design innovativeness has a mean of 2.28 and a standard deviation of 1.14. Sixty percent of the cars have a score of 2 or lower; 19% have a score of 4 or 5.

Adopting the same procedure for the motorcycle industry, I reviewed the following magazines: Motorcyclist, Motorcycle Consumer News, Cycle World, and Motorcycle USA. After studying 90 reviews, I concluded that the dictionary in Appendix A could be applied to the motorcycle industry as well. Two research assistants (different from those used for the car industry) then rated the design innovativeness of all motorcycle models. I met with the research assistants to review the ratings and resolve discrepancies. At the end of this process, the inter-rater reliability was 82%. Design innovativeness has a mean of 2.85, and a standard deviation of 1.11; 40% of the motorcycles have a score of 2 or lower; 28% have a score of 4 or 5. Appendix A provides examples of cars/motorcycles for each level of design innovativeness and excerpts of reviews.

Model technological innovativeness. I also measure technological innovativeness using the historical method, the same reviews used to measure design innovativeness, and the dictionary provided in Appendix B. The inter-rater reliability for both industries is 87%. Appendix B provides examples of models for each level of technological innovativeness along with review excerpts. In the car industry, technological innovativeness has a mean of 2.18 and a standard deviation of 1.01; in the motorcycle industry, it has a mean of 1.99 and a standard deviation of 1.12.

Brand strength. This variable reflects the strength of a brand the year a new model was launched. I use a brand's past advertising expenditures, accumulated before the launch of a new model, as a proxy for its strength. Because the effect of brand advertising declines over time, I use a five-year period to construct my measure of brand strength, with a depreciation factor of 1/6 every year. I collect yearly data on brand advertising expenditures from Brandweek Directory.

Brand advertising expenditures. This is a cumulative variable that accounts for the brand expenditures since the year of a new model introduction. Also in this case, I use a depreciation factor of 1/6 every year to account for the diminishing effect of advertising expenditures on sales.

I use five control variables in the model.

Model price. Because price may reduce sales, I control for the Manufacturer's Suggested Retail Price (MSRP) of each model. I collect data from the same magazines described above as well as Consumer Reports.

Future generation. Successful models are typically followed by new generations (Blonigen et al. 2013). I control for this with a dummy variable that takes on a value of 1 if the model is followed by another generation, and 0 otherwise.

Number of previous generations. Consumers may interpret the number of previous generations as a sign that a company is constantly upgrading its product, and hence as an indication of superior quality of the new model (Strausz 2009). Alternatively, consumers may anticipate the introduction of a new generation, wait for that, and stop buying the old generation (Purhoit 1992), thus causing later sales of the older model to decline. I control for the number of generations that preceded a model. For instance, Dodge introduced two generations of the Intrepid: 1992 and 1998. This variable takes on 0 for the 1992 model and 1 for the 1998 model.

Prior brand design innovativeness. Consumers may be more favorably disposed toward brands with a history of radical design products. Thus, I control for the average design innovativeness of the models that a brand introduced in the years preceding the introduction of the focal model.

Brand quality. Consumers may be more favorably disposed toward products introduced by high quality brands. I calculate the average quality of the models that a brand introduced in the year preceding the introduction of the focal model. I use Consumer Reports' Vehicle Ratings for cars and Motorcycle Consumer News for motorcycle models.

5. Model Estimation

The data consists of repeated observations of sales over time nested within car/motorcycle models, which are in turn nested within brands and categories.[4] Treating this longitudinal data as multilevel and nested enables researchers to examine the existence, nature, and causes of within-model sales changes over time (Deadrick et al. 1997). Hence, I use individual growth curve analyses using a Stata xtmixed procedure to determine changes over time in sales, and to estimate the effects of design innovativeness. The procedure involves three main steps: (1) performing a set of expectation-maximization iterations to refine the starting values; (2) when convergence is reached, maximization switches to iterative gradient-based optimizations based on the Newton-Raphson algorithm, which requires the calculation of a gradient vector and Hessian matrix; (3) reparameterizing from the matrix-based parameterization to the natural metric of variance components and their estimated standard errors. This last step is necessary to interpret the estimated parameters individually, rather than the element of a matrix logarithm. Following Singer (1998), I fit an unconditional means model and an unconditional growth model. The results are then used to build the foundation for the subsequent analyses shown. To test for the hypothesized effects, I account for the implicit variable of time in the growth model.

5.1. Unconditional Means Model

First, an unconditional (no predictors) four-level model is estimated. At the first level, car model[5] sales at each time period are modeled as a function of car model mean sales plus a random error

$$\text{Level 1: } \text{Sales}_{tmbc} = Y_{tmbc} = \pi_{0mbc} + e_{tmbc}, \tag{1-1}$$

where t, m, b, and c denote time, car model, brands, and categories, respectively; π_{0mbc} is the mean sales (across time) of car model m in brand b in category c; e_{tmbc} is the time-level random error and represents variance *across* time. It is assumed to be distributed normally, with a mean of zero and variance of σ^2, which is assumed to be uniform among the observations within each of the m models.

At the second level of analysis, the car model mean sales over time, π_{0mbc}, is simultaneously modeled as an outcome, varying randomly around some brand b in category c mean

$$\text{Level 2: } \pi_{0mbc} = \beta_{00bc} + r_{mbc}, \tag{1-2}$$

[4] For cars, I identify the following nine categories: compact, coupe, large, luxury, medium, minivan, sedan, sporty, and subcompact. For motorcycles, I identify the following nine categories: all-around, cruiser, dirt bike, motocross, naked, scooter, sport, enduro, and touring.

[5] Here I describe the analysis procedure for the car models. The procedure is the same for motorcycle models.

where β_{00bc} is the mean sales of the car model in brand b and category c; and r_{mbc} is the random *between-car model* residual assumed to be normally distributed, with a mean of zero and variance of τ_π. This between-car model variance is assumed to be uniform across car models within each of the b brands and c categories.

Level 3 models variation between brands within categories as a function of category-level variation

$$\text{Level 3: } \beta_{00bc} = \gamma_{000c} + \upsilon_{bc}, \tag{1-3}$$

where γ_{000c} is the mean sales of brands in category c; υ_{bc} is the random *between-brands* residual, assumed to be normally distributed with mean zero and variance τ_β (the between-brand variance).

