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Abstract

This dissertation explores the antecedents and consequences of design innovativeness, integrating several streams of marketing literature with the insights from evolutionary biology and shape theory to provide a deeper perspective on design innovation and product design evolution. It is composed by three essays. The first paper, titled "Product Design Evolution: Antecedents of Design Innovativeness" explores the drivers of product design evolution and mechanism behind product design upgrades. Second paper, titled "Design Innovativeness and Its Effect on Performance: Insights from Shape Theory" extends the framework introduced in the first paper and examines the effect of design variation within a category and brand's share of design variation in the category on new product performance. The third and last paper, titled "Category- and Brand-Level Design Innovativeness: Concept and Effect and Performance" conceptualizes design innovativeness as a construct that exists at two levels: category level and brand level, arguing for relevance of previously overlooked brand-level design innovativeness. It explores the effect of both category-level and brand-level design innovativeness on sales evolution.

In sum, each paper provides an original contribution to the literature on design innovation. The first essay focuses on previously unexplored in the literature antecedents of design innovativeness and product design evolution, while the last two papers contribute to the deeper understanding of performance implications of design innovativeness. Overall, they bring an evolutionary biology perspective to the marketing field and show that the mechanisms of shape evolution described in evolutionary biology hold in the product design context, affecting not only the design innovativeness of the products introduced in the subsequent period, but also existing products' performance in terms of sales.

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Contents

1 PRODUCT DESIGN EVOLUTION: ANTECEDENTS OF DESIGN INNOVATIVENESS **15**
1.1 Introduction 15
1.2 Theoretical Framework 19
1.2.1 Design innovativeness and related concepts 19
1.2.2 Design and sales 20
1.2.3 Drivers of product design evolution 20
1.2.4 Hypotheses 25
1.3 Data and Method 27
1.3.1 Data 27
1.3.2 Measures 28
1.3.3 Model Specification 35
1.4 Results 40
1.4.1 Selection model results 40
1.4.2 Main model results 40
1.4.3 Tests of hypotheses 41
1.4.4 Robustness checks 42
1.5 Additional analyses 42
1.5.1 Effect of design innovativeness on sales 42
1.5.2 Comparison with alternative objective design innovativeness measures . 45
1.6 General Discussion 48
1.6.1 Theoretical Contributions 48
1.6.2 Managerial Implications 50
1.6.3 Opportunities for Future Research 51
Reference 53
Figures 57
Tables 62
Appendix 72

2 DESIGN INNOVATIVENESS AND ITS EFFECT ON PERFORMANCE: INSIGHTS FROM SHAPE THEORY **75**

2.1 Introduction 75
2.2 Theoretical Framework 78
2.2.1 Design innovativeness and sales 78
2.3 Data and Method 87
2.3.1 Data 87
2.3.2 Measures 88
2.3.3 Model Specification 93
2.4 Results 96
2.4.1 Tests of hypotheses 96
2.4.2 Robustness checks 97
2.5 General Discussion 98
2.5.1 Theoretical and Managerial Implications 99
2.5.2 Limitations and Opportunities for Further Research 100
Reference 102
Figures 106
Tables 113
Appendix 122

3 CATEGORY- AND BRAND-LEVEL DESIGN INNOVATIVENESS: CONCEPT AND EFFECT ON PERFORMANCE **125**

3.1 Introduction 125
3.2 Theoretical Framework 127
3.2.1 Hypotheses 130
3.3 Data and Method 131
3.3.1 Data 131
3.3.2 Measures 132
3.3.3 Model Specification 135
3.4 Results 139
3.4.1 Additional analysis 140
3.5 General Discussion 140
Reference 143
Figures 147
Tables 152
Appendix 156

PREFACE

This dissertation explores the antecedents and consequences of design innovativeness, integrating several streams of marketing literature with the insights from evolutionary biology and shape theory to provide a deeper perspective on design innovation and product design evolution. It is composed by three essays. The first essay identifies the antecedents of design innovation and explores two questions: (1) When will a company upgrade the design of its product? (2) How innovative will be this design upgrade? The second essay explores the effect of design innovativeness of performance and shows that the variables coming from evolutionary biology and shape theory can be applied in the product design context to explain the effect of design innovativeness on sales. While the first two essays focus on design innovativeness with respect to the product category, the third paper introduces the concept of brand-level design innovativeness and explores the effect of both category-level and brand-level design innovativeness on sales evolution.

The first paper, titled "Product Design Evolution: Antecedents of Design Innovativeness" explores the drivers of product design evolution and mechanism behind product design upgrades. Design innovation is often cited as a source of competitive advantage; however, research also suggests that design innovation creates just a temporary competitive advantage, which is eroded when competitors introduce novel designs (Schumpeter 1939, Candi and Saemundsson 2011). To sustain this advantage, it is important to understand the timing of upcoming design upgrades as well as the innovativeness of these new designs. Yet, past research has overlooked the antecedents of design innovativeness and the mechanisms behind the product design evolution that would allow to predict introduction of design innovations on the market.

Addressing this gap, I build on evolutionary biology theories and sociocognitive product markets perspective and establish two main independent variables that affect the design innovativeness of product design upgrades: a) design variation within a category, and b) brand's share of design variation in the category. I examine their effect on design innovativeness and also establish category-, brand- and product-level characteristics that affect emergence of design upgrades and design innovativeness of new product generations.

To explore the evolution of product design I focus on product design upgrades in US automobile industry. I operationalize design in terms of shape and define design innovativeness as a **degree of novelty in the shape of a product**, compared to the design standards established in the category prior to the new product introduction. I also introduce a novel methodology to quantify design innovativeness, design variation, and brand's share of design variation, which is borrowed from evolutionary and developmental biology and relies upon shape theory and landmark-based geometric morphometrics.

From theoretical perspective, this research paper brings an evolutionary biology perspective to the marketing field and shows that the mechanisms of shape evolution described in evolutionary biology hold in the product design context too. I find that design variation in the category facilitates the emergence of more novel designs, while the brands that more contribute to design variation in the category tend to introduce product upgrades with lower design innovativeness. Further, this paper unveils the interaction effects between the two critical antecedents of design innovativeness. I find that in categories with high design variation, brands that greatly contribute to the overall design variation of a category tend to introduce more novel design upgrades. Third, this research reveals the category and brand characteristics that influence the timing of the introduction of design upgrades in the category.

The findings help gain a better understanding of when a design upgrades are likely to emerge and the design innovativeness of these upgrades, given a set of product-market characteristics. These predictions can be used by managers to build competitive intelligence allowing to guard their market share from competitors' attacks.

Second paper, titled "Design Innovativeness and Its Effect on Performance: Insights from Shape Theory" extends the framework introduced in the first paper and examines the effect of design variation within a category and brand's share of design variation in the category on new product performance. In this paper, I suggest that these two variables not only affect the design innovativeness of the products introduced in the subsequent period, but also interact with design innovativeness in the current period affecting existing products' performance in terms of sales.

The findings explain how the effects of product design innovativeness on sales vary depending on the level of category design variation and brand's share of design variation in the category. Category design variation positively moderates the effect of design innovativeness on sales, indicating that more innovative designs are more successful in the categories with high design variation, where the range of acceptable designs is wider. On the opposite, in the categories with low design variation, where the influence of a category design prototype is stronger, products with high design innovativeness perform worse in terms of sales.

I find a negative moderation effect of brand's share of design variation on relationship between design innovativeness and sales. This result indicates that brands with a history of radical design products do not benefit from consecutive introductions of highly novel designs. Contrary to a belief that consumers may expect more innovative designs from these brands, traditional designs introduced by these brands achieve higher sales. Sales of more innovative products are higher for the brands with low share of design variation. It implies that more traditional brands can benefit from the introduction of more eccentric designs.

These findings provide important implications for managerial practice. Managers may consider this study's insights as additional inputs making decisions about the design of new products, and offer the products with the optimal level of design innovativeness based on category conditions and brand's own position with regard to the category typical design.

The third and last paper, titled "Category- and Brand-Level Design Innovativeness: Concept and Effect and Performance" conceptualizes design innovativeness as a construct that exists at two levels: category level and brand level, arguing for relevance of previously overlooked brand-level design innovativeness. Building on the habituation-tedium theory and processing fluency arguments, I propose and evaluate differential effects of category-level and brand-level design innovativeness, as well as their interaction effect, on new product performance in terms of sales. Since the effect of design novelty changes with the level of exposure (Tellis 1997), it is important to disentangle the short- and long-term effect of design innovativeness. I employ growth curve analysis, which allows to estimate the effects of design category-level and brand-level design innovativeness, as well as their interaction effect, on initial sales status and sales growth rates.

I find that category-level design innovativeness negatively affects initial sales status but positively affects sales growth rates. Brand-level design innovativeness has positive effect on initial sales status and no effect on sales growth. I also find support for the negative interaction effect of category- and brand-level design innovativeness on initial sales status and no significant effect on sales growth.

This study addresses a need for a deeper integration between brand and innovation management exploring the under-researched interrelationship between branding and innovations (Brexendorf, Bayus and Keller, 2015). From managerial perspective, this analysis can provide guidance on styling of new products, and suggest when new products should look similar or different to the products on the market and brand's own product portfolio.

To conclude, each paper provides an original contribution to the literature on design innovation. The first essay focuses on previously unexplored in the literature antecedents of design innovativeness and product design evolution, while the last two papers contribute to the deeper understanding of performance implications of design innovativeness. Overall, they bring an evolutionary biology perspective to the marketing field and show that the mechanisms of shape evolution described in evolutionary biology hold in the product design context, affecting not only the design innovativeness of the products introduced in the subsequent period, but also existing products' performance in terms of sales.

Chapter 1

PRODUCT DESIGN EVOLUTION: ANTECEDENTS OF DESIGN INNOVATIVENESS

1.1 Introduction

A vast body of research has shown that design innovation helps firms protect their product from imitation, thereby creating a competitive advantage during which firms can extract rents in terms of increased sales and profitability (Candi and Saemundsson 2011, Eisenman 2013, Landwehr et al. 2013, Rubera 2015). For instance, Rubera (2015) finds that the sales of a car model increase by \$434 million per each increase in design innovativeness over the average car's lifetime of eight years.

To date, most of the research exploring design novelty, which we summarize in Table 1, has focused on its consequences in terms of sales. However, this research also suggests that design innovation, like any other innovation, creates just a temporary competitive advantage, which is eroded when competitors introduce novel designs (Schumpeter 1939, Candi and Saemundsson 2011). For this reason, it is extremely important for a firm to gain a better understanding of *when* a competitor is about to upgrade the design of its products as well as of the *magnitude* of the expected design novelty of this new offering. In this way, firms can develop competitive intelligence tools to predict the timing and innovativeness of competitors' novel design, which can help them effectively guard their market share from competitors' attacks.

No prior studies to our knowledge have attempted to explore the antecedents of design innovativeness and reveal the mechanisms behind the product design evolution that would allow to predict introduction of design innovations on the market. Given this gap, we aim to answer two related questions: (1) When is a company going to upgrade the design of its product? (2) How innovative will be this design upgrade? This is relevant, since as noted above, firms can create competitive advantage with design innovation, however, such competitive advantage is temporary and can be lost with the design innovations introduced by competitors.

Moreover, it is becoming harder to sustain this design-based advantage as product design process is being improved upon. For example, in automobile industry it previously took over five years to bring a car from inception to showroom. The use of computer aided design tools and refined design processes, has drastically accelerated the design process and requires less involvement of designers (Osborn et al. 2006). Before, designers who are the most important resource of design process, used to be also the means of a competitive advantage protection making design potentially resistant to imitation (Candi and Saemundsson 2011). However, in the setting where design process is becoming more dynamic and automatized, ability to predict competitors' actions is becoming an important part of a competitive strategy aimed at sustaining the competitive advantage.

In this paper, we define design innovativeness as a **degree of the deviation in the shape of a product from a current design state** (Talke et al. 2009, 2017; Mugge and Dahl 2013). Specifically, we compare the shape of a novel product to the design standards established in the category prior to the new product introduction. We use evolutionary biology theories to define the antecedents of design innovativeness and apply geometric morphometric methodology to measure design innovativeness. We follow the product design literature that defines design a shape of the product (Ranscombe, Hicks, Mullineux, and Singh, 2012; McCormack et al. 2004). This conceptualization allows us to use geometric representation of the product design and draw on evolutionary biology that explores the evolution of shapes of the species and defines the mechanisms and drivers of morphological innovations.

To explore the evolution of product design we focus on product design upgrades in US automobile industry. Specifically, we analyze design novelty of new model generations that automobile makers introduce and which represent about 50% of all new product introductions in the US automobile market. We focus on design changes over successive product generations because products having several generations become so-called "lead products", have higher importance in the brand portfolio and create strong brand presence on the market (Karjalainen and Snelders 2010). Hence, the main design challenge from the product line and portfolio viewpoint is the redesign of existing car models throughout the product generations, rather than the design of completely new models (Karjalainen and Snelders 2010).

Following evolutionary theory, we establish two main independent variables that affect the design innovativeness of product design upgrades: a) design variation within a category (Erwin 2007) and b) brand's share of design variation in the category (Zelditch et al. 2012, Foote 1997). We define design variation as overall shape variety within a product category. Brand's share of design variation in the category is a relative contribution of a brand to overall variation within product category, or the proportion of design variation accounted by all the products in the brand's portfolio.

We test our hypotheses in the US automotive industry, using car models sold in the US from 2000 to 2013, including 310 new generations of existing models introduced by 38 brands in six product categories (e.g., sedan, SUV, etc.). We assemble a unique database where we collect pictures of car shapes to measure design innovativeness from the portal

Msn.com/autos and sales data from Ward's Auto Yearbook. We also introduce a novel methodology to quantify design innovativeness, design variation, and brand's share of design variation, which we borrow from evolutionary and developmental biology and relies upon shape theory and landmark-based geometric morphometrics (Webster and Sheets, 2010).

We make the following four contributions to the marketing theory. First, we bring an evolutionary biology perspective to the marketing field and show that the mechanisms of shape evolution described in evolutionary biology hold in the product design context too. Second, we unveil the drivers of product design evolution and mechanism behind product design upgrades. We find that design variation in the category facilitates the emergence of more novel designs, while the brands that more contribute to design variation in the category tend to introduce product upgrades with lower design innovativeness. Further, we unveil the interaction effects between the two critical antecedents of design innovativeness. We find that in categories with high design variation, brands that greatly contribute to the overall design variation of a category tend to introduce more novel design upgrades. Third, we reveal the category and brand characteristics that influence the timing of the introduction of design upgrades in the category.

Managers can use our findings to gain a better understanding of when a competitor is about to upgrade the design of its offerings as well as about the innovativeness of these upgrades. Finally, we contribute to the emerging literature on design by introducing an objective measure of design innovativeness based on shape theory that allows to quantify design innovativeness more precisely than the previous measures used in the literature. We provide empirical support for our contention.

1.2 Theoretical Framework

1.2.1 Design innovativeness and related concepts

The literature has adopted various concepts to describe the degree of novelty in product design, such as design newness, design novelty, design prototypicality, and design innovativeness. In Table 1 we provide an overview of the key papers and motivate this research. Design innovativeness is defined as the degree of novelty in a product's external appearance (Rubera 2014), while design newness is a deviation in a product design from a current design state (Talke et al. 2009, 2017; Mugge and Dahl 2013). Prototypicality or typicality is a slightly different concept that captures the current position of the product's design within a category, and is defined as extent to which a product is representative of an overarching category (Hekkert et al. 2003; Landwehr et al. 2011, 2013; Liu et al. 2017).

Researchers in the field of product design define design as the form or shape of a product (Ranscombe et al. 2012, McCormack et al. 2003, Osborn et al. 2008), and follow shape analysis methodologies to analyze product appearance and explore similarity between designs. This approach allows to evaluate design as a whole taking into account all the category and brand attributes in product design with their complex geometric principles and relationships (Kreuzbauer and Malter 2005), making it possible to quantify design differences and develop an objective measure of design innovativeness. Such objective measure is more reliable than subjective evaluations of novelty in design, especially when estimating innovativeness of the products in the past.

To measure the degree of novelty in a product's appearance at the time of its introduction, we need to compare it with a typical product design at that time. However, the raters' perception of typicality is heavily affected and biased by the designs currently found on the market (Blijlevens et al. 2013, Loken and Ward 1990, Meyvis and Janiszewski 2004).

Objective design innovativeness measure allows to build the typical category design in the past, and compare each product with this prototype avoiding this bias.

Accordingly, we operationalize design in terms of shape and define design innovativeness as a **degree of novelty in the shape of a product**, compared to the design standards established in the category prior to the new product introduction.

1.2.2 Design and sales

Most of the existing research has demonstrated the effect of design innovativeness on sales. For example, Talke et al. (2009) find positive impact of design newness on sales right after the introduction that persists in strength over time. Rubera (2015) reveals that design innovativeness diminishes initial sales' status but increases sales' growth rate. Landwehr et al. (2013) propose that more novel designs initially evoke negative consumer reactions, but tend to become more appealing at higher exposure levels, while typical designs lose appeal after multiple exposures. The interaction between design typicality and exposure affects sales suggests that atypical designs are more successful in the long run. Liu et al. (2017) find support for an inverted U-shaped relationship between design prototypicality and performance. Exploring products' prototypicality with regard to luxury/economy segments, they conclude that consumer preference for an aesthetic design is highest at a moderate level of segment prototypicality. Talke et al. (2017), instead, find a positive, linear effect of design novelty on sales but fail to find a U-shaped relationship.

1.2.3 Drivers of product design evolution

We first provide a brief overview of two theories that we use to develop our hypotheses about the antecedents of design innovativeness: evolutionary biology (Foote 1997,1994, Erwin

2007, Zelditch et al. 2012) and sociocognitive theory of markets evolution (Rosa et al. 1999). We select these two theories because they provide complementary views about design innovativeness: evolutionary biology defines the physical constraints of design innovations; the sociocognitive theory of markets evolution defines the cognitive and socially acceptable boundaries of design innovations.

Evolutionary biology and shape theory

Evolutionary biology is the study of the origin and evolution of species. Evolutionary biologists research the processes and causes of evolution and biodiversity, determine relationships between species, and the causes of variation and innovation of biological shapes. Since variety of biological processes produce differences in shape between individuals or their parts during evolutionary diversification, shape comparisons have always been a focus of evolutionary studies (Zieldich et al. 2012). Shape analysis, or morphometrics, is a quantitave approach used in evolutionary biology to understand biological shape, shape variation, and morphological innovation. Even though it is mostly used in biology to describe organisms, this methodology can be used to describe the shape of any object.

In order to understand how innovative each new object is, evolutionary biology considers the "shape space", namely the multidimensional space in which each object is represented by a single point, and all existing objects are plotted around the average or typical shape of the category. This typical shape is defined "reference" (in the Methodology section, we explain how to identify the reference shape and build the shape space). In addition to the distribution of the existing shapes around the reference, the surface of a shape space includes all the possible feature combinations that a design of an object from a category can have. Thus, shape space represents a constrained environment within which the evolution of different objects belonging to the same category can occur.

The basic assumption in this theory is the so-called "constraints on form": distribution of existing shapes in the shape space provides the boundaries that define evolutionary patterns of shape innovation and can be used to predict innovativeness of new emerging shapes (Foote 1997, Erwin 2007). Evolutionary theory maintains that space shape determines the boundaries within which design innovativeness can occur in the category: there is a limit to how far from the reference a novel design can be.

According to evolutionary theory, two elements drive the design innovativeness of a new object: category design variation (Erwin 2007) and share of category design variation (Foote 1993).

Category design variation. Category design variation is a measure of the variety of shapes within a category (Foote 1990, Zelditch et al. 2012). Variation is measured in terms of squared distances between shapes (corresponding to a variance). When design variation is low, then all the objects within a category have similar shapes and tend to be close to a typical shape (or the reference) of the category. In contrast, objects in categories with high design variation have very different shapes. These objects are more distant from the reference shape and tend to occupy a bigger area of the space shape.

Take for instance the case of two different categories in the car industry (see Figure 1). As noted before, shape space is multidimensional non-Euclidean space. Accordingly, to obtain the graphical representation of a shape space of those two categories, we first run PCA analysis, find the axes of greatest variation in a data set, and plot the scores corresponding to each car model in two-dimensional representation of a shape space. The pickup category in 2011 has very low design variation (we explain in the Methodology section how to compute it). All the models are close to the reference shape, graphically represented by the point where the two axes cross each other, and they occupy a small portion of the total space shape available in the category. Differently, the SUV category in 2000 has high design variation.

In this case, SUVs tend to be further away from the reference and occupy a bigger area of the total space shape than pickups.

Evolutionary theory maintains that category design variation constraints the design innovativeness of new objects, in the sense that new objects tend to fill in the shape space within the range of design variation achieved previously (Foote 1994) so that increased diversity in terms of number of species (products) is accommodated upon the spectrum of designs established earlier (Erwin 2007). We represent the concept of design variation range graphically on Figure 2. Let the circle represent the shape space including all possible designs of an object belonging to the category, with the reference or typical shape located in the center of the circle. The black points represent existing objects in the category. Dotted line depicts the range of design variation in the category, based on the variation of existing objects. Evolutionary biology findings suggest that new shapes emerging in the category will be located within the range of design variation, or within the dotted line. It implies that new designs emerging in the shape space on the Figure 2a will be less innovative (located closer to the reference shape in the center) than designs emerging in the shape space on the Figure 2b. Thus, category design variation positively affects design innovativeness of shape innovations introduced in subsequent period.

Share of category design variation. Each object contributes to the overall design variation of a category, with objects more distant from the reference contributing more than others. This individual contribution to overall category design variation can be calculated in terms of proportion of variance accounted by individual object. Objects are grouped in subgroups within a category. For instance, cats are a subgroup of the category “mammals”. In the product context, we consider brands as subgroups of a certain product category. For instance, Jeep is a subgroup of the SUV category. The sum of variance contributions of each member of the subgroup determines the share of category design variation, or relative contribution of each subgroup to the overall category design variation (Foote 1993).

We can translate this to the product context. We define brand's share of category design variation as a relative contribution of a brand to overall variation within product category, or the proportion of design variation accounted by all the products in the brand's portfolio. Hence, the brand's share of category design variation is the sum of variance contributions of each product in the brand's portfolio. Brands with more eccentric product designs that are positioned further away from a category reference contribute more to overall design variation. Take for instance the SUV category in 2000 represented in Figure 1. We can say that, for instance, the relative contribution of the subgroup Nissan to the overall design variation of the category SUV is the sum of variance proportions contributed by Pathfinder and Xterra. Also, we can conclude that Hummer is the brand that contributes the most to overall SUV design variation because it produces Hummer H1, the most eccentric design (i.e., the further away from the reference). Differently, Nissan has the lowest share of category design variation because its two models are very close to the reference.

This share of category design variation also affects the design innovativeness of the products introduced by this brand in a category. Evolutionary studies suggest that groups that occupy higher range of shape space and include peripherally positioned products fail to generate as much design diversity in the following phases of innovation (Erwin 2007), and apparently achieve maximum variation filling in the potential space earlier and retarding subsequent increases in design variation, so that the new shapes introduced by these groups will be positioned closer to the reference or typical shape (Foote 1994).

We contend that the theory of shape can be fruitful applied in the product design context. We conceive each product as an object, whose design represents its shape. All the products in a certain category (e.g., SUV cars, smart phones, tablets) represent the shape space within which novel products, with different levels of design innovativeness, emerge. For each category, we can identify the reference as the average shape of all the products in the category. Following evolutionary theory, and focusing on category design variation and brand's share of category design variation, we can then predict the design innovativeness of each new product introduced within the category.

Sociocognitive theory of markets evolution

Rosa et al. (1999) view product markets as dynamic sociocognitive phenomena, where markets are constructed through the interactions among producers, customers, and the media who develop shared knowledge structures, or schemas. While evolutionary biology focuses on physical product shape boundaries within the category, Rosa et al. (1999) explains market boundaries and categories as socially constructed cognitive orderings. Exploring the emergence of a generic schema for the minivan category, the authors conclude that as stabilization occurs around a category prototype, the range of acceptable product design diminishes. In unstable product categories, however, products with radically different attribute value configurations will be considered equally acceptable members of the category.

Category design variation reflects the stability of the category design, so that category design variation is lower for stable categories, and higher for unstable categories. Consequently, sociocognitive perspective also suggests that higher category design variation is associated with higher design innovativeness of new products introduced in category.

1.2.4 Hypotheses

Evolutionary research suggests that higher existing design variation provides wider range for the upcoming designs (Foote 1994). In the product context, it implies that category design variation positively affects design innovativeness of product design upgrades introduced in this category in subsequent period, since wider design range is open for the upcoming product designs. For instance, design variation in a category presented in Figure 2b provides wider range for design innovations (depicted by a dotted line) than the design variation in a category shown in Figure 2a.

According to sociocognitive prespective (Rosa et al. 1999), less stable product categories offer wider range of designs for new product introductions. Since less stable product categories are those that have lower design variation, we expect that higher design variation within product category is associated with higher design innovativeness of the product design upgrades introduced in this category in subsequent period.

Thus, we offer H_1:

H_1: The higher the design variation in the product category, the higher the design innovativeness of the product design upgrade.

With regard to brand's share of design variation in the category, evolutionary studies suggest that the brands contributing more to overall category diversity fail to introduce new products with highly innovative designs in the subsequent periods (Erwin 2007, Foote 1994). Since they are already positioned peripherally in the shape space, they are forced to fill in the space closer to the reference. Accordingly, we expect negative effect brand's share of design variation in the category on design innovativeness of product design upgrades introduced by the brand in this category in subsequent period.

Thus, we offer H_2:

H_2: The higher the brand's share of design variation in the product category, the lower the design innovativeness of the product design upgrade.

Next, we explore the interaction effects between the two critical antecedents of design innovativeness. As discussed above, category design variation defines a range of future design innovations. Since brands with high share of design variation are those that have in their portfolio products with most eccentric and distinct designs, brand's share of design variation represents the ability of a brand to produce highly innovative design. We expect that brands with such ability can successfully utilize the wide design range provided by high category design variation, and introduce more innovative design upgrades.

Thus, we offer H_3:

H_3: The higher the brand's share of design variation in the product category, the stronger the positive effect of design variation on design innovativeness of the product design upgrade

1.3 Data and Method

1.3.1 Data

Product design and design novelty have been studied by the existing literature in the context of US automotive industry, since the issues of product appearance and design innovation are relevant for cars as the products that are consumed in fairly visible social settings (Bloch 1995, Eisenman 2013). We chose automotive industry also because of existence of defined product categories (such as sedan, SUV, minivan etc.) and importance of brand distinctive design.

Our sample consists of car models sold in the US from 2000 to 2013, total of 3503 model-year observations. From the portal Msn.com/autos we collect retail price, category, and performance, technology, interior and exterior specifications (total of 196 specifications). We also collect the pictures of each car model (front and side view). Our sample consists 440 car models by 38 brands (overall 748 distinct car model designs including the new generations of the same car model), and assigned to six categories. Description of the sample is provided in Table 2. We identify 634 new models (including 310 new generations of existing models). Table 3 represents definitions of the main constructs, measures, and data sources.

1.3.2 Measures

Design innovativeness. Quantifying design and developing an objective measure of design difference would allow to compare large datasets of different products without relying on subjective evaluations. The difficulty is that category and brand attributes in product design are not reduced to single elements but determined by complex geometric principles and relationships (Kreuzbauer and Malter, 2005), which needs to be evaluated as a whole. Researchers in the field of product design define design is defined as the form or shape of a product (Ranscombe et al. 2012, McCormack et al. 2003, Osborn et al. 2008), and use shape analysis to analyze product appearance and explore similarity between products in design studies. Accordingly, we operationalize design innovativeness in terms of shape and define design innovativeness of the new car model generation is the degree of novelty in the shape of new generation compared to the established typical shape in the category c in the previous period.

To obtain this deviation measure, we employ shape theory and landmark-based geometric morphometric analysis, a methodology used in evolutionary biology to quantify shape and shape variation (Webster and Sheets 2010). This approach uses geometric coordinates instead of exact measurements, so that data can be easily collected from digital photographs. Another advantage of geometric representation is that size variation in picture, scale and rotational effects are mathematically removed from the analysis. This methodology has been applied in developmental biology to estimate the average shape and compare the shapes of the species. If we follow the definition of product design as a shape, we can apply shape theory and morphometric methods to generate the typical product shape, analyze product appearance and quantify the similarity between products. In this framework car shape is a configuration of landmarks representing a car model, which are marked on the product images, which we collect from the website Msn.com/autos.