At the fourth level of analysis, the intercept of the brand-level model is simultaneously modeled as an outcome varying randomly around a grand mean

$$\text{Level 4: } \gamma_{000c} = \theta_{0000} + v_c, \tag{1-4}$$

where θ_{000} represents the grand mean of car model sales across brands and categories, and v_c is the random *between-categories* residual. It is assumed that v_c is normally distributed with mean zero and variance τ_γ, which represents the between-categories variance.

This model partitions the total variability in the outcome Y_{tmbc} to four components: Level 1 across time σ^2, Level 2 among car models within brands, τ_π, Level 3 among brands within categories, τ_β, and Level 4 among categories, τ_γ. The amount of total variance attributable to each level is calculated as follows: $\sigma^2/(\sigma^2+\tau_\pi+\tau_\beta+\tau_\gamma)$ is the proportion of variance across time; $\tau_\pi/(\sigma^2+\tau_\pi+\tau_\beta+\tau_\gamma)$ is the proportion of variance between car models; $\tau_\beta/(\sigma^2+\tau_\pi+\tau_\beta+\tau_\gamma)$ is the proportion of variance between brands; and $\tau_\gamma/(\sigma^2+\tau_\pi+\tau_\beta+\tau_\gamma)$ is the proportion of variance between categories.

5.2. Unconditional Growth Model

I now introduce the time variable (i.e., years). The Level 1 equation estimates the individual car model's trajectory of sales growth (π_{1mbc} and π_{2mbc}) in addition to the mean (π_{0mbc}). The Level 2 equation simultaneously partitions the three estimates into sample averages and error components

$$\text{Level 1: } \text{Sales}_{tmbc} = \pi_{0mbc} + \pi_{1mbc}\text{Time}_{tmbc} + \pi_{2mbc}\text{Time}^2_{tmbc} + e_{tmbc}, \tag{2-1}$$

$$\text{Level 2: } \pi_{0mbc} = \beta_{00bc} + r_{0mbc}, \quad r_{0mbc} \sim N(0, \tau_{\pi 0}), \tag{2-2a}$$

$$\text{Level 2: } \pi_{1mbc} = \beta_{10bc} + r_{1mbc}, \quad r_{1mbc} \sim N(0, \tau_{\pi 1}), \tag{2-2b}$$

$$\text{Level 2: } \pi_{2mbc} = \beta_{20bc}, \tag{2-2c}$$

$$\text{Level 3: } \beta_{00bc} = \gamma_{000c} + \upsilon, \quad {}_{00bc}\upsilon_{00bc} \sim N(0, \tau_{\beta 00}), \tag{2-3a}$$

$$\text{Level 3: } \beta_{10bc} = \gamma_{100c}, \tag{2-3b}$$

$$\text{Level 3: } \beta_{20bc} = \gamma_{200c}, \tag{2-3c}$$

$$\text{Level 4: } \gamma_{000c} = \theta_{0000} + v_{000c}, \quad v_{000c} \sim N(0, \tau_{\gamma 000}), \quad \text{(2-4a)}$$

$$\text{Level 4: } \gamma_{100c} = \theta_{1000}, \quad \text{(2-4b)}$$

$$\text{Level 4: } \gamma_{200c} = \theta_{2000}, \quad \text{(2-4c)}$$

where π_{0mbc}, π_{1mbc}, π_{2mbc} represent initial status, growth rate, and curvilinear growth rate, respectively, for car model m, in brand b, in category c. The time variable represents the number of years since the car model was introduced. Although I did not hypothesize the quadratic effects determined by π_{2mbc} I use the coefficients to determine the shape of the nonlinear results.

In Level 2, the initial status for each individual model m, in brand b, in category c is modeled as a function of the initial status for brand b, in category c (i.e., β_{00bc}) and its random effect. Similarly, the (quadratic) growth rate is modeled as the (quadratic) growth rate for brand b, in category c.

In Level 3, the fixed effect coefficients γ_{000c}, γ_{100c}, and γ_{200c} represent mean initial status, mean growth rate, and mean quadratic growth rate, respectively, across brands for category c. The random effect v_{00bc} captures each brand's deviation from the category c mean initial status.

In Level 4, θ_{0000}, θ_{1000}, and θ_{2000} represent the grand mean initial status, grand mean growth rate, and grand mean acceleration, respectively.

5.3. Conditional Growth Model

I then add the car model-level predictors to investigate whether growth in sales depends on car-level and brand-level predictors (I show this model in Table 1). The final model is as follows:

$$\text{L1: } \text{Sales}_{tmbc} = \pi_{0mbc} + \pi_{1mbc}\text{Time}_{tmbc} + \pi_{2mbc}\text{Time}^2_{tmbc} + e_{tmbc}, \quad \text{(3-1)}$$

$$\text{L2: } \pi_{0mbc} = \beta_{00bc} + \beta_{01bc}DI_{mbc} + \beta_{02bc}TI_{mbc} + \beta_{03bc}(DI_{mbc} \times TI_{mbc}) + r_{0mbc}, \quad r_{0mbc} \sim N(0, \tau_{\pi 0}), \quad \text{(3-2a)}$$

$$\text{L2: } \pi_{1mbc} = \beta_{10bc} + \beta_{11bc}DI_{mbc} + \beta_{12bc}TI_{mbc} + \beta_{13bc}(DI_{mbc} \times TI_{mbc}) + r_{1mbc}, \quad r_{1mbc} \sim N(0, \tau_{\pi 1}), \quad \text{(3-2b)}$$

$$\text{L2: } \pi_{2mbc} = \beta_{20bc}, \quad \text{(3-2c)}$$

$$\text{L3: } \beta_{00bc} = \gamma_{000c} + \gamma_{001c}BStr_{bc} + \gamma_{002c}BAd_{bct} + v_{00bc}, \quad v_{00bc} \sim N(0, \tau_{\beta 00}), \quad \text{(3-3a)}$$

$$\text{L3: } \beta_{01bc} = \gamma_{010c} + \gamma_{011c}BStr_{bc} + \gamma_{012c}BAd_{bct}, \quad \text{(3-3b)}$$

$$\text{L3: } \beta_{10bc} = \gamma_{100c} + \gamma_{101c}BStr_{bc} + \gamma_{102c}BAd_{bct}, \quad \text{(3-3c)}$$

$$\text{L3: } \beta_{11bc} = \gamma_{110c} + \gamma_{111c}BStr_{bc} + \gamma_{112c}BAd_{bct}, \quad \text{(3-3d)}$$

$$\text{L4: } \gamma_{000c} = \theta_{0000} + v_{000c}, \quad v_{000c} \sim N(0, \tau_{\gamma 000}), \quad \text{(3-4a)}$$

where *DI* stands for Design Innovativeness, *TI* for Technological Innovativeness, *BStr* for Brand Strength before launch and *BAd* for brand advertising expenditures after launch. Following Singer (1998), I center model-level variables at their grand mean and brand-level variables at their category mean. For the sake of simplicity, I omit the control variables detailed above.