The key construct of a shape theory is the Kendall's (1977) definition of shape: "Shape is all the geometrical information that remains when location, scale, and rotational effects are filtered out from an object." Landmark-based geometric morphometrics uses a set of landmarks to describe shape. Landmarks are points of correspondence on each object that match between and within populations, or homologous anatomical loci recognizable on all objects in the study (Bookstein 1991, Dryden and Mardia 1998). It means that each landmark has to be present on every studied object; if a landmark is not present it either has to be marked approximately or it cannot be used at all. Since the results that are generated by this method directly depend on the quality of landmarks, landmark configurations should be selected to offer an adequate summary of morphology and should be consistently replicable with a high degree of accuracy (Webster and Sheets 2010).

As noted before, the choice of landmarks is critical for the shape analysis. We base our selection on two types of car shape studies. First is the shape grammar literature (McCormack et al. 2004, Osborn et al. 2006, Osborn et al. 2008) which has focused on defining key features that sufficiently describe the shape of the car, and encoding these features into a set of rules, so-called "design language", that is able to generate cars models consistent with brand and product category. Here each characteristic is defined by a curve or set of curves that are captured manually for the front, side, and rear views of the car, then the principal component analysis is used to determine the fundamental characteristics within vehicle classes.

According to Osborn et al. (2006, 2008) the following vehicle characteristics are the most relevant for adequate definition of the form of the vehicle: front wheels, rear wheels, front wheel well, rear wheel well, front fender, rear fender, front bumper, rear bumper, front windshield, rear windshield, grill, headlight, hood, roof, trunk, taillight, rocker, door, front side window, rear side window, door handle, ground, and belt line.

We also follow the work of Ranscombe et al. (2012) that investigates design features that influence how the consumers recognize the brand a category of a car model. This paper proposes a procedure that isolates the geometry in car images and visually decomposes the designs to identify the key aesthetic features and assess their influence on brand and category recognition. These features provide important input into our geometric morphometric representation of a car, since they would determine the landmarks that affect the perception of novelty and typicality of the car shape by the consumers. Ranscombe et al. (2012) decompose front, side and rear images of car models using the different level of detailing, show them to the participants and evaluate whether they were able the correctly identify the vehicle's category and brand. Levels of detailing are the following:

1. Outline or the silhouette – the boundary created between the vehicle and space surrounding it.
2. Daylight Opening (DLO), defined by the front and rear windshields and side windows.
3. Muscles – treatments given to surfaces or paneling, often in the form of creases or curves created by raising or lowering sections of the surface.
4. Graphics – details such as headlamps, radiator grille and number plate.
5. Explicit detail – a subcategory of graphics that is made up of graphic features which explicitly indicate vehicle brand, such as badges and logos.

The results show that images of the front view that include the “Graphics” feature category received the greatest number of correct responses. Moreover, Ranscombe et al. (2012) report that the number of correct identifications did not increase proportionally with the increasing level of information (number of feature categories included) in each image, suggesting that some feature categories, namely the “Graphics” category, have greater influence on ability to identify vehicle brand than others. There were more correct responses based on front views and less correct responses with respect to side and rear views. The majority of responses using the side view of the car were incorrect, despite the expectation of the authors that the vehicle outline and DLO would clearly indicate segment. Overall, this study suggests that the graphics feature category in the front view is the most powerful in communicating vehicle brand and category.

Based on these studies, we focus on the front view of the car, and define 50 landmarks that fully describe the shape or the car and communicate the category and brand membership for the consumers, including those on the outline, windshield, grill, headlight etc. (Figure 3). We point the landmarks on all the pictures of car models existing on the market from 2000 to 2013, overall 748 distinct car models.

Geometric morphometric analysis is based on several basic kinds of geometric spaces. We start with a Euclidean *landmark space*, in which landmarks are plotted on the product image. However, the morphometric analysis is not performed in this space. Key concept of shape theory is the “configuration” of landmarks; the full set of landmarks recorded for each object. All comparisons of shapes are between matching configurations of landmarks, not between individual landmarks. An individual landmark is not an object of comparison because it does not satisfy the definition of shape (Zelditch et al. 2012). In shape theory, every configuration of K landmarks having M coordinates is thought of as a single point in a space with K $\times$ M dimensions, which is called *configuration space*. Configuration space is a geometric space of K $\times$ M dimensions, which represents the set of all possible KM matrices. Each landmark configuration (i.e., an individual object, entire set of landmarks) is a single point within this space. When two-dimensional landmark coordinates are extracted for the analysis from a digital image of an object, the configuration space is created. For a car shape represented by 50 2-dimensional landmarks, we work with a 100-dimensional configuration space.

Having obtained the raw landmark data for a number of objects, the next step of morphometric analysis is to translate and rotate the landmark configurations into a common position and remove size differences between them, and build so-called *Kendall shape space*. This procedure is called Procrustes superimposition, and is required to filter out the variation associated with differences in location, orientation, and size, since following the definition by Kendall (1977) these differences are irrelevant in a comparison of configuration shape. An important implication of this definition is that we evaluate pure differences in shape, which is problematic to achieve with other methods.

Superimposition procedure is described in detail in the Appendix 1, and includes following steps (Zelditch et al. 2012):

1. Center each configuration of landmarks at the origin by subtracting the coordinates of its centroid from the corresponding (X or Y) coordinates of each landmark. This translates each centroid to the origin (and the coordinates of the landmarks now reflect their deviation from the centroid).

2. Scale the landmark configurations to unit centroid size by dividing each coordinate of each landmark by the centroid size of that configuration.

3. Rotate the configurations to minimize the summed squared distances between homologous landmarks (over all landmarks) between the shapes. When there are more than two

objects, all are rotated to optimal alignment on the first; the average shape is then calculated and all are rotated to optimal alignment on the average shape, which is the new reference. At this point, the average shape is recalculated. If it differs from the previous reference, the rotations are recalculated using this newest reference. When the newest reference is the same as the previous, the iterations stop. The final reference shape is the one that minimizes the average distances of shapes from the reference and represents the average or typical shape of a sample. This result does not depend on the shape of the first object used in the alignment; instead, it depends on the distribution of shapes in the sample.

In our case, we build the reference that represents the average car shape for each the category in each period. Prototypes are constructed by the consumers from an "average" of designs currently found on the market (Blijlevens et al. 2013). However, we need to take into account that more widely distributed and used products are perceived as more typical (Loken and Ward 1990, Meyvis and Janiszewski 2004). To make sure that our objective measure reflects the consumers' perception of typicality, we weight car models' contribution to the average shape according to the sales proportion in the year prior to introduction of the new model.

After Procrustes superimposition the configuration space is transformed removing position, size and rotation, eliminating several dimensions in the process and resulting in a shape space. *Shape space* is the Non-Euclidean space of $\mathrm{K} \times \mathrm{M}$-4 dimensions in which configurations are plotted after scaling, translation, and rotation. The shape space of the car shape sample consists of 96 dimensions.

The surface of the shape space represents all the possible landmark configurations that can potentially represent shape of the object, and all existing shapes are represented as single points along the surface. The location of each individual object on the shape space depends on their distance from the reference located in the center, which is called Procrustes distance.

Procrustes distance is the main measure of shape difference in geometric morphometrics. Procrusrustes distance between two shapes (landmark configurations) is a distance along the surface of the shape space after scaling, rotation and translation. It is analogous to Euclidean distance but in the curved non-Euclidean shape space. The true difference between shapes can be evaluated only after superimposition procedure explained above. Average shape, computation of which is described in the step 3 of the superimposition procedure, is the shape whose sum of squared Procrustes distances to the other objects is minimal.

In sum, to build the measure of design innovativeness, first we apply superimposition procedure to remove the size, scale and rotational effects from the pictures. Next, we build the shape space and the typical shape of the car for each category. Procrustes distance to the mean category shape represents the measure of the design innovativeness of each car model.

Category design variation. Design variation indicates overall shape variety within a category and is measured in terms of squared distances between forms, corresponding to a variance (Foote 1990/1993, Zelditch et al. 2012). It indicates the range of shape space occupied and a magnitude of morphological variation within a category.

Our measure of design variation represents shape variety within a car category, and is constructed using the design innovativeness measures of the car models in the category calculated before:

$$CDV_{ct} = \frac{\sum DI_i^2}{N-1} \tag{1}$$

Where ID is design innovativeness of car model i in category c in year t; N – number of models in category c in year t.

Brand's share of design variation. Brand's share of design variation represents the contribution of all the products in the brand's portfolio to the overall category design variation.

The contribution of individual objects to the category design variation is weighted by their position in the shape space, so that the more morphologically eccentric, the greater its contribution to sample variation (Deline 2009). The major reason for using a variance as a measure of design variation in evolutionary research is that variances are additive (Zelditch et al. 2012), which allows to calculate the overall variation of a category, then partition it into the contribution made by each individual or subgroup (Foote 1993). While evolutionary biology is interested in measuring the contribution of a subclade to the morphological disparity in a larger clade, we can build the analogous measure representing the contribution of the brand's portfolio to the design variation of the category.

The brand's share of design variation in the category is calculated as sum of the variance contributions of each individual product:

$$BSDV_{bct} = \frac{\sum_{\text{brand}} DI_i^2}{N^{-}1} \tag{2}$$

Where DI is design innovativeness of brand's b model i in category c in year t; N – number of models in category c in year t.

Control variables. Following (Srinivasan et al. 2009) we include category size, category growth rate, brand's market share in the category, and category concentration category as control variables in the main model in addition to the selection model (Table 3). Sales data that is used to build these variables is collected from Ward's Auto Yearbook. We also control for technological innovativeness of the car model (based on Msn.com/auto data).

1.3.3 Model Specification

In our data, the observations of the new generations' design innovativeness are nested within car models, which are in turn nested within brands and categories. To handle the within-cluster correlation arising from the nested nature of the data we employ multilevel mixed-effects modeling procedure. Since car models can simultaneously be nested within two different higher-level categories, brands and car categories, we use a cross-classified three-level mixed model that takes this structure into account and explicitly models the group effects.

According to Ranscombe et al. (2012), design and development of vehicle styling is a lengthy process that takes 3-4 years. After the decision to introduce a new car model generation, several stages take place within the styling design process, including ideation, realization and refinements. The new model year is then introduced one to two years ahead of the calendar year in which the sales actually start. Taking into account this context of design development process in automotive industry, we lag the variables in the selection model (described below) and the control variables by 3 years to reflect the conditions when the decision to produce new car model generation was made, and the design variables by 2 years.

First, following the procedure described by Singer (1998), we estimate the unconditional means model, where we partition the variance in design innovativeness into the variance associated with differences across categories (σ_c^2), the variance across brands (σ_b^2), the variance across car models (σ_m^2), and variance across generations of the same car model (σ_e^2):

$$\begin{gathered}\text{DesignInnovativeness}_{tmbc} = Y_{tmbc} = \theta_{000} + \upsilon_{00c} + \upsilon_{00b} + r_{0mbc} + e_{tmbc}, \\ e_{tmbc} \sim N(0, \sigma_e^2), \quad r_{0mbc} \sim N(0, \sigma_m^2), \quad \upsilon_{00c} \sim N(0, \sigma_c^2), \quad \upsilon_{00b} \sim N(0, \sigma_b^2)\end{gathered} \tag{3}$$

where t, m, b, and c denote time of new car model generation introduction, car models, brands, and categories; θ_{000} represents the grand mean of car model design innovativeness across brands and categories; e_{gmbc} is the generation-level random error; r_{0mbc} is the random between-car modelresidual; υ_{00b} is the random between-brandsresidual; υ_{00c} is the random between-categoriesresidual.

To build the compact model presented above, at the first level we model design innovativeness of each new car model generation as a function of mean design innovativeness across car model generations plus a random error:

$$\text{Level 1: DesignInnovativeness}_{tmbc} = Y_{tmbc} = \pi_{0mbc} + e_{gmbc}, \quad e_{tmbc} \sim N(0, \sigma_e^2), \tag{4}$$

where π_{0mbc} is the mean design innovativeness of car model m in brand b in category c; e_{tmbc} is the generation-level random error and represents variance across car modelgenerations.

At the second level, the mean design innovativeness across car model generations, π_{0mbc}, is simultaneously modeled as an outcome varying randomly around some brand b in category c mean:

$$\text{Level 2:}\, \pi_{0mbc} = \beta_{00bc} + r_{0mbc}, \quad r_{0mbc} \sim N(0, \sigma_m^2), \tag{5}$$

where β_{00bc} is the mean design innovativeness of the car model in brand b and category c; and r_{0mbc} is the random between-car modelresidual. The between-car model variance σ_m^2 is assumed to be uniform across car models within each of the b brands and c categories.

Level 3 models variation between brands and within categories:

$$\text{Level 3: } \beta_{00bc} = \theta_{000} + \upsilon_{00b} + \upsilon_{00c}, \quad \upsilon_{00b} \sim N(0, \sigma_b^2), \quad \upsilon_{00c} \sim N(0, \sigma_c^2), \tag{6}$$

where θ_{000} is grand mean of design innovativeness across brands and categories, υ_{00b} is the random between-brandsresidual, σ_b^2 is the between-brand variance, υ_{00c} is the random between-categoriesresidual, and σ_c^2 represents the between-categories variance.

The total variability in the outcome Y_{tmbc} includes four components: at Level 1 variance across car model generations (σ_e^2), at Level 2 – among car models within brands and categories (σ_m^2), and at Level 3 – among brands (σ_b^2) and among categories (σ_c^2). We can estimate the proportion of each level's variance in total variance as follows: $\sigma_e^2/(\sigma_e^2 + \sigma_m^2 + \sigma_b^2 + \sigma_c^2)$ is the proportion of variance across car model generations; $\sigma_m^2/(\sigma_e^2+\sigma_m^2+\sigma_b^2+\sigma_c^2)$ is the proportion of variance between car models; $\sigma_b^2/(\sigma_e^2+\sigma_m^2+\sigma_b^2+\sigma_c^2)$ is the proportion of variance between brands; and $\sigma_c^2/(\sigma_e^2+\sigma_m^2+\sigma_b^2+\sigma_c^2)$ is the proportion of variance between categories. This estimation allows us to test the nested structure of the model and determine whether there is significant variation across groups. These results of unconditional model are used to make the decisions about the model specification and estimate the performance of the full conditional model.