6. Results

The demand-side theories maintain that consumers rely on collective tastes to evaluate a novel design and that this collective process becomes more evident as the innovativeness of a design increases. Supporting this contention, I find that the variance of sales decreases as the level of design innovativeness increases (i.e., standard deviation ranges from 78,506 to 28,877 as design innovativeness increases from 1 to 5 in the car industry and from 2,893 to 2,547 in the motorcycle industry). This reduced variance indicates that consumers react more alike, or collectively, as design innovativeness increases. Conversely, the variance of sales increases as technological innovativeness increases (from 53,857 to 111,131 in the car industry; from 2,290 to 3,246 in the motorcycle industry). Thus, I find support for the contention that the evaluation of design innovativeness is a collective process, while the evaluation of technological innovativeness is more individual.

I now present results for the car and motorcycle samples, separately, as well as the results of the robustness analysis. I use a maximum restricted likelihood estimation approach.

6.1. Car Sample

The results for the car sample are provided in Table 1. Although not shown in Table 1, I first estimate the unconditional means model to calculate the proportion of sales variance that occurs across time, between car models, brands, and categories. The variance in sales that occurs across time is 39.7%; between car models, 24.3%; between brands, 18.4%; and between categories, 7.3%. The unconditional growth model (not reported here, but available from the author) indicates that the average car model has initial sales of 56,359 units ($p < 0.001$), and that sales increase by 5,676 units per year ($p < 0.001$). The quadratic term is significant ($\theta = -1{,}074.53$, $p < 0.001$), which indicates that sales grow but at a decreasing rate. I then compared the main effects model with a full model, also including the interaction effects. The likelihood test indicates that the full model has a better fit ($\Delta\chi^2(6) = 104.67$, $p < 0.001$). Thus, I use the full model for hypotheses testing. I find a negative relationship between design innovativeness and initial sales' status ($\theta = -9{,}950.61$; $p < 0.01$), which indicates that the higher the design innovativeness

Table 1 **Results of the Growth Curve Modeling Analysis**

	Car sample	Motorcycle sample
Intercept	42,462.19 (9,342.37)***	1,648.02 (250.93)***
Fixed effects: Initial status		
Time	3,240.91 (1,513.57)**	−139.32 (47.20)***
Time^2	−985.87 (151.48)***	5.98 (3.24)*
Design innovativeness H1A (−)	−9,950.61 (3,128.75)***	−380.18 (104.95)***
Tech innovativeness	1,291.93 (2,669.70)	312.84 (80.29)***
Design innov. × Tech innov. H2A (−)	−7,649.96 (2,393.30)***	−336.18 (67.08)***
Brand strength	0.03 (0.02)	0.02 (0.05)**
Brand advertising	0.02 (0.006)***	0.03 (0.009)***
Design innov. × Brand strength H3A (−)	−0.08 (0.02)***	−0.02 (0.004)***
Design innov. × Brand advert. H4A (+)	−0.01 (0.004)*	−0.01 (0.006)*
Fixed effects: Growth rates		
Design innov. × Time H1B (+)	2,596.78 (636.52)***	95.38 (25.01)***
Tech innov. × Time	−25.94 (514.17)	−51.54 (19.23)***
Design innov. × Tech innov. × Time H2B (+)	1,423.50 (499.72)***	83.92 (16.30)***
Brand strength × Time	−0.004 (0.005)	−0.003 (0.001)***
Brand advertising × Time	−0.003 (0.001)***	−0.003 (0.001)***
Design innov. × Brand strength × Time H3B (+)	0.02 (0.004)***	0.002 (0.001)**
Design innov. × Brand advert. × Time H4B (+)	0.002 (0.0001)***	0.002 (0.001)***
Control variables		
Price	−0.40 (0.21)*	−0.05 (0.02)*
Price × Time	−0.13 (0.05)***	0.01 (0.006)
Price × Time^2	0.02 (0.005)***	−0.0002 (0.0005)
Future generation	14,781.07 (5,665.34)***	−762.15 (393.94)
Future generation × Time	2,932.62 (1,040.39)***	188.02 (95.58)
Number prior generations	10,296.89 (1,812.30)***	265.96 (277.18)
Number prior generations × Time	−389.05 (306.88)	43.95 (59.61)
Brand prior design innovativeness	−5,834.19 (3,625.72)	362.06 (165.71)**
Brand quality	−4,208.03 (3,821.9)	−2.21 (7.62)
Random effects		
r_{1mbc} (time)	7,293.57**	173.49**
r_{0mbc} (model)	42,294.95**	1,356.26**
υ_{00bc} (brand)	42,219.23**	419.65**
v_{000c} (category)	18,991.45**	233.58**
e_{tmbc}	18,300.06***	1,229.62**
−2 log-likelihood	21,467.76	20,980.37

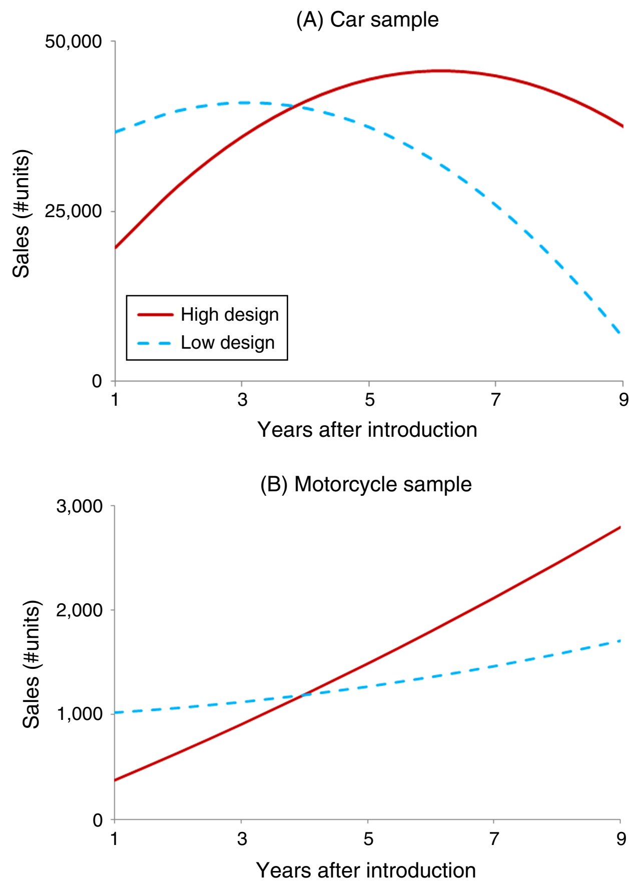
Note. Standard errors are reported in parentheses.
$^*p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

of a car model, the lower its sales in the first year, in support of H1A. The positive interaction effect between design innovativeness and time ($\theta = 2{,}596.78$, $p < 0.01$) indicates that design innovativeness positively affects the growth rate of car sales, in support of H1B. I also test for a possible interaction effect between design innovativeness and time squared. I find that this interaction effect is not significant ($\theta = -146.01$, $p > 0.05$), thus indicating that sales grow in a nonlinear way, i.e., design innovativeness increases growth rates, but this increase does not vary over time. Figure 1(A) depicts the sales' evolution of car models at high and low levels of design innovativeness (i.e., one standard deviation above/below the mean).

Technological innovativeness has no effect on initial sales' status ($\theta = 1{,}291.93$; $p > 0.05$) and growth rates ($\theta = -25.94$, $p > 0.05$). Brand strength has no effect on initial sales' status ($\theta = 0.03$; $p > 0.05$) and growth rates ($\theta = -0.004$, $p > 0.05$). Brand advertising expenditures increase initial sales ($\theta = 0.02$; $p < 0.01$) and decrease growth rates ($\theta = -0.003$; $p > 0.01$). To alleviate possible concerns about reverse causality, I ensured that I have sufficient time variation in advertising and performed the Granger causality Wald tests. The results indicate that product sales do not "Granger cause" brand advertising ($\chi(1) = 2.57$, $p > 0.05$). I believe that the fact that I measure advertising at the brand level, rather than at the product level, may explain the lack of reverse causality in this study. Indeed, it may be difficult for a single product to influence, by itself, the advertising expenditures of an entire brand, which has several products on the market, each with different growth rates.

The interaction effect between design and technological innovativeness decreases initial sales' status ($\theta = -7{,}649.96$; $p < 0.01$), but does increase sales' growth

Figure 1 (Color online) Sales' Evolution for Products with Low vs. High Design Innovativeness (Desinn)



rates ($\theta = 1{,}423.50$; $p < 0.01$), supporting H2A and H2B. Also, there is a negative interaction effect between design innovativeness and brand strength on sales' initial status ($\theta = -0.08$; $p < 0.01$), supporting H3A. This negative interaction effect is consistent with prior studies that have shown that innovation is more beneficial for brands with low quality (e.g., Nowlis and Simonson 1996). Also, I find a positive interaction effect between brand strength and sales' growth rate ($\theta = 0.02$; $p < 0.01$), supporting H3B. The case of the BMW 7 Series replicates these findings very well. When BMW unveiled the 7 Series in 2001, customers reacted vehemently against the odd form that was completely distant from the classic "pouncing cat" profile for which BMW is famous. Initially, BMW buyers were so irritated that some of them even campaigned to have Bangle, the chief of design responsible for the new model, fired. However, over time, BMW leveraged its brand strength to communicate to consumers the value of the new design. Eventually, the new model became the most successful BMW series ever, in terms of sales.

Design innovativeness and brand advertising expenditures have a negative interaction effect on initial sales' status ($\theta = -0.01$; $p < 0.10$), albeit at the 10% level only, rejecting H4A. A possible explanation may be the fact that salespeople interpret advertising expenditures as an indication of the brand's commitment to support its products, and thus believe that products from brands that heavily invest in advertising will sell by themselves. Thus, salespeople prefer to focus on products from brands with low advertising investments to support them (Ahearne et al. 2010). The high relevance of salespeople in determining which car consumers eventually buy may explain the negative effect that I find. Design innovativeness and brand advertising expenditures have a positive interaction effect on growth rates ($\theta = 0.002$; $p < 0.01$), supporting H4B.

Summarizing, the negative effect of design innovativeness on initial sales' status becomes more negative at higher levels of brand strength and brand advertising expenditures. Conversely, the positive effect of design innovativeness on sales' growth rates increases at increasing levels of brand strength and brand advertising expenditures.

I find that price has a negative effect on initial sales' status ($\theta = -0.40$; $p < 0.10$) and growth rates ($\theta = -0.13$; $p < 0.01$). The positive interaction effect with time squared ($\theta = 0.02$; $p < 0.01$) indicates that the effect of price on the growth rate of sales becomes more negative at an increasing rate. Thus, as time passes, consumers become more sensitive to price. Models followed by a future generation have higher initial sales ($\theta = 14{,}781.07$; $p < 0.01$) and sales growth ($\theta = 2{,}932.62$; $p < 0.01$): The existence of a future generation indicates that the model has been successful. Models preceded by more previous generations have higher initial status ($\theta = 10{,}296.89$; $p < 0.01$) but not higher growth ($\theta = -389.05$; $p < 0.05$). I conclude that, initially, consumers infer the quality of a model from the number of previous generations because they have little information about the real quality of a model. As time passes and consumers become better informed, such clues lose relevance.

Finally, I run a variance decomposition analysis to estimate (a) the proportion of variance of sales explained by the independent variables, and (b) the proportion of variance explained for each level. To do this, I examine the estimates of random effects. The final model explains 23.1% of the variance in the model level (calculated as $(r^{UM}_{0mbc} - r^{CG}_{0mbc})/r^{UM}_{0mbcb}$), where UM refers to the unconditional means model and CG to the conditional growth model presented in Table 1; 24.9% of the variance in the time level; 10.4% of the variance in the brand level; and 9.5% of the variance in the category level. The model explains 17% of the total variance in car sales.