Next, we estimate the full conditional model:

$$\begin{gathered}\mathbf{DesignInnovativeness}_{\boldsymbol{tmbc}} = \boldsymbol{\theta_{000}} + \boldsymbol{\theta_{001} CDV_{(t-2)c}} + \boldsymbol{\theta_{002} BSDV_{(t-2)bc}} + \\ + \boldsymbol{\theta_{003}(CDV_{(t-2)c} x BSDV_{(t-2)bc}) + e_{tmbc} + r_{0mbc} + \upsilon_{00b} + \upsilon_{00c}}\end{gathered} \tag{7}$$

To build this model, we add the category- and brand-level predictors at the third level:

$$\text{Level 1:} \quad \text{DesignInnovativeness}_{tmbc} = \pi_{0mbc} + e_{tmbc}, \tag{8}$$

$$\text{Level 2:} \quad \pi_{0mbc} = \beta_{00bc} + r_{0mbc}, \quad r_{0mbc} \sim N(0, \sigma_{m0}^2) \tag{9}$$

$$\begin{gathered}\text{Level 3:} \quad \beta_{00bc} = \theta_{000} + \theta_{001} CDV_{(t-2)c} + \theta_{002} BSDV_{(t-2)bc} + \\ + \theta_{003}(CDV_{(t-2)c} x BSDV_{(t-2)bc}) + \upsilon_{00b} + \upsilon_{00c}, \quad \upsilon_{00b} \sim N(0, \sigma_b^2), \quad \upsilon_{00c} \sim N(0, \sigma_c^2),\end{gathered} \tag{10}$$

Where CDV is category design variation; BSDV is brand's share of design variation. Independent variables in the model are centered at the grand mean.

Selection model. Since the design innovativeness of a new generation is observed only if the new generation was introduced, we need to correct for the sample selection bias following Heckman (1979). First, we estimate the probability of new generation introduction. In this selection equation, which is estimated with a probit, introduction of a new car model generation is the dichotomous dependent variable. Next, we compute predicted values of the latent variable. Finally, we correct for the selection bias by incorporating a transformation of these predicted individual probabilities as an additional explanatory variable (the inverse Mills ratio). To test whether we need to accommodate the nested structure of our data for the selection model, we again use the Singer (1998) procedure and estimate the unconditional means model analogous to the model (1):

$$\begin{gathered}\text{NewGenerationIntro}_{tmbc} = Y_{tmbc} = \theta_{000} + \upsilon_{00c} + \upsilon_{00b} + r_{0mbc} + e_{tmbc}, \\ e_{tmbc} \sim N(0, \sigma_e^2), \quad r_{0mbc} \sim N(0, \sigma_m^2), \quad \upsilon_{00c} \sim N(0, \sigma_c^2), \quad \upsilon_{00b} \sim N(0, \sigma_b^2)\end{gathered} \tag{11}$$

The partition of the variance at each level reveals that there is not significant variation across groups that would support the nested structure in case of new generation introduction, since most of the variation (99,6%) occurs at the first level of the model. Accordingly, we should proceed with the estimation of the selection model using a regular probit. As noted before, we lag the variables in the selection model by 3 years to account for the automobile industry design cycle.

We specify the selection model as:

$$\begin{gathered}\text{NewGenerationIntro}_{tmbc} = \beta_0 + \beta_1(\text{Model-level variables})_{(t-3)mbc} + \\ +\beta_2(\text{Category-level variables})_{(t-3)c} + \beta_{3k}(\text{Brand-level variables})_{(t-3)bc} + \epsilon\end{gathered} \tag{12}$$

Model-level variables that can serve as the drivers of the new generation introduction include sales growth and technical innovativeness of the previous generation. Following (Srinivasan et al. 2009) we include four category-level variables – category size, category growth rate, brand's market share in the category, and category concentration. Competitive category conditions such as category concentration and brand's market share in the category can affect the decisions about whether to innovate in the category, and whether to develop new generation of existing car model or introduce completely new model name. We also include brand-level controls such as number of brand's products in the category, category relevance for the brand, and brand sales growth.

1.4 Results

1.4.1 Selection model results

Results of selection model, presented in Table 5, suggest that brands with higher market share in the category are more likely to introduce a products design upgrade ($b = 2.189$, $p < .05$). Category concentration negatively affects the probability of the design upgrade introduction ($b = -0.972$, $p < .05$). Brands are also less likely to introduce design upgrade in a growing category ($b = -0.046$, $p < .05$). In fact, high-growth categories may facilitate introduction of completely new car models instead of design upgrades in form of new generations of the existing car models because of expected higher sales, less aggressive competitive reactions to new-product introductions and overall lower competitive intensity (Srinivasan et al. 2009).

1.4.2 Main model results

We run the unconditional means model using Stata *mixed* command to calculate the proportion of design innovativeness variance that occurs across car model generations, between car models, brands, and categories. The variance in design innovativeness that occurs across car model generations is 49%; between car models is 27%; between brands 16%; between car categories 7.6%.Since the variation between categories in the unconditional model is less than 10%, and the conditional model doesn't show significant variation of a category level, we proceed estimating the nested model with only brand as a third level group variable. The results are presented in Table 6. Full conditional model decreases overall variance compared to unconditional model by 18%; while there is no significant improvement of the variance on a model level, the variance on a brand level is decreased by 57%, and by 16% on the car model generation level. Inverse Mills ratio is significant indicating that the selection process takes place as we expected.

1.4.3 Tests of hypotheses

First, we estimate the main effects model to test the hypotheses 1 and 2. The results are presented in Column 2 of Table 6 support the hypothesis about the positive effect of design variation in the category on design innovativeness of the new car model generation ($b = 0.012$, $p < 0.01$) indicating that more novel designs can be introduced in more diverse categories. The results reveal negative effect of brand's share of design variation on design innovativeness ($b = -0.007$, $p < 0.01$) in support of H2. Next, we introduce interaction term and test the moderation effect of brand contribution to design variation. Column 3 of Table 6 indicates positive interaction effect of category design variation and brand's share of design variation ($b = 0.005$, $p < 0.002$) suggesting that combination of brand's ability to introduce radical designs and high design variation in category will lead to the introduction of more distinct and novel product design upgrades. We represent the interaction plot on Figure 4.

Overall, the results show that structural shape space variables, category design variation and brand's share of design variation, are relevant in product design context and can be used to anticipate the competitor's actions on the market and product design evolution in the future.

Effects of control variables on design innovativeness suggest that if the previous generation of the car model was successful, which is indicated by model sales growth, brands will not attempt to step away from the traditional design ($b = -0.217 \times 10^{-4}$, $p < 0.01$). Negative coefficient on technological innovativeness ($b = -0.634 \times 10^{-4}$, $p < 0.1$) suggests that if the previous generation was more technologically advanced, design upgrade will also be more traditional. Brands are also less likely to introduce more novel design in larger categories ($b = -0.3 \times 10^{-8}$, $p < 0.1$), and if they hold high market share in the category ($b = -0.388$, $p < 0.05$). On the opposite, in more concentrated ($b = 0.152$, $p < 0.05$) and growing categories ($b = 0.007$, $p < 0.05$) the producers aim to differentiate their product design upgrades introducing more novel designs.

1.4.4 Robustness checks

As noted before, we lag the variables in the selection model and the control variables by 3 years, and the design variables by 2 years. We also run the robustness analysis with 1-year lag for the design variables and 4-year lag for the selection model and control variables, and the results do not change (Table 7).

1.5 Additional analyses

1.5.1 Effect of design innovativeness on sales

We run additional analysis to estimate the impact of design innovativeness on performance in terms of sales using car sales data in US from 2000 to 2013 collected from Ward's Automotive Yearbook. Overall, our sample includes 3503 model-year observations of 748 car models (including the new generations of the same car model) by 38 brands in 6 car categories. We measure design innovativeness of each car model every year it is present on the market, so that our design innovativeness measure varies in time, and as expected, it is decreasing over time as the product is longer present on the market. We include measures of category design variation and brand's share of design variation as control variables. We also control for technological innovativeness of car model, number of previous generations, price

(MSRP), car model and brand advertising, brand strength, and year and country of origin fixed effects.

Model-free evidence presented in Figure 5, suggests negative impact of design innovativeness on sales, supporting the notion of consumers' preference for typicality (Landwehr et al. 2011, 2013). However, we expect also a positive effect of innovativeness that takes place as the product is present longer on the market. Processing fluency and mere exposure theory (Zajonc 1980, Veryzer 1999), as well as habituation-tedium theory (Berlyne 1970, Sawyer 1981, Tellis 1997) suggest that more innovative designs initially evoke negative consumer reactions, however additional exposure leads to increased familiarity and liking. We expect it to manifest in negative impact of design innovativeness on initial sales status, but positive impact on sales growth. This effect can be captured by a growth model.

We employ multilevel mixed-effects modeling procedure, where the repeated observations of sales over time are nested within car models, which are in turn nested within brands and categories and estimate a cross-classified three-level growth model. First, we estimate the unconditional means model:

$$\text{Sales}_{tmbc} = Y_{tmbc} = \theta_{000} + \upsilon_{00c} + \upsilon_{00b} + r_{0mbc} + e_{tmbc},$$

$$e_{tmbc} \sim N(0, \sigma_e^2), \quad r_{0mbc} \sim N(0, \sigma_m^2), \upsilon_{00c} \sim N(0, \sigma_c^2), \quad \upsilon_{00b} \sim N(0, \sigma_b^2)$$

$$\text{Level 1:} \quad \text{Sales}_{tmbc} = Y_{tmbc} = \pi_{0mbc} + e_{tmbc}, \quad e_{tmbc} \sim N(0, \sigma_e^2)$$

$$\text{Level 2:} \quad \pi_{0mbc} = \beta_{00bc} + r_{0mbc}, \quad r_{0mbc} \sim N(0, \sigma_m^2)$$

$$\text{Level 3:} \quad \beta_{00bc} = \theta_{000} + \upsilon_{00b} + \upsilon_{00c}, \quad \upsilon_{00b} \sim N(0, \sigma_b^2), \quad \upsilon_{00c} \sim N(0, \sigma_c^2),$$

where t, m, b, and c denote time, car model, brands, and categories; θ_{000} represents the grand mean of car model sales across brands and categories; e_{tmbc} is the time-level random error;

r_{0mbc} is the random between-car modelresidual; υ_{00b} is the random between-brandsresidual; υ_{00c} is the random between-categoriesresidual.

Next, we introduce the time variable representing the number of years since the car model was introduced, include random slope of time to allow each car model to follow separate growth trajectory, and estimate unconditional growth model:

$$\text{Sales}_{tmbc} = \theta_{000} + \theta_{100}\text{Time}_{tmbc} + \theta_{200}\text{Time}^2_{tmbc} + \upsilon_{00c} + \upsilon_{00b} + r_{0mbc} + r_{1mbc}Time_{tmbc} + e_{tmbc}$$

Finally, we add our measures of design innovativeness on the first level, since they are calculated yearly and estimate a **conditional growth model**:

$$\boldsymbol{\text{Sales}_{tmbc} = \theta_{000} + \theta_{300}DI_{tmbc} + \theta_{400}(DI_{tmbc}x\text{Time}_{tmbc}) + \theta_{100}\text{Time}_{mbc} +}$$
$$\boldsymbol{+\theta_{200}\text{TIME}^2_{tmbc} + e_{tmbc} + r_{0mbc} + r_{1mbc}\text{Time}_{tmbc} + \upsilon_{00c} + \upsilon_{00b}}$$

Where DI is the design innovativeness; e_{tmbc}, r_{0mbc}, υ_{00c}, and υ_{00b} are random effects, $r_{1mbc}\text{Time}_{tmbc}$ represents random slope in time.Coefficient θ_{300} represents the effect of design innovativeness on initial sales status, θ_{400} – effect on sales growth rates, and θ_{200} isgrowth rate acceleration.

The results of unconditional means model are presented in Table 8. Variance in sales that occurs across time is 9%, between car models is 58%, between brands 15%, and 17% between car categories. Unconditional growth model shows that on average car sales initiate from 49868 units and grow with time ($b = 2414.45$, $p < 0.01$), but at a decreasing rate ($b = -650.63$, $p < 0.01$).

Results of full conditional model support negative impact of design innovativeness of initial sales status ($b = -11289.47$, $p < 0.01$). However, we find also a positive novelty effect showing that design innovativeness positively affects sales growth ($b = 1005.165$, $p < 0.05$). This analysis also supports the findings of Rubera (2014) and Landwehr (2013), who found that liking of atypical designs increases at higher exposure levels. Design variety in the category is also a strong predictor of sales ($b = 3787.871$, $p < 0.05$), indicating that new designs can benefit in terms of performance from being a part of a categories with higher design diversity. This result can be explained by arguments of Rosa et al. (1999), who suggest that more in more unstable product categories that are not strongly aligned around a category product prototype, more products with different attributes will be positively accepted.

Overall, additional analyses reveal that design variables derived from shape theory and evolutionary biology are also relevant for the performance new product or design upgrade performance and can be used not only to predict the evolution of product design within the category, but also to explore the design-performance relationship.

1.5.2 Comparison with alternative objective design innovativeness measures

Shape theory and geometric morphometric analysis provide a useful approach to quantifying product design and a measure of design difference. In this framework, as described before, design is a configuration of landmarks representing a product, which are marked on the product images. This methodology allows to calculate average shape of the sample, which can represent the typical shape of the product. Next, we obtain the measure of design innovativeness as a Procrustes distance of each product from the average shape.

Key advantage of this methodology compared with other landmark-based methods, such as face morphing (Landwehr et al. 2011, 2013) is the superimposition procedure that it strictly follows the definition of a shape and ensures that only true shape differences are measured. Face morphing methodology is concerned with creating an average realistically looking image, which includes averaging of two distinctive features: shape and texture of the image, instead of focus on pure shape measures as in geometric morphometric. The authors using this methodology admit that since they define shape through a collection of points, they should use the Kendall shape space to build the average shape. However, since in this methodology the texture and visual representation of average shape is more important than its precise measurements, they approximate that by doing the arithmetic mean of feature points (Valenzano et al. 2006). This approximation however doesn't allow to separate the effect of design from that of size, position and rotation and capture pure shape difference.

Morphometric approach, on the opposite, mathematically removes all the possible distortions in positioning and rotations of the object on the picture. Even if some alignment of the images is included in the morphing procedure, it does not follow the proper superimposition procedure, so that the pairwise distances between shapes calculated by this approach can distort (under- or overestimate) distances between the shapes. In fact, when the studies of facial attractiveness that traditionally use image morphing to build average faces are concerned with a measure of geometric typicality, in addition to morphing procedure that creates the average images to be shown to participants for subjective evaluations, they apply geometric morphometrics to develop an objective measure of typicality (Valenzano et al. 2006).

Moreover, design distance measure calculated in morphing procedure is just the sum of squared distances between corresponding landmarks in two shapes, but not the distance between the shapes in the shape space. Since these in morphing the products' images don't go through superimposition procedure, the shape space is not constructed. As noted in the Methodology section, shape space represents all the possible variations of product design within category, along with the distribution of existing products. Morphing methodology without the shape space uses the information only about existing products. We only can calculate the variance of existing designs that would approximate the category design variation measure of the shape space, and partition it into the brands contributions. From the shape theory perspective, these approximate variance measures do not represent the boundaries in the shape space; thus, they cannot be meaningful predictors of design innovativeness. However, we attempt to build these measures and test their performance.