6.2. Motorcycle Sample

The results for the motorcycle sample are provided in Table 1. The unconditional means model reveals that the variance in sales across time is 5.3%; between motorcycle models, 39.5%; between brands, 17.9%; and between categories, 6%. The unconditional growth model (not reported here, but available from the author) shows that initial sales for the average motorcycle model are 2,075 ($p < 0.001$) and increase by 102 units per year ($p < 0.001$). The quadratic term of time is negative ($\theta = -8.33$; $p < 0.001$), indicating that sales grow but at a decreasing rate.

Because the full model has a better fit than the main effects only model ($\Delta\chi^2(6) = 67.31$; $p < 0.01$) I use the full model for hypotheses testing. Design innovativeness negatively influences initial sales' status ($\theta = -380.18$; $p < 0.01$), but it positively influences the growth rate of motorcycle sales ($\theta = 95.38$; $p < 0.01$), supporting H1A and H1B. The interaction effect between design innovativeness and time squared is not significant ($\theta = 2.56$; $p > 0.05$). Figure 1(B) depicts sales' evolution of motorcycle models at high (i.e., one standard deviation above the mean) and low (i.e., one standard deviation below the mean) levels of design innovativeness. Technological innovativeness has a positive effect on initial sales' status ($\theta = 312.84$; $p < 0.01$), but a negative effect on growth rate ($\theta = -51.54$; $p < 0.01$). Brand strength has a positive effect on initial sales' status ($\theta = 0.02$; $p < 0.01$), but a negative effect on growth rate ($\theta = -0.003$; $p < 0.01$). Brand advertising increases initial sales' status ($\theta = 0.03$; $p < 0.01$), but decreases growth rates ($\theta = -0.003$; $p < 0.01$). The results of the Wald test indicate that product sales do not "Granger cause" brand advertising ($\chi(1) = 0.89$; $p > 0.05$). Also in this case, I have meaningful variation in advertising over time to run a Granger test.

The interaction effect between design and technological innovativeness decreases initial sales' status ($\theta = -336.18$; $p < 0.01$), but increases sales' growth rates ($\theta = 83.92$; $p < 0.01$), in support of H2A and H2B. The interaction between design innovativeness and brand strength negatively influences initial sales' status ($\theta = -0.02$; $p < 0.01$) and positively influence sales' growth rate ($\theta = 0.002$; $p < 0.05$), supporting H3A and H3B. Finally, the interaction effect between design innovativeness and brand advertising expenditures on initial sales' status is negative ($\theta = -0.01$; $p < 0.10$), albeit at the 10% level, rejecting H4A; the effect on sales' growth rates is positive ($\theta = 0.002$; $p < 0.01$), supporting H4B. Price has a negative effect on initial sales' status ($\theta = -0.05$; $p < 0.10$), but not on growth rates ($\theta = 0.01$; $p > 0.05$). The interaction with time squared ($\theta = -0.0002$; $p > 0.05$) is not significant. Thus, in this industry, consumers are sensitive to price, but only initially, even after accounting for random effects of model, brand, category, and time.[6] The existence of a succeeding generation and the number of previous generations has no effect on initial sales' status or growth rates. I attribute these nonsignificant results to the fact that, in my samples, new generations are much less frequent in the motorcycle industry than in the car industry. The model explains 26.4% of the total variance in motorcycle sales; 29.7% of the variance in the model-level; 30.7% of the variance in the time-level; 48.1% of the variance in the brand-level; and 8.2% of the variance in the category-level.

[6] In both the car and motorcycle industries, I also run an analysis with fixed effects at the model, brand, and category levels. The price estimates are consistent with those of the main analysis.

6.3. Robustness Analyses

I test the robustness of the findings in several ways.

Log sales. To control for possible heteroskedasticity, I estimate my models with the log of sales as dependent variables. Results, available from the author, remain the same.

Different measures of innovativeness. Results, available from the author, do not change when I measure the level of design and technological innovativeness as a dichotomous variable (i.e., incremental versus radical). Also, because my innovativeness measures are categorical, I used a Helmert coding to estimate the direct effects model. The results, available from the author, show that the effect of design innovativeness on sales' initial status decreases at increasing levels of design innovativeness, while the effect on sales' growth rates increases at increasing levels of design innovativeness. Thus, the results are robust with respect to different measures of innovativeness.

Cumulative sales. The theoretical framework relies on the social contagion process. Thus, I include cumulative sales as a proxy of this process. Because the theory suggests that the effect of social contagion becomes stronger at increasing levels of design innovativeness, I also test for the interaction effect with design innovativeness. The results, reported in Table 2, indicate that the hypothesized effects remain invariant when cumulative sales enter the model. Furthermore, while cumulative sales have a negative effect in the car sample, they have a positive effect in the motorcycle sample. This difference may be due to the fact that cumulative sales may be subject to a saturation effect in the car market, while they suggest the existence of an imitation effect in the motorcycle market. The existence of a significant and positive interaction effect between cumulative sales and design innovativeness in both samples provides support for the critical assumption in the demand-side theories that social contagion becomes more relevant as design innovativeness increases. I also test for a possible effect of cumulative sales on growth. The effect is not significant both in the car ($\theta = 0.01$; $p > 0.05$) and motorcycle industries ($\theta = 0.001$; $p > 0.05$).

Omitted-variable bias. The literature has identified four main variables that may shift both my measures of design innovativeness and sales. These variables