First, we build design innovativeness measure following the morphing procedure as the sum of squared distances between corresponding landmarks in two shapes without the superimposition procedure and shape space construction. Next, we measure the variance for each car category, and partition it into proportion of variance accounted by each brand. This, we construct approximate measures of category design variation and brand's share of design variation. Next, we use these measures as the predictors of design innovativeness. Model with morphing-based measure of design innovativeness as a dependent variable doesn't support the nested structure, so we don't have to use a mixed model. The results are presented in Table 9. As expected, approximate measures of category design variation and brand's share of design variation build with morphing approach are not significant predictors of design innovativeness. Moreover, the geometric morphometric-based model has better fit, as shown by AIC and BIC values.

Despite the fact that morphing-based measures cannot be used to predict design innovativeness, it is possible that the approximate measure of design innovativeness produced by the morphing procedure can be used as a predictor of sales. We run a simple sales model including two competing measures of design innovativeness. Results, presented in Table 10, suggest that morphing-based measure is only marginally significant ($p < 0.1$). Moreover, our measure explains higher proportion of variance (6% on a category level, 4% across time and 3% on a brand level) compared to unconditional model than morphing-based measure does.

1.6 General Discussion

Design innovation is frequently cited in the literature as a source of competitive advantage. However, the competitive advantage coming from design innovation is inherently short-lived (Candi and Saemundsson 2011) and is lost when competitors introduce novel designs. To sustain this advantage, it is important to understand the timing of upcoming design upgrades as well as the innovativeness of these new designs. Yet, past research has overlooked the antecedents of design innovativeness and the mechanisms behind the product design evolution that would allow to predict introduction of design innovations on the market.

Addressing this gap, we build on evolutionary biology theories and sociocognitive product markets perspective and propose category design variation and brand's share of design variation as antecedents of design innovativeness. We examine their effect on design innovativeness and also establish category-, brand- and product-level characteristics that affect emergence of design upgrades and design innovativeness of new product generations. We conclude with a discussion of the paper's theoretical contributions, the managerial implications of the findings, and limitations and opportunities for future research.

1.6.1 Theoretical Contributions

The paper's findings contribute to the literature in marketing that explores design innovation and product design evolution. First, evolutionary processes of variation, selection, and retention characterize product category evolution (Anderson and Tushman 1990, Tushman and Murmann 1998). Viewed in this evolutionary perspective, we open the discussion of the period of variation with regard to aesthetic design. Second, we extend literature on design innovation that has been focused on the consequences of design innovativeness (e.g. Talke et al. 2009, 2017; Landwehr et al. 2011, 2013; Rubera 2014) by offering the first study of design innovativeness antecedents and product design evolution drivers. Third, we provide insight into evolutionary process and management of design changes over successive product generations, which are particularly important from the product line and portfolio viewpoint (Karjalainen and Snelders 2010).

Moreover, we bring an evolutionary biology perspective to the marketing field and show that the mechanisms of shape evolution described in evolutionary biology hold also in the product design context. We also contribute to the design literature by introducing an objective measure of design innovativeness that allows to quantify design innovativeness more precisely than the previous measures used in the literature. Following the product design literature (Ranscombe et al. 2012; McCormack et al. 2004) we define design a shape of the product, which allows us to use shape theory to measure design innovativeness and apply evolutionary biology theory explaining shape innovations to reveal the antecedents of design innovativeness.

Our findings demonstrate that design variation in the category positively affects design innovativeness of the product upgrades. It implies that product upgrades introduced in highly disperse categories tend to have more innovative designs. On the opposite, in a more stable category with more consistent designs, we can expect new designs to be more traditional and closer to the typical design. In this case, the range of design variation established in the category defines a design space available space for future product generations. We find that brands with history of radical designs overall tend to introduce more traditional designs. However, the interaction effect between category design variation and brand's share of design variation suggests that only in categories with high design variation these brands do introduce highly innovative design upgrades (Figure 4).

We also establish other variables affecting design innovativeness of product design upgrades. Sales growth of the previous generation of the products, as well as its technological innovativeness, negatively affects design innovativeness of a new product generation. In the categories with higher growth rates and concentration, producers tend to introduce more novel design upgrades, while design innovativeness of the product upgrades introduced in larger categories tends to be lower. Brands with higher market share of the category introduce more typical product upgrades.

Next, we reveal category-, brand- and product-level drivers of emergence of design upgrades. We find that the probability of product design upgrade introduction is lower in more concentrated categories. Category growth rate also has negative effect on the probability of a product design upgrade introduction. Brands with higher market share in the category are more likely to introduce a design upgrade.

As an additional analysis, we apply our measure of design innovativeness to test its effect on sales evolution. The results of a growth model demonstrate that design innovativeness has negative impact on initial sales status, and positive impact on sales growth. These results support findings of the previous research showing that more typical designs are more successful initially, while more novel designs are more beneficial for the performance in the long run (Landwehr et al. 2011, 2013; Rubera 2014).

1.6.2 Managerial Implications

The study's findings also generate useful implications for business practice. Product design upgrades erode the competitive advantage achieved by previous design innovation (Schumpeter 1939; Candi and Saemundsson 2011). Moreover, when these new designs differ significantly from existing standards, they destabilize existing categories and trigger shifts in existing product evaluations, since product evaluations are thus dynamic, and the same product models are evaluated differently depending on a category's stability (Rosa et al. 1999, 2005).

Our findings help gain a better understanding of when a design upgrades are likely to emerge and the design innovativeness of these upgrades, given a set of product-market characteristics. These predictions can be used by managers to build competitive intelligence allowing to guard their market share from competitors' attacks. Managers can use them to understand what product categories are unstable and more likely to introduce new product designs, and which products fall under the risk of lower evaluations, and use this information to inform their marketing strategies.

1.6.3 Opportunities for Future Research

This study has some limitations that present opportunities for further research. In this first work on design innovativeness antecedents, we focused on product design upgrades. However, product design evolution can occur not only in form of a new product generation, but also as the introduction of a completely new product, which can also have more or less novel design with regards to the category standards. To extend the findings from this study, future research could address the emergence of a new product and expected design innovativeness of this new offering.

Next, study focuses on evaluating design innovativeness with regard to a product category design standards. However, design affects also so-called brand categorization, i.e., how a product is perceived as a new member of a particular brand family (Kreuzbauer and Malter, 2005). Accordingly, design innovativeness can also be evaluated at a brand level as a deviation of a product shape from a typical design of brand. Further research may explore product design evolution with regard to brand design standards and reveal both the antecedents and consequences of brand-level design innovativeness.

Finally, in this study we follow up on the discussion in the literature about effect of design innovativeness on sales, and show that our measure of design innovativeness provides the results consistent with previous studies. Our model also shows that category design variation has impact on sales, so that sales are higher in categories with more design variation. Future research can further explore the effect of design variation and brand's share of design variation, as well as their interaction with design innovativeness, on sales. For example, more novel designs can be more successful in categories with higher design variation, where highly novel designs can receive more favourable consumer evaluations compared to more stable categories (Rosa et al. 1999). Research on this topic can provide further useful insights, explaining the performance of more or less novel designs depending on the category and brand design characteristics.

In sum, we view this study on the antecedents of design innovativeness as a useful first step in exploring the drivers of product design evolution. In doing so, this research introduces key variables shaping design innovation and provides the competitive intelligence tools to predict the timing and innovativeness of competitors' novel design. Managers can use these tools to guard the market share from competitors' attacks. We hope this paper stimulates further work exploring the mechanisms of design innovation and providing insights on how brands can sustain design-based competitive advantage.

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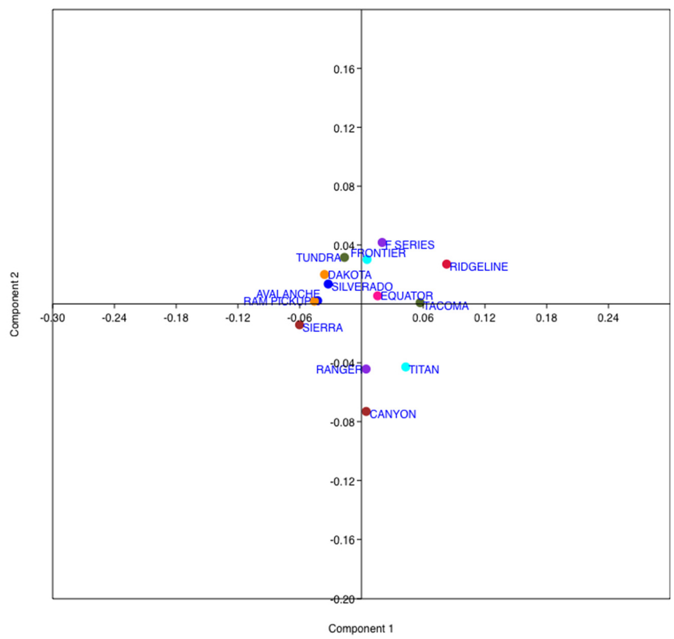
Figures

Figure 1. Examples of Categories with Low and High Design Variation

(a) Pickup 2011: low design variation



(b) SUV 2000: high design variation

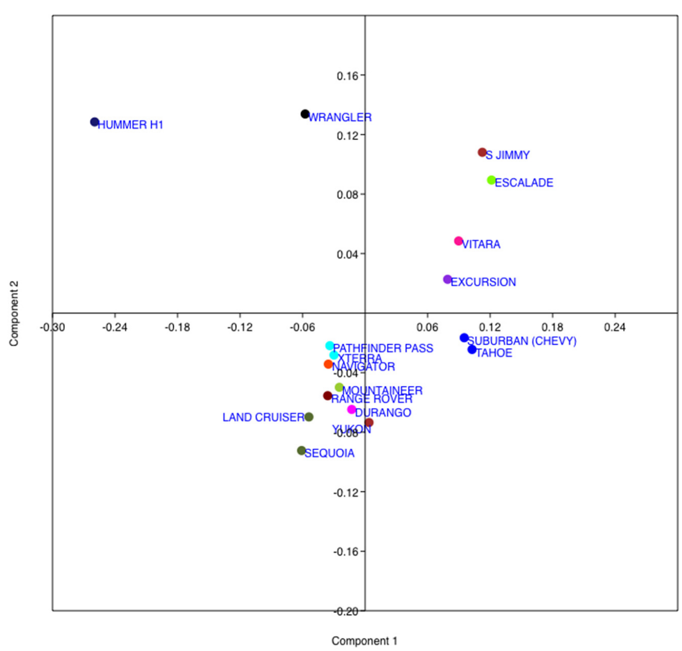
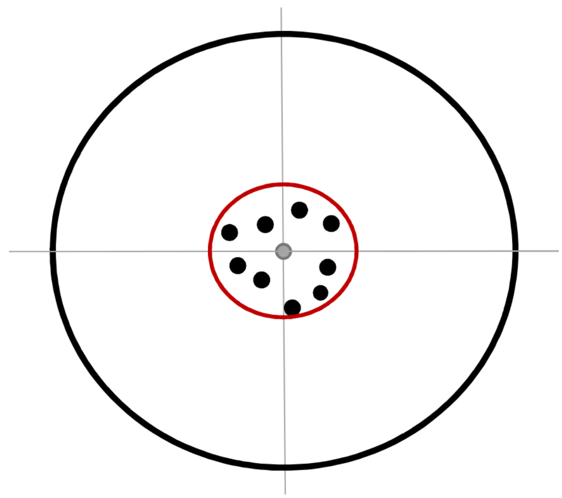


Figure 2. Shape space boundaries: range of design innovativeness

(a) Shape space with low design variation



(b) Shape space with high design variation

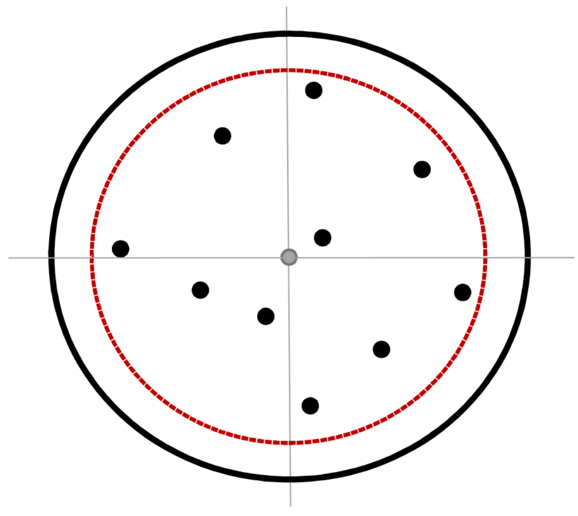


Figure 3. Landmarks representing the car shape

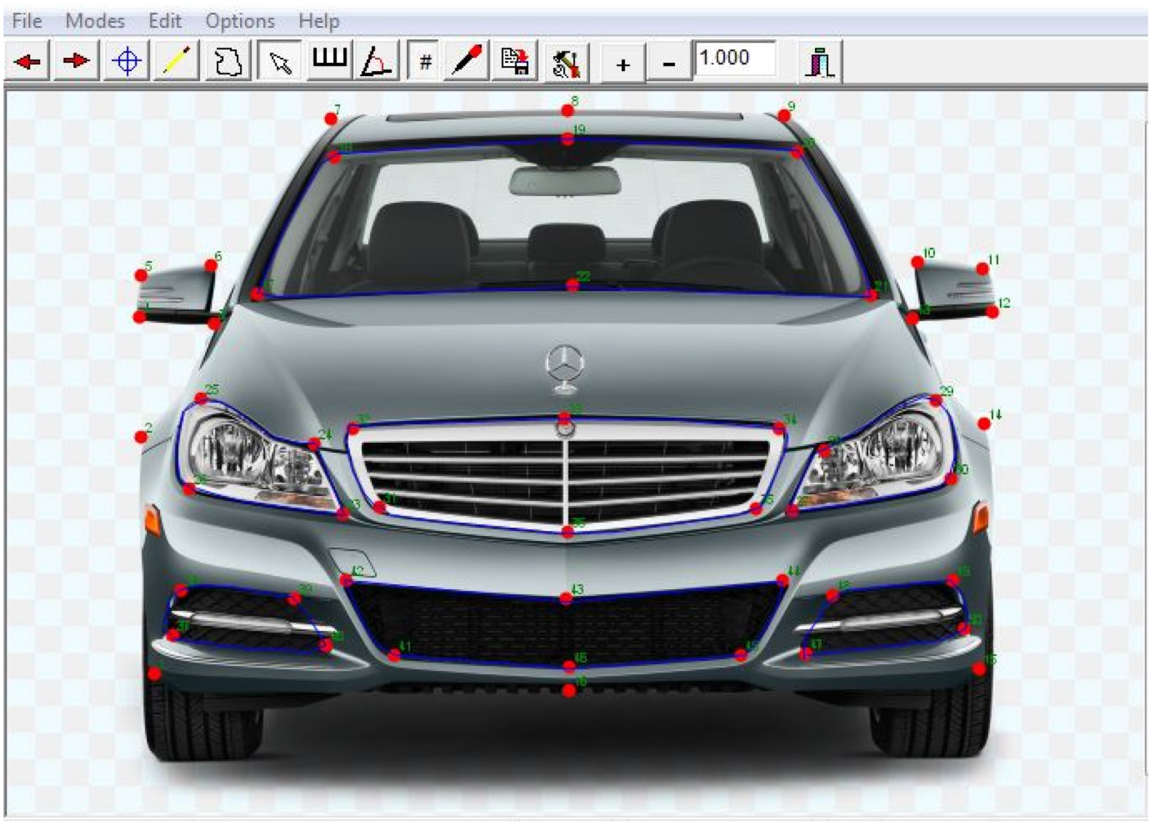


Figure 4. Interaction effect between category design variation and brand's share of design variation