Table 2 Results of the Growth Curve Modeling Analysis

	Car sample		Motorcycle sample	
Intercept	39,899.56	(9,450.09)***	1,631.01	(241.28)***
Fixed effects: Initial status				
Time	5,842.19	(1,565.31)***	−152.97	(46.62)**
Time^2	−1,017.45	(149.51)***	5.06	(3.23)
Design innovativeness H1A (−)	−10,015.36	(3,180.16)***	−357.10	(102.73)***
Technology innovativeness	583.10	(2,679.94)	317.99	(79.24)***
Design innov. × Technology innov. H2A (−)	−7,118.96	(2,397.26)***	−329.75	(66.25)***
Brand strength	0.02	(0.02)	0.02	(0.005)***
Brand advertising	0.03	(0.006)***	0.03	(0.009)***
Design innov. × Brand strength H3A (−)	−0.07	(0.02)***	−0.02	(0.005)***
Design innov. × Brand advert. H4A (+)	−0.01	(0.004)**	−0.012	(0.006)**
Fixed effects: Growth rates				
Design innov. × Time H1B (+)	1,739.49	(840.77)**	56.04	(25.38)*
Technology innov. × Time	355.67	(572.39)	−52.40	(18.03)***
Design innov. × Tech innov. × Time H2B (+)	1,202.60	(557.26)**	75.69	(15.31)***
Brand strength × Time	0.004	(0.005)	−0.003	(0.001)***
Brand advertising × Time	−0.003	(0.001)***	−0.003	(0.001)***
Design innov. × Brand strength × Time H3B (+)	0.02	(0.005)***	0.002	(0.0001)***
Design innov. × Brand advert. × Time H4B (+)	0.002	(0.0006)***	0.002	(0.001)***
Cumulative sales	−0.05	(0.009)***	0.03	(0.009)***
Cumulative sales × Design Innovativeness	0.02	(0.008)**	0.04	(0.007)***
Control variables				
Price	−0.02	(0.22)	−0.04	(0.02)**
Price × Time	−0.22	(0.05)***	0.006	(0.006)
Price × Time^2	0.02	(0.0065)***	−0.0004	(0.0004)
Future generation	13,255.55	(5,698.07)*	−699.74	(386.96)
Future generation × Time	4,092.92	(1,169.05)**	153.62	(87.78)
Number prior generations	10,120.36	(1,821.47)***	301.84	(273.77)
Number prior generations × Time	63.49	(361.22)	34.21	(54.41)
Brand prior design innovativeness	−6,220.51	(3,660.88)*	345.59	(163.49)*
Brand quality	−4,137.88	(3,858.93)	−2.10	(7.46)
Random effects				
r_{1mbc} (time)	8,937.26**		134.20**	
r_{0mbc} (model)	42,497.86**		1,329.21**	
υ_{00bc} (brand)	42,264.8**		438.74**	
v_{000c} (category)	19,404.34**		298.62**	
e_{tmbc}	17,390.81**		1,245.47**	
−2 log-likelihood	21,449.84		20,967.08	

Note. Standard errors are reported in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

are: competitive intensity, market dominance, market size, and market growth rate (e.g., Pauwels et al. 2004, Rubera and Kirca 2012). The results (available from the author) do not change on introducing these variables and year fixed effects.

Centering within context. The literature has identified some brand-level variables (e.g., competitor orientation, customer orientation) that may influence product innovativeness and product sales (Szymanski, Troy, and Kroff 2007). Because these variables are typically measured through primary data, I cannot add them to the analysis. However, I can remove all of the variation at the brand level by centering design (and technological) innovativeness at the brand level. While centering at the grand mean yields slopes that are a mixture of both *between*-brand and *within*-brand variations, centering at the brand mean yields slope coefficients purified from all between-brand variation (Enders and Tofighi 2007). The results (available from the author) do not change.

Definition of initial sales period. I collect information about the month in which a model was introduced to account for the fact that the first year's sales may be lower for models introduced later in the year. Unfortunately, I could find reliable sources of information for only 266 cars. I run a robustness analysis in which, for models introduced in the second semester of the year, I consider the subsequent year to be the first year of sales. For instance, if a model were introduced in August of 2000, I consider 2001 as the first year of sales. Although I now have a much smaller sample size ($n = 878$), the results do not change.

Different error variance-covariance matrices. Following Singer (1998), I compare the unstructured matrix with two other possible structures, i.e., compound symmetry and autoregressive with a lag of 1. Using either of the other two error structures does not change the results.

Different time periods. I split the sample into two time periods, i.e., before and after (including) 1997. The hypothesized results available from the author remain the same, with the only exception being the interaction effect between design innovativeness and brand advertising expenditures (the latter being not significant in the car industry before 1997).

Selection bias. Potentially, growth rates may be biased upwards because, over time, unsuccessful models exit the market. I control for selection bias by running two analyses. First, I test the direct effects of design innovativeness on initial sales' status and growth rates in the following subsamples, i.e., cars that remained in the market for 3 years (or fewer), 4, 5, 6, 7, 8, and 9 years, and for 10 years or more; and motorcycles that remained in the market for 4 years (or fewer), 5, 6, 7, 8, and 9 years, and 10 years or more. I find that design innovativeness has a negative effect on initial sales' status and a positive effect on growth rates in every subsample. Then, I add the effects of all other control variables, while pooling the effects of design innovativeness. Because of the higher number of parameters to be estimated, I need bigger sample sizes than in the previous analysis. Thus, I create groups of models with similar market-life, i.e., cars that remained in the market for 3 years or fewer; 4–5; 6–7; 8–9; and 10 years or more; and motorcycles that remained in the market for 4 years or fewer; 5–6; 7, 8 or 9; and 10 years or more. The results (available from the author) indicate that design innovativeness has a negative effect on initial sales' status and a positive effect on growth in every subsample. Collectively, these results alleviate concerns about selection bias.

Estimation. I re-estimate the models with a restricted maximum likelihood approach. The results (not reported here but available from the author) remain invariant.

Takeoff. Following Golder and Tellis (1997), I calculated the takeoff of car and motorcycle models. A group-comparison analysis reveals that there is no significant difference between pairs of groups in the percentage of models that have been removed from the market before taking off (e.g., the percentage of cars that scored 1 in design innovativeness and did not take off is not significantly higher than the percentage of cars that scored 5 and did not take off). Thus, if managers strategically remove unsuccessful models from the market, this phenomenon seems to equally affect the models, regardless of their design innovativeness.

Relationship between initial sales' status and growth rates. It may be argued that cars with high design innovativeness grow more than cars with low design innovativeness, simply because they start from a lower initial status (i.e., they have a lower intercept). To reassure the readers that sales and growth are two separate dimensions influenced by innovativeness, I created pairs of cars/motorcycles with the same initial sales' status, but with different levels of design innovativeness. For instance, the second generation of the Dodge Stratus was paired with the Dodge Intrepid because both cars have almost identical initial sales' status (i.e., 88,948 versus 89,127). However, the Stratus has low design innovativeness, while the Intrepid has high design innovativeness. Similarly, I paired the Suzuki DR-Z400 (low design innovativeness) with the Yamaha YZFR6L (high design innovativeness). The two motorcycles have almost identical initial sales' status (2,545 versus 1,938). In the same fashion, I identified 53 pairs of cars and 49 pairs of motorcycles. Within each pair, I then computed the difference in sales between the car/motorcycle with high design innovativeness and the one with low design innovativeness. I tracked how this difference evolved over time. Data (available from the author) shows that cars with high design innovativeness grow more over time than cars with low design innovativeness, despite the fact that they have the same level of initial sales' status. Also, given the same level of initial sales' status, motorcycles with high design innovativeness grow less than motorcycles with low design innovativeness in the first three years, but afterwards grow more. Thus, I rule out the possibility that growth is due to initial sales' status, rather than to design innovativeness.

7. Discussion

In the last decade, innovating by changing the design of a product has become increasingly popular across firms. To date, however, quantitative research on the effect of design innovativeness on product sales is scant. Specifically, little is known about the effect of design innovativeness (and its interaction with technological innovativeness, brand strength, and brand advertising expenditures) on sales' evolution over time. This paper aims to fill this gap by disentangling the effect of design innovativeness on initial sales' status and sales' growth rates. The analysis yields the following main results:

- Design innovativeness diminishes sales' initial status but increases sales' growth rates.
- Design innovativeness and technological innovativeness have a negative interaction effect on sales' initial status, but a positive effect on sales' growth rates.
- Brand-strength and brand-advertising expenditures worsen the negative effect of design innovativeness on initial sales' status, while boosting its positive effect on growth rates.

7.1. Theoretical and Managerial Implications

This research makes three main contributions to theory and to managers.

The effect of design innovativeness on product sales evolution. I use the findings to estimate the incremental revenues that an average model could generate if it had higher design innovativeness. Taking an average price model of $31,252,[7] the revenues of a car model increase by $434 million per each increase in design innovativeness over the average car's lifetime of eight years. For instance, innovating several elements of a car's design, rather than introducing no innovation (i.e., scoring 3 rather than 1 on the design innovativeness scale) would generate additional revenues of $868 million in the U.S. market. A similar increase in terms of technological innovativeness would only generate an additional $293 million. Similarly, considering an average price model of $14,000, revenues increase by an additional $25 million for each increase in the design innovativeness of a motorcycle model over an average lifetime of eight years in the U.S. market (versus the additional $15 million that a similar increase in technological innovativeness would produce). In light of these estimates, I conclude that investment in design seems well justified. However, I estimate that in the first three years after the introduction, car/motorcycle models always benefit more from lower design innovativeness. In the fourth year, models have similar sales regardless of their level of design innovativeness. The benefit in terms of extra revenue for models with higher design innovativeness becomes evident from the fifth year on. Thus, managers should be prepared to initially receive cool acceptance for products whose design dramatically differs from the norm. Pulling the plug too soon on products with a radical design would waste their sales potential.

This research also sheds light on the different effects of design and technology innovativeness on product sales. For instance, in the motorcycle industry, design innovativeness has a negative effect on initial sales' status, while technological innovativeness has a positive effect. Also, design innovativeness positively influences sales' growth rates, while technological innovativeness has either no effect (car) or a positive effect (motorcycle). I theoretically ascribe this difference to the different evaluation processes through which consumers assess the value of design and technology. Consumers' evaluation of technology is a utilitarian, individual assessment of the technology's capability to better perform a certain task. As the superiority of a new technology can be assessed quantitatively along a primary dimension (e.g., screen resolution, storage capacity…) (Sood and Tellis 2005), consumers naturally move toward technologies with higher functionality (Miller et al. 1993). Conversely, as it is not possible to identify an objective standard to evaluate novel design, consumers tend to rely on collective tastes. The finding that the variance of sales decreases as the level of design innovativeness increases, while the variance of sales increases as technological innovativeness increases, corroborates the contention that the evaluation of design innovativeness is a collective process, while the evaluation of technological innovativeness is more individual. This collective process also suggests that individuals' considerations about the beauty of a product play little or no role in influencing consumers' decisions to buy a novel design.

The interaction effect between design innovativeness and technological innovativeness. A critical contribution of this research is the investigation of the interaction effect between design and technological innovativeness. To our knowledge, this is the first study to empirically assess the interaction effect between the two types of innovativeness on sales' evolution in a real product context. The analysis reveals that, initially, consumers react negatively to products that are novel in both the aesthetic and functional dimensions, perhaps because they do not have the cognitive resources necessary to reconcile both types of novelty, and need a reference point (either design or technological) to make sense of the new product. However, in the long run, products that are novel from a design and technological point of view seem to perform better than other products.

For managers, this research answers a critical question: Should technological innovation be wrapped in a novel form or should it maintain visual similarity to existing products? This paper reveals that incorporating technological innovations into radical product designs is the best solution in the long run. Managers should be aware, however, that this strategy has negative consequences in the short term. To avoid this drawback, managers could adopt a strategy of subsequent innovations: First, introduce a new technology within a traditional design; then, innovate the product's design once the excitement related to the new technology has faded. Cell phone producers seem to have successfully adopted this strategy. Initially, cell phones were designed to resemble cordless home phones. Only when consumers fully understood the functionalities of cell phones did producers begin introducing a vast array of new designs.

The role of brand strength. I find that design innovativeness and brand strength act as substitutes in the short term, but they complement each other in the long run. This finding has great managerial implications, especially in the current competitive scenario where new brands from emerging markets are threatening the position of many established brands. The results

[7] http://www.foxnews.com/leisure/2013/09/06/car-prices-hit-record-as-buyers-load-in-options/.

suggest that weak brands can use design innovativeness to gain ground on strong brands, but the benefits of this strategy are short-lived. In the long run, design innovativeness looks more like a shield that strong brands can leverage to widen the gap with competitors.

The role of brand advertising expenditures. I show that brand advertising expenditures increase initial sales' status, but that this positive effect is smaller for products with high design innovativeness. This finding may initially appear to be at odds with the previous literature that found advertising to be particularly beneficial for radical innovations (Rubera and Kirca 2012). However, prior research has mainly analyzed technological innovations where communication from firms to consumers can be sufficient to convey the value of a radical innovation. This top-down approach may be less effective in the case of radical design innovations because consumers are not simply recipients of information, but actively contribute to define the value of a radical design. I also find that sales of products with high design innovativeness grow faster when they are supported by brands that invest heavily in advertising expenditures. This finding indicates that advertising sustains the social construction process that eventually leads to the acceptance of radical design innovations. Thus, I conclude that, for design innovations, although advertising still plays the traditional informative role described in prior research, this positive effect is delayed.