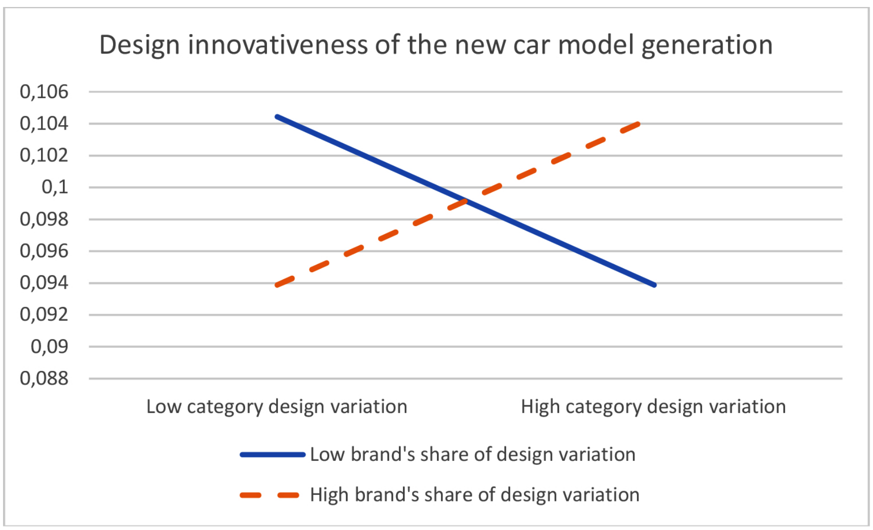
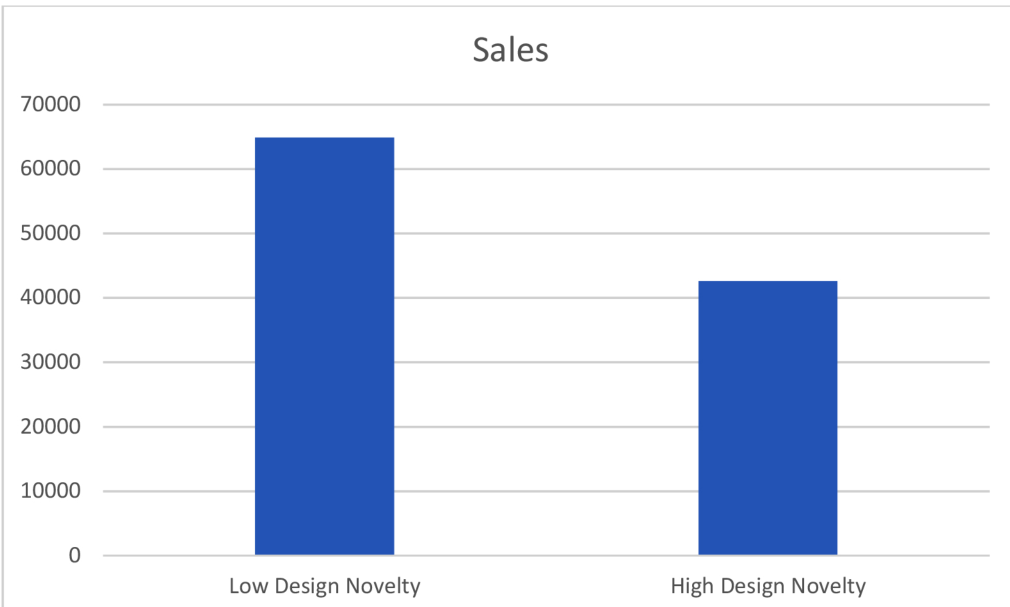


Figure 5. Model-free impact of design innovativeness on sales



$$t(3360) = 7.6448, \quad P < 0.0000$$

Tables

Table 1. Literature review

Reference	Concept	Definition	Measure	Effects	Antece-dents	Dependent Variable	Context	Sample size
Talke et al. (2009)	Design newness	Deviation in a product design from a current design state	Rating based on survey (1-7)	Yes	No	Sales	German car market	157 car models
Landwehr et al. (2011)	Design prototypicality	Extent to which an object is representative of an overarching category	Euclidean distance from average shape (picture morphing)	Yes	No	Sales	German car market	28 car models
Landwehr et al. (2013)	Design prototypicality	Extent to which an object is representative of an overarching category	Euclidean distance from average shape (picture morphing)	Yes	No	Aesthetic liking Sales	German car market	28 car models
Mugge and Dahl (2013)	Design newness	Deviation in a product design from the current design state of a certain product category	Manipulation: 3D line drawings of products with a high or low level of design newness	Yes	No	Consumer evaluations	Lab experiment	130 participants
Rubera (2014)	Design innovativeness	Degree of novelty in a product's external appearance	Rating based on expert reviews (1-5)	Yes	No	Sales	US car market US motorcycle market	520 new car models
Liu et al. (2017)	1. Segment Prototypicality 2. Brand Consistency 3. Cross-segment mimicry	Extent to which an object is representative of an overarching category	Euclidean distance from average shape (picture morphing)	Yes	No	Market share	US car market	202 car models
Talke et al. (2017)	Design newness	Deviation in a product design from a current design state	Rating based on survey (1-7)	Yes	No	Sales	German car market	109 car models
Our Study	**Design innovativeness**	**Degree of novelty in the product's shape**	**Procrustes distance from the typical shape in product category in the period prior to the product introduction**	**Yes**	**Yes**	**1. Design innova-tiveness 2. Sales**	**US car market**	**746 car models, including 623 new models (310 new generations)**

Table 2. Sample description

Category	Number of brands	Number of car models (including new generations of the same model)	MSRP range, USD
Passenger car	32	217 (379)	8895 – 213200
Crossover	32	66 (129)	16325 – 146000
Pickup	14	23 (39)	20131 – 54145
Sport	16	28 (46)	21287 – 440000
SUV	26	74 (112)	18680 – 139771
Van	18	32 (43)	20980 – 47510

Table 3. Variable description and data sources

Variable	**Definition / Measure**	**Data source**
Design innovativeness of the new car model generation	Degree of novelty in the shape of new generation of car model i. Measured as a Procrustes distance from the typical shape in category c in the previous period $(t-1)$	Frontal pictures of car models from MSN Autos
Category design variation	Indicates overall shape variety within a category: $$DV_{ct} = \frac{\sum DI_i^2}{N^{-1}}$$ Where DI is design innovativeness of car model i in category c in year t; N – number of models in category c in year t	Frontal pictures of car models from MSN Autos
Brand's share of design variation	The relative contribution of the brand to design variation: $$BDV_{bct} = \frac{\sum_{\text{brand}} DI_i^2}{N^{-1}}$$ Where DI is design innovativeness of brand's b model i in category c in year t; N – number of models in category c in year t	Frontal pictures of car models from MSN Autos
Control variables		
Technological innovativeness of the previous car model generation	Degree of novelty in the technological performance of the previous generation of car model i. Measured as a distance from the average performance in the category in terms of horsepower and fuel economy	MSN Autos
Number of brand's products in the category	Number of car models of the brand b in the category c in year t	Ward's Auto Yearbook
Category relevance to the brand	Proportion of brand b sales in category c to the total sales of the brand in year t	Ward's Auto Yearbook
Category size*	Total sales in year t for category c	Ward's Auto Yearbook
Category growth rate*	Measure of relative attractiveness of the category. Measured as a ratio of category growth rate of category c to total growth rate for all auto sales	Ward's Auto Yearbook
Market share*	Market share of brand b in category c in year t	Ward's Auto Yearbook
Category concentration*	Sum of the market share of the top three brands within category c in year t	Ward's Auto Yearbook

*Category control variables (Shuba Srinivasan, Koen Pauwels, Jorge Silva-Risso, Dominique M. Hanssens (2009) Product Innovations, Advertising, and Stock Returns. Journal of Marketing)

Table 4. Descriptive statistics and correlation matrix

Variable	Mean	SD	Min	Max		2	3	4	5	6	7	8	9
1. Design innovativeness	0.103	0.037	0.042	0.297	1								
2. Category design variation	0.012	0.003	0.006	0.022	0.228^{***}	1							
3. Brand's share of design variation	0.786×10^{-3}	0.885×10^{-3}	0.044×10^{-3}	0.651×10^{-2}	0.398^{***}	0.585^{***}	1						
4. Number of brand's products in the category	3.464	2.039	1	9	-0.042	-0.311^{***}	-0.04	1					
5. Category relevance	0.449	0.309	0	1	0.041	-0.381^{***}	-0.195^{***}	0.552^{***}	1				
6.Category size	4008596	2584590	56179	7439277	-0.119^{**}	-0.53^{***}	-0.438^{***}	0.665^{***}	0.673^{***}	1			
7. Category growth rate	1.002	2.068	-6.032797	6.978	-0.079	0.075	0.093	-0.024	-0.05	-0.094^{*}	1		
8. Market share	0.061	0.067	0.725×10^{-6}	0.426	0.038	0.274^{***}	0.487^{***}	-0.087	-0.272^{***}	-0.355^{***}	0.129^{**}	1	
9. Category concentration	0.449	0.117	0.346	0.809	0.067	0.477^{***}	0.539^{***}	-0.442^{***}	-0.43^{***}	-0.63^{***}	0.266^{***}	0.551^{***}	1

$^{*}\ p < 0.1, \quad ^{**}\ p < 0.05, \quad ^{***}\ p < 0.01$

Table 5. Selection model results

	Selection model
Intercept	-1.601 $(0.183)^{***}$
Category relevance	0.254 (0.277)
Brand sales growth	-0.002 (0.077)
Sales growth of the previous generation	0.158×10^{-3} (0.11×10^{-3})
Technological innovativeness of previous generation	0.341×10^{-3} (0.395×10^{-3})
Number of brand's products in the category	-0.037 (0.033)
Category size	7.36×10^{-9} (2.77×10^{-8})
Category growth rate	-0.046 $(0.018)^{**}$
Market share	2.189 $(0.952)^{**}$
Category concentration	$-(0.972)$ $(0.424)^{**}$
Year fixed effects	Yes

Standard errors in parentheses.
$^{*}\,p < 0.1$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$

Table 6. Main model results

	Unconditional means model	Conditional model: Main effects	Conditional model: Interactions
Intercept	0.104 (0.005)***	0.533 (0.146)***	0.537 (0.145)***
Fixed effects			
Category design variation (H1)		0.012 (0.004)***	0.01 (0.004)***
Brand's share of design variation (H2)		−0.007 (0.003)**	−0.009 (0.003)***
Category design variation × Brand's share of design variation (H3)			0.005(0.002)**
Control variables			
Sales growth of the previous generation		-0.217×10^{-4} $(0.735 \times 10^{-5})^{***}$	-0.221×10^{-4} $(0.731 \times 10^{-5})^{***}$
Technological innovativeness of previous generation		-0.634×10^{-4} $(0.324 \times 10^{-4})^{*}$	-0.677×10^{-4} $(0.323 \times 10^{-4})^{**}$
Number of brand's products in the category		0.003 (0.002)	0.004 (0.002)*
Category size		-0.3×10^{-8} $(0.18 \times 10^{-8})^{*}$	-0.341×10^{-8} $(0.181 \times 10^{-8})^{*}$
Category growth rate		0.007 (0.003)**	0.007 (0.003)**
Market share		−0.388 (0.158)**	−0.402 (0.157)**
Category concentration		0.152 (0.059)**	0.158 (0.059)***
Year fixed effects		Yes	Yes
Inverse Mills ratio		−0.212 (0.073)***	−0.217 (0.072)***
Random effects			
e_{tmbc}	0.554×10^{-3} $(0.742 \times 10^{-4})^{**}$	0.481×10^{-3} $(0.708 \times 10^{-4})^{**}$	0.475×10^{-3} $(0.702 \times 10^{-4})^{**}$
r_{0mbc} (model)	0.302×10^{-3} $(0.901 \times 10^{-4})^{**}$	0.34×10^{-3} $(0.937 \times 10^{-4})^{**}$	0.333×10^{-3} $(0.921 \times 10^{-4})^{**}$
v_{00b} (brand)	0.183×10^{-3} $(0.878 \times 10^{-4})^{**}$	0.861×10^{-4} $(0.635 \times 10^{-4})^{**}$	0.899×10^{-4} $(0.617 \times 10^{-4})^{**}$

Standard errors in parentheses.

$^{*}\, p < 0.1$, $^{**}\, p < 0.05$, $^{***}\, p < 0.01$

Table 7. Robustness checks

	Main effect: Design variables lagged 1 year, Control – 3 years	Interaction: Design variables lagged 1 year, Control – 3 years	Main effect: Design variables lagged 2 years, Control – 4 years	Interaction: Design variables lagged 2 years, Control – 4 years
Intercept	0.58 $(0.145)^{***}$	0.568 $(0.143)^{***}$	0.382 $(0.115)^{***}$	0.403 $(0.113)^{***}$
Fixed effects				
Category design variation (H1)	0.012 $(0.003)^{***}$	0.008 $(0.004)^{**}$	0.01 $(0.004)^{***}$	0.009 $(0.004)^{**}$
Brand's share of design variation (H2)	-0.007 $(0.003)^{**}$	-0.009 $(0.003)^{***}$	-0.008 $(0.004)^{**}$	-0.009 $(0.004)^{***}$
Category design variation × Brand's share of design variation (H3)		0.007 $(0.002)^{***}$		0.007 $(0.003)^{**}$
Category design variation (H1)				
Sales growth of the previous generation	$-.237 \times 10^{-4}$ $(0.729 \times 10^{-5})^{***}$	-0.231×10^{-4} $(0.72 \times 10^{-5})^{***}$	0.731×10^{-4} (0.743×10^{-4})	0.748×10^{-4} (0.735×10^{-4})
Technological innovativeness of previous generation	-0.725×10^{-4} $(0.321 \times 10^{-4})^{**}$	-0.728×10^{-4} $(0.317 \times 10^{-4})^{***}$	-0.105×10^{-3} $(0.457 \times 10^{-4})^{*}$	-0.117×10^{-3} $(0.454 \times 10^{-4})^{**}$
Number of brand's products in the category	0.004 $(0.002)^{*}$	0.004 $(0.002)^{*}$	0.001 (0.002)	0.003 $(0.002)^{*}$
Category size	-0.358×10^{-8} $(0.175 \times 10^{-8})^{**}$	-0.379×10^{-8} $(0.173 \times 10^{-8})^{**}$	-0.339×10^{-9} (0.158×10^{-8})	-0.141×10^{-9} (0.157×10^{-8})
Category growth rate	0.008 $(0.003)^{***}$	0.008 $(0.003)^{***}$	-0.0002 (0.0008)	0.0002 (0.0008)
Market share	-0.452 $(0.155)^{***}$	-0.445 $(0.153)^{***}$	$-.2362905$ $.1195025)^{**}$	$-.2764302$ $.1191487)^{**}$
Category concentration	0.171 $(0.058)^{***}$	0.175 $(0.058)^{***}$	0.179 $(0.076)^{**}$	0.195 $(0.076)^{***}$
Year fixed effects	Yes	Yes	Yes	Yes
Inverse Mills ratio	-0.236 $(0.072)^{***}$	-0.232 $(0.071)^{***}$	-0.185 $(0.076)^{**}$	-0.199 $(0.075)^{***}$
Random effects				
e_{tmbc}	0.466×10^{-3} $(0.695 \times 10^{-4})^{**}$	0.458×10^{-3} $(0.691 \times 10^{-4})^{**}$	0.52×10^{-3} $(0.945 \times 10^{-4})^{**}$	0.52×10^{-3} $(0.931 \times 10^{-4})^{**}$
r_{0mbc} (model)	0.362×10^{-3} $(0.963 \times 10^{-4})^{**}$	0.345×10^{-3} $(0.937 \times 10^{-4})^{**}$	0.295×10^{-3} $(0.12 \times 10^{-3})^{**}$	0.308×10^{-3} $(0.12 \times 10^{-3})^{**}$
v_{00b} (brand)	0.764×10^{-4} $(0.652 \times 10^{-4})^{**}$	0.773×10^{-4} $(0.611 \times 10^{-4})^{**}$	0.956×10^{-4} $(0.789 \times 10^{-4})^{**}$	0.979×10^{-4} $(0.828 \times 10^{-4})^{**}$

Standard errors in parentheses.
$^{*}\, p < 0.1$, $^{**}\, p < 0.05$, $^{***}\, p < 0.01$

Table 8. Effect of Design Innovativeness on Sales: Cross-Classified Growth Model Results

	Unconditional means model	Unconditional growth model	Conditional growth model
Intercept	47261.01 (16695.8)***	49868 (19337.12)***	58598.09 (18862.43)***
Fixed effects: Initial sales status			
Time		2414.45 (590.22)***	4811.225 (834.0541)***
Time^2		-650.63 (62.104)***	-727.714 (68.259)***
Design innovativeness			-11289.47 (2679.366)***
Fixed effects: Sales growth			
Design innovativeness			1005.165 (405.345)**
Control variables			
Category design variation			3787.871 (1716.006)**
Brand's share of design variation			828.03 (1172.073)
Technological innovativeness			-21.011 (16.497)
Previous generations			22249.28 (6455.326)***
MSRP			-0.016 (0.067)
Model advertising			0.131 (0.013)***
Brand advertising			0.015 0.006)***
Brand strength			0.008 (0.002)***
Year fixed effects			Yes
Country of origin fixed effects			Yes
Random effects			
r_{1mbc} (time)		9.51×10^7 (7.25×10^6)**	9.61×10^7 (7.25×10^6)**
e_{tmbc}	7.23×10^8 (1.95×10^7)**	2.9×10^8 (8.95×10^6)**	2.43×10^8 (7.84×10^6)**
r_{0mbc} (model)	4.75×10^9 (2.64×10^8)**	5.58×10^9 (3.13×10^8)**	6.03×10^9 (3.58×10^8)**
υ_{00b} (brand)	1.2×10^9 (3.35×10^8)**	1.93×10^9 (1.21×10^9)**	1.6×10^8 (1.18×10^8)**
υ_{00c} (category)	1.39×10^9 (8.81×10^8)**	1.93×10^9 (1.21×10^9)**	1.46×10^9 (9.28×10^8)**

Standard errors in parentheses.
$^{*}\, p < 0.1$, $^{**}\, p < 0.05$, $^{***}\, p < 0.01$

Table 9. Comparison with morphing methodology: design innovativeness antecedents

	Main effects: Our measure	Main effects: Morphing measure	Interaction effect: Our measure	Interaction effect: Morphing measure
Intercept	0.533 (0.146)***	370.513 (81.026)***	0.537 (0.145)***	362.265 (82.239)***
Fixed effects				
Category design variation (H1)	0.012 (0.004)***	−15.986 (19.075)	0.01 (0.004)***	−15.309 (19.13)
Brand's share of design variation (H2)	−0.007 (0.003)**	7.236 (12.944)	−0.009 (0.003)***	−6.685 (26.225)
Category design variation × Brand's share of design variation (H3)			0.005 (0.002)**	7.217 (11.819)
Control variables				
Sales growth of the previous generation	-0.217×10^{-4} (0.735×10^{-5})***	−0.01 (0.013)	-0.221×10^{-4} (0.731×10^{-5})***	−0.01 (0.013)
Technological innovativeness of previous generation	-0.634×10^{-4} (0.324×10^{-4})*	−0.144 (0.123)	-0.677×10^{-4} (0.323×10^{-4})**	−0.149 (0.123)
Number of brand's products in the category	0.003 (0.002)	1.887 (9.489)	0.004 (0.002)*	2.069 (9.504)
Category size	-0.3×10^{-8} (0.18×10^{-8})*	-6.79×10^{-6} (7.46×10^{-6})	-0.341×10^{-8} (0.181×10^{-8})*	-6.75×10^{-6} (7.47×10^{-6})
Category growth rate	0.007— (0.003)**	13.458 (6.442)**	0.007 (0.003)**	13.063 (6.483)**
Market share	−0.388 (0.158)**	53.407 (277.641)	−0.402 (0.157)**	34.133 (279.76)
Category concentration	0.152 (0.059)**	−300.648 (132.82)**	0.158 (0.059)***	−290.54 (134.006)**
Year fixed effects	Yes	Yes	Yes	Yes
Random effects				
e_{tmbc}	0.481×10^{-3} (0.708×10^{-4})**	-	0.475×10^{-3} (0.702×10^{-4})**	-
r_{0mbc} (model)	0.34×10^{-3} (0.937×10^{-4})**	-	0.333×10^{-3} (0.921×10^{-4})**	-
υ_{00b} (brand)	0.861×10^{-4} (0.635×10^{-4})**	-	0.899×10^{-4} (0.617×10^{-4})**	-
AIC	−1161.417	3769.509	−1163.38	3763.252
BIC	−1077.572	3849.631	−1075.889	3832.448

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

Table 10. Comparison with morphing methodology: effect on sales

	Unconditional means model	Our measure	Morphing measure
Intercept	47261.01 (16695.8)***	47946.14 (16194.27)***	51220.08 (16760.44)***
Design Innovativeness		-5774.40 (2269.44)**	-3299.248 (1981.189)*
Random effects			
e_{tmbc}	7.23×10^8 $(1.95 \times 10^7)^{**}$	6.96×10^8 $(1.92 \times 10^7)^{**}$	7.02×10^8 $(1.95 \times 10^7)^{**}$
r_{0mbc} (model)	4.75×10^9 $(2.64 \times 10^8)^{**}$	4.75×10^9 $(2.66 \times 10^8)^{**}$	4.81×10^9 $(2.7 \times 10^8)^{**}$
v_{00b} (brand)	1.2×10^9 $(3.35 \times 10^8)^{**}$	1.17×10^9 $(3.28 \times 10^8)^{**}$	1.2×10^9 $(3.36 \times 10^8)^{**}$
v_{00c} (category)	1.39×10^9 $(8.81 \times 10^8)^{**}$	1.3×10^9 $(8.26 \times 10^8)^{**}$	1.37×10^9 $(8.68 \times 10^8)^{**}$
Variance reduced compared to unconditional model			
e_{tmbc}	-	4%	3%
r_{0mbc} (model)	-	0%	-1%
v_{00b} (brand)	-	3%	0%
v_{00c} (category)	-	6%	1%

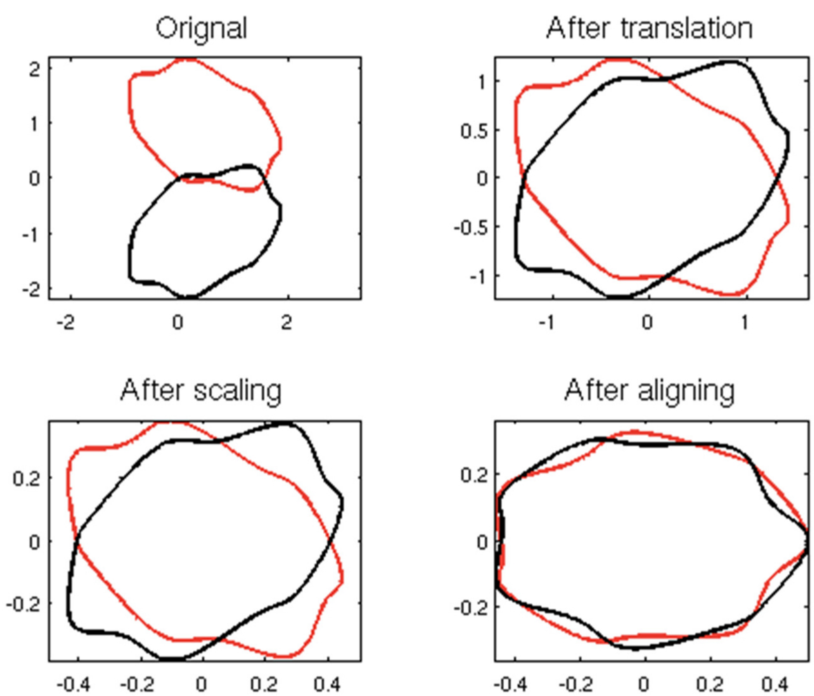
Standard errors in parentheses.

$^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Appendix 1. Superimposition Procedure

Procrustes superimposition aligns shapes and minimizes differences between them to ensure that only real shape differences are measured:

1. Translation: centers all shapes at the origin (0,0)
2. Scaling of all shapes to the same size
3. Aligning: rotates each shape around the origin until the sum of squared distances among them is minimized (similar to least-squares fit of a regression line)
4. Ensures that the differences in shape are minimized



To center all shapes at the origin $(0,0)$, 2-dimensional coordinates (X, Y) of all the landmarks are averaged:

$$X_C = \frac{1}{K}\sum_{j=1}^{K} X_j$$

$$Y_C = \frac{1}{K}\sum_{j=1}^{K} Y_j$$

Then the centered configuration matrix XC by subtracting the centroid coordinate from the corresponding coordinate of each landmark:

$$XC = \begin{bmatrix} (X_1 - X_C) & (Y_1 - Y_C) \\ (X_2 - X_C) & (Y_2 - Y_C) \\ \vdots & \vdots \\ (X_K - X_C) & (Y_K - Y_C) \end{bmatrix}$$

Next, we rescale each shape so that its centroid size is one. The formula for centroid size is:

$$CS(X) = \sqrt{\sum_{i=1}^{K}\sum_{j=1}^{M}(X_{ij} - C_j)^2}$$

Dividing each coordinate of the centered shape by its centroid size produces the pre-shape space where the surface of a hypersphere centered on the origin, and the sum of all squared landmark coordinates is one:

$$\sum_{i=1}^{K}\sum_{j=1}^{M}(X_{ij})^2 = 1$$

Next step is to rotate each shape around the origin until the sum of squared distances among them is minimized. The sum of the squared Euclidean distances between the K landmarks of the rotated target and the reference is:

$$D^2 = \sum_{j=1}^{k}\left[\left(X_{Rj} - \left(X_{Tj}\cos\theta - Y_{Tj}\sin\theta\right)\right)^2 + \left(Y_{Rj} - (X_{Tj}\sin\theta + Y_{Tj}\cos\theta)\right)^2\right]$$

where (X_{Rj}, Y_{Rj}) are the coordinates of the landmark in the reference. To minimize this squared distance as a function of θ, we take the derivative with respect to θ and set it equal to zero:

$$-\sum_{j=1}^{K}\left[\begin{array}{c} 2(X_{Rj}-(X_{Tj}\cos\theta-Y_{Tj}\sin\theta))(-X_{Tj}\sin\theta-Y_{Tj}\cos\theta) \\ \\ +2(Y_{Rj}-(X_{Tj}\sin\theta+Y_{Tj}\cos\theta))(X_{Tj}\cos\theta-Y_{Tj}\sin\theta) \end{array}\right]=0$$

and solve for θ:

$$\theta = \text{arctangent}\left(\frac{\sum_{j=1}^{K} Y_{Rj}X_{Tj}-X_{Rj}Y_{Tj}}{\sum_{j=1}^{K} X_{Rj}X_{Tj}+Y_{Rj}Y_{Tj}}\right)$$

which gives the angle by which to rotate the target to minimize its distance from the reference.

Chapter 2

DESIGN INNOVATIVENESS AND ITS EFFECT ON PERFORMANCE: INSIGHTS FROM SHAPE THEORY

2.1 Introduction

In recent years, product aesthetic design and design innovation has emerged as a fertile area of research. Scholars have proposed that design is an important strategic tool and a source of a competitive advantage that also contributes to resistance to imitation, profitability and sales (Candi and Saemundsson 2011, Eisenman 2013, Landwehr et al. 2013; Rubera 2014). Moreover, existing research suggests that there exists optimal degree of design innovativeness that would allow to achieve higher consumer evaluations and improve the performance (Hekkert et al. 2003).