To provide helpful suggestions to managers who have to decide whether to allocate resources to increase product design innovativeness or brand advertising expenditures, I compare the sales of products with high design innovativeness and low brand advertising expenditures with the sales of products with low design innovativeness and high brand advertising expenditures. In the car industry, the former generate higher sales than the latter from the fifth year on, and in the motorcycle industry from the second year on. Thus, managers interested in product growth should focus on increasing product design innovativeness more than brand advertising.

7.2. Limitations and Directions for Future Research

This paper presents some limitations that might represent interesting directions for future research. First, I test the hypotheses in the car and motorcycle industries. Future research could try to replicate these findings in different product categories, particularly in nondurable product categories. Second, recent research has shown that innovativeness has different effects on sales and firm value as assessed by investors (Rubera and Kirca 2012). Future research should investigate the effect of design innovativeness on investor response. Third, prior works have shown that the introduction of new models influence, positively or negatively, the value of old models in the second-hand market (Purhoit 1992). Future research should investigate the effect of design innovativeness, compared to technological innovativeness, on the resale value of second-hand products. Fourth, I investigate the effect of brand advertising expenditures on product sales. Future research could analyze the effect of advertising expenditures at the product level. Finally, I acknowledge that I did not correct for price endogeneity. Given my focus on design innovativeness rather than prices, this was beyond the scope of this paper, but would be an interesting topic for future research.

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Appendix A. Content Analysis Outline—Design Innovativeness

(1) *The design presents no innovation at all*

Interior/exterior is fairly conventional.

The design would mimic the styling of … (other car or motorcycle models).

The design breaks no new ground.

1986 Volkswagen Jetta-second generation: *"The car is essentially unchanged."*

2001 Aprilia RSV Mille: *"Design is pretty much conventional."*

(2) *The design presents some minor, incremental changes in just one or two elements (e.g., grille, headlights, rear end, front end …)*

There are minor modifications/upgrades from other models in the market.

It presents cosmetic exterior and interior differences from other models in the market.

There are minor styling upgrades.

2001 Kia Optima: *"The four-door Optima borrows some of the Sonata's styling but has a unique nose with a cross-hatch grille as its most distinguishing difference from the Hyundai version." The front end looks like nothing but Chevrolet Corsica and Mitsubishi Galant in the rear. Sorry, but those tail lamps are just too derivative for my taste.*

2008 Suzuki GSX-R750: "It presents revised headlights and new colors."

(3) *Several elements of the design present incremental changes*

Several upgrades in the design

Many improvements introduced

A revised version …

1989 Cadillac DeVille: *"In reversing a trend of downsizing, the new DeVille is larger than the previous model. It has a longer wheelbase, longer length, roomier interior and larger trunk—all on a classy chassis. The "new" look is somewhat aerodynamic with restyled grille, bumpers, and front and rear fascia."*

2000 BMW R1150GS: *"BMW has updated its most exaggerated model: the R1150GS. BMW took aim at three major areas, tinkered with a host of smaller details, called it a "midlife rejuvenation." The Y2K styling department threw on bright asymmetrical twin* *headlamps and a new upper fender that ducts air into the larger (from the R1100RT), repositioned oil cooler.*

(4) *Several elements of the design present changes, and it is the first time these elements are introduced in the model's category*

Moves the design language one step further in this category

A departure from the style of models in the same category

2003 Scion xB: *"The xB takes the boxy look established by the recently introduced Honda Element and sends it a step further. It has an unusual mini-truck styling. It represents a radical departure from all cars in its category."*

2006 Triumph Daytona 675: *"In one single stroke it has redefined just how a middleweight sports bike should look like. Triumph, though, seems poised to change completely this stasis of design, and* [...] *plans to reinvent the sportbike class with the debut of its all-new Daytona 675."*

(5) *The design is completely new for the car (motorcycle) industry*

The design establishes a connection to the car (motorcycle) of the future.

The design/style sets new ground.

The design/style is ahead of the curve.

The model represents a design breakthrough.

Futuristic style

1991 Acura NSX: *"Every so often-about once a millennium or so-there comes along a machine like this. Dramatic package. Distinct. Unique"; "The Acura NSX looks like no other car on the road, with its cabin-forward design and long rear deck."*

2004 Triumph Rocket: Without doubt the Rocket III has forever expanded the parameters of motorcycle design." "The look and style of the Rocket III is unique." "The Rocket III represents a quantum leap ahead."

Appendix B. Content Analysis Outline—Technological Innovativeness

(1) *The technology presents no innovation at all*

It is unaltered.

It is still the same.

Virtually unchanged

2001 Kia Optima: *"average fuel economy" "The Optima is derived from the Hyundai Sonata platform." "The Optima is a clone of the front-drive Hyundai Sonata* [...]. *It will use the same 149-horsepower 2.4-liter four-cylinder and 170-hp 2.5-liter V-6 engines as the Sonata."*

(2) *There are minor, incremental changes in just one or two functionalities (e.g., acceleration, gas consumption ...)*

Minor modifications

The (motor) has evolved.

Updated technological features

2003 Suzuki GSX-R1000: *"Combustion efficiency has been improved inside this more compact version of the 988cc four. [It has] faster, smarter engine-control electronics."*

(3) *Several functionalities present incremental changes*

Many improvements introduced

A revised version...

Several upgrades in the functionalities

2008 Suzuki GSX-R750: *"New engine, new EFI, new S-DMS, new ISC, new SAES, multi-mode power adjustments and more."*

(4) *Several functionalities present changes, and it is the first time this technological innovation is introduced in the model's category*

Advanced technology for cars/motorcycles in this category

Raised the bar in this class

First car/motorcycle in this class

It sets new standards for this type of car/motorcycle.

A new record for this type of car/motorcycle

1984 Ford Tempo: *First sedan to offer a driver's side airbag*

(5) *The technology is completely new for the car (motorcycle) industry.*

The very best technology

The absolute maximum in performance

The most stunning advanced technology

The ultimate in...

The world's first

For the first time ever

1999 Honda Insight: *"Insight is the first car available in the United States with a hybrid propulsion system, a small gasoline engine supplemented by an electric motor."*

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