Existing studies, however, have obtained inconsistent results concerning the relationship between design innovativeness and performance. In Table 1, we provide an overview of the key papers and their findings. Much of this work has examined the effect of design innovativeness and related concepts on sales (Landwehr et al. 2011, 2013; Talke et al. 2009, 2017; Rubera 2014). The findings reported by these studies range from consumer preference for typicality (Landwehr et al. 2011) to positive effect of design novelty (Talke at al. 2009, 2017).

In this study, we propose the variables that moderate the relationship between design innovativeness and sales and thus can explain the contradictory results. We extend the framework introduced in the first paper, where we use evolutionary biology theories to define the antecedents of design innovativeness and establish two independent variables that affect the design innovativeness: a) design variation within a category and b) brand's share of design variation in the category. In this paper, we suggest that these two variables not only affect the design innovativeness of the products introduced in the subsequent period, but also interact with design innovativeness in the current period affecting existing products' performance in terms of sales.

We follow design literature (Ranscombe et al. 2012, McCormack et al. 2003, Osborn et al. 2008) defining product design as the shape of the product, and conceptualize design innovativeness is as a **degree of novelty in the shape of a product**, compared to the design standards established in the category prior to the new product introduction. Category design variation is overall shape variety within a product category. Brand's share of design variation in the category represents relative contribution of a brand to overall variation within product category, or the proportion of design variation accounted by all the products in the brand's portfolio.

We integrate theoretical ideas from the extant literature to demonstrate the relevance of these two variables and support the hypotheses. To develop our hypotheses about moderating effect of category design variation on the effect of design innovativeness on sales, we draw on categorization theory (Barsalou 1985; Loken and Ward 1990), processing fluency theory (Landwehr et al. 2011, 2013; Veryzer and Hutchinson 1998), and sociocognitive theory of product markets (Rosa et al. 1999). We follow brand prototypicality literature (Batra et al. 2010, Goedertier et al. 2015) to develop our hypotheses about moderating effect of brand's share of design variation.

We test our hypotheses in the setting of US automotive industry, using car models sold in the US from 2000 to 2013, including 634 new make-models (from which 310 new generations of existing models) introduced by 38 brands, and assigned to six product categories (sedan, SUV, pickup etc.). We collect design and technological data from the portal Msn.com/autos and sales data from Ward's Auto Yearbook. To quantify design innovativeness, category design variation and brand's share of design variation in the category we use shape theory and landmark-based geometric morphometrics that are used in evolutionary and developmental biology to quantify biological shape and shape variation (Webster and Sheets 2010).

The paper's findings make several theoretical contributions. First, we extend the literature on design innovativeness by considering the role of category design variation and brand's share of design variation in the category. Second, our results explain how the effects of product design innovativeness on sales vary depending on the level of category design variation and brand's share of design variation in the category, illuminating boundary conditions and providing a deeper perspective on the relationship between design innovativeness and sales. Finally, we reveal that the variables coming from evolutionary biology and shape theory can be applied in the product design context to explain the effect of design innovativeness on sales.

Our findings suggest that category design variation positively moderates the effect of design innovativeness on sales, indicating that more innovative designs are more successful in the categories with high design variation, where the range of acceptable designs is wider. On the opposite, in the categories with low design variation, where the influence of a category design prototype is stronger, products with high design innovativeness perform worse in terms of sales.

We find a negative interaction effect between brand's share of design variation and design innovativeness on sales. Namely, highly innovative designs introduced by brands with high share of design variation in the category suffer lower performance. Conversely, high innovativeness of designs introduced by brands that account for low design variation in the category, results in higher sales. This somewhat contradictory result is explained by the theory of brand prototypicality as a risk-reducing cue (Goedertier et al. 2015). Since brands with low share of design variation are more prototypical with regard to a category design, they reduce the perceived uncertainty and the purchase risk associated with novelty thus improving the acceptance of innovative designs.

These findings have high managerial relevance since they explain when introduction of more innovative or more traditional designs is more beneficial based on category conditions and brand's own design profile. Managers can take these factors into consideration making decisions about the design of new products.

The remainder of the paper is organized as follows. We first develop the theory and hypotheses. Following that, we describe the data, method, and results. We conclude with a discussion of the paper's theoretical contributions, managerial implications, and limitations and opportunities for further research.

2.2 Theoretical Framework

2.2.1 Design innovativeness and sales

First, we provide the definitions of concepts used in the literature to describe the degree of novelty in products' design and summarize current findings about effect on sales. To define design novelty, existing research has used the concepts of design prototypicality, design newness, and design innovativeness. Design newness is a deviation in a product design from a current design state (Talke et al. 2009, 2017; Mugge and Dahl 2013); design innovativeness is defined as the degree of novelty in a product's external appearance (Rubera 2014). Prototypicality or typicality is the extent to which a product is representative of an overarching category (Hekkert et al. 2003; Landwehr et al. 2011, 2013; Liu et al. 2017). In this paper, we follow design literature (Ranscombe et al. 2012, McCormack et al. 2003, Osborn et al. 2008) that defines product design as the shape of the product. Accordingly, we define design innovativeness as a **degree of novelty in the shape of a product**, compared to the design standards established in the category prior to the new product introduction.

Most of research exploring the design novelty that we summarize in Table 1, has been focused on capturing its effect on performance in terms of sales. Past studies, however, have obtained inconsistent results concerning the relationship between design novelty and sales. For example, Talke et al. (2009) find positive impact of design newness on sales, while Landwehr et al (2011) instead provide support for the positive impact of typicality. Liu et al. (2017) propose nonlinear relationship between design prototypicality with regard to luxury and economy segments and performance; their findings suggest that consumers prefer designs with a moderate level of segment prototypicality. Talke et al. (2017), instead, find a positive, linear effect of design novelty on sales but fail to find a U-shaped relationship.

The explanation for contradictory findings may be in a boundary condition or moderator variable. Existing research has focused on two moderators affecting relationship between design innovativeness and sales – technological innovativeness and time on the market as a measure of consumer exposure to the novel design. However, these studies also provide contradicting results. Regarding the interaction effect between design and technological innovativeness, Talke et al. (2009) report no significant results, while Rubera (2014) finds negative interaction effect on initial sales' status and positive interaction effect on sales' growth rates. Results of Mugge and Dahl (2013) support negative impact of design innovativeness for radical innovations and no significant effect for incremental innovations.

Including the time on the market variable that approximates the exposure of the consumers to a novel design, Landwehr et al. (2013) find that more innovative designs initially evoke negative consumer reactions, but tend to gain in appeal at higher exposure levels. Typical designs, however, lose appeal after multiple exposures, making atypical designs are more successful in the long run. Talke et al. (2009) find positive impact of design innovativeness on sales right after the introduction that persists in strength over time. Results of Rubera (2014) show that design innovativeness, on the opposite, diminishes initial sales' status but increases sales' growth rate.

In this study, we extend the framework introduced in the first paper, where we use evolutionary biology theories to define the antecedents of design innovativeness. There we establish two main independent variables that affect the design innovativeness: a) design variation within a category (Erwin 2007) and b) brand's share of design variation in the category (Zelditch et al. 2012, Foote 1997). In this paper, we suggest that these two variables not only affect the design innovativeness of the products introduced in the subsequent period, but also interact with design innovativeness in the current period and affect existing products' performance in terms of sales.

First, we provide definitions of these variables and briefly explain the theories supporting their relevance. Next, we apply these theories to develop our hypotheses about the moderating effect of category design variation and brand's share of design variation on the relationship between design innovativeness and sales.

Category design variation

Definition of category design variation. We define design variation as overall shape variety within a product category (Foote 1990, Zelditch et al. 2012). In order to measure category design variation, evolutionary biology considers the "shape space", namely the multidimensional space in which each object is represented by a single point, and all existing objects are plotted around the average or typical shape of the category. This typical shape is defined "reference" (in the Methodology section, we explain how to identify the reference shape and build the shape space). In addition to the distribution of the existing shapes around the reference, the surface of a shape space includes all the possible feature combinations that a design of an object from a category can have. Category design variation is measured in terms of squared distances between forms (corresponding to a variance). In this framework, category design variation defines the range of currently accepted designs in the category (Foote 1994). We represent the concept of design variation range graphically on Figure 2. Let the circle represent the shape space including all possible designs of an object belonging to the category, with the reference or typical shape located in the center of the circle. The black points represent existing objects in the category. Dotted line depicts the range of design variation in the category, based on the variation of existing objects. When design variation is low (pictured on Figure 2a), then all the objects within a category have similar shapes and tend to be close to a typical shape (or the reference) of the category. In contrast, objects in categories with high design variation (Figure 2b) have very different shapes. These objects are more distant from the reference shape and tend to occupy a bigger area of the space shape.

In sum, category design variation is a measure of overall design variety within a category that determines category design boundaries providing a range of currently acceptable design based on distribution of existing products in the shape space. It is lower in more stable categories, where most of the products are concentrated around a category protototype, as depicted on Figure 3, which graphically represents the shape space of pickup product category in 2011. Since shape space is multidimensional non-Euclidean space, we run PCA analysis and plot PCA scores corresponding to each car model in two-dimensional representation of a shape space. All the models are close to the category prototype, located at the point where the two axes cross each other, so that the pickup category in 2011 has low design variation (we explain in the Methodology section how to compute it). On the opposite, the SUV category in 2000 (represented on Figure 3a) has high design variation. In this case, SUVs are located further away from the category prototype and occupy a wider area of the total space shape than pickups.

Category design variation and sales. To develop our hypotheses about effect of category design variation on sales, we draw on categorization theory (Barsalou 1985; Loken and Ward 1990), processing fluency theory (Landwehr et al. 2011, 2013; Veryzer and Hutchinson 1998), and sociocognitive theory of product markets (Rosa et al. 1999).

A vast body of research suggests that stimuli that are typical of their category elicit more positive responses than those that are atypical (Loken and Ward 1990, Zajonc 1980, Veryzer and Hutchinson 1998, Hekkert et al. 2003). As consumer preferences affect sales, more innovative products suffer lower evaluations and sales (Landwehr et al. 2011, 2013). One of the most influential explanations for the consumer preference for typicality is based on the concept of fluency (Veryzer 1999, Reber et al. 2004). People can categorize and thus process typical stimuli are more efficiently, thereby leading to feelings of fluency, which in turn elicits positive affect (Reber et al. 2004).

Previous exposure to the category provides a prototype to which to newly encountered product designs are compared. Sociocognitive perspective of product markets (Rosa et al. 1999), in agreement with processing fluency research, suggests that the mismatch between a category prototype and specific product attributes results in negative product evaluation. However, it proposes that product evaluations are dynamic, and the product with the same attribute sets are evaluated differently depending on a category's stability (Rosa et al. 1999).

The authors find that in unstable product categories, products with radically different attributes are considered equally acceptable members of the category. However, if stabilization around a category prototype occurs, the range of acceptable products diminishes. As category stability with regard to category prototype changes, some category members are likely to decline in acceptability without any physical change to their attributes, or improve their standing also without changing (Rosa et al. 1999).

As noted before, category design variation defines the range of acceptable product designs based on currently existing designs. Applied in sociocogntive framework, this measure reflects the stability of the category design, so that category design variation is lower for stable categories, and higher for unstable categories. Design innovativeness represents the distance of the product design from the prototype (we explain in the Methodology section how we calculate its measure). Accordingly, sociocognitive theory of product markets suggests that the concept of category design variation can be fruitful in explaining the novel product evaluation and performance.

Brand's share of design variation

Brand's share of design variation definition. Brand's share of design variation in the category is a relative contribution of a brand to overall variation within product category, or the proportion of design variation accounted by all the products in the brand's portfolio. It is calculated as the sum of variance contributions of each product in the brand's portfolio (Foote 1993). Brands with more eccentric product designs that are positioned further away from a category prototype contribute more to overall design variation.

Take for instance the SUV category in 2000 represented in Figure 3a. We can say that, for instance, the relative contribution of the subgroup Nissan to the overall design variation of the category SUV is the sum of variance proportions contributed by Pathfinder and Xterra. Also, we can conclude that Hummer is the brand that contributes the most to overall SUV design variation because it produces Hummer H1, the most eccentric design (i.e., the further away from the reference). Differently, Nissan has the lowest share of category design variation because its two models are very close to the category prototype.

Brand's share of design variation and sales. To develop our hypotheses about effect of brand's share of design variation in the category on sales, we follow brand prototypicality literature (Batra et al. 2010, Goedertier et al. 2015). Brand prototypicality is defined as the degree to which a particular brand's design overlaps with or differs from the typical design of the product category (Goedertier et al. 2015). Brand prototypicality increases the salience of the brand–category association, because prototypicality is, by definition, a function of the degree to which a category member has attributes in common with other category members (Loken and Ward 1990, Batra et al. 2010).

Goedertier et al. (2015) propose that brand prototypicality has a positive effect on acceptance of innovations and explain it with the following mechanism. According to Chandy and Tellis (2000), highly innovative products are characterized by high levels of risk and uncertainty leading to lower evaluation of innovations and hampering their adoption. In order to overcome the perceived uncertainty, consumers tend to search for information to decrease perceived risk. Goedertier et al. (2015) suggest that brand prototypicality within a product category serves as an important cue reducing purchase risk, since consumers perceive prototypical brands as particularly familiar and low-risk. In this framework, brand prototypicality positively moderates the effect of product innovativeness on performance, since it helps to overcome perceived uncertainty about novel products and increases consumer acceptance.

Our measure of brand's share of design variation in the category is an inverse measure of brand prototypicality with regard to design. The more prototypical brand is for its category, the closer are the products in its portfolio to the category prototype, which is reflected by lower value of brand's share of category design variation. Hence, brand's share of design variation serves as a risk-reducing cue that can moderate the effect of novelty on sales.

We contend that the variables coming from theory of shape that we have introduced in the first paper, can be applied in the product design context not only to explore the drivers of design evolution, but also to explain the effect of design innovativeness on sales. In the first paper, we explore how these variables shape the design in the future. Namely, we use current category design variation and brand's share of design variation to predict innovativeness of designs that are to be introduced in the subsequent periods. In this study, we explore how these variables affect current consumers' perceptions and product design evaluations and thus moderate the effect of design innovativeness on sales.

Hypotheses

With regard to main effect of design innovativeness on sales, we follow the categorization and processing fluency arguments (Barsalou 1985; Loken and Ward 1990; Landwehr et al. 2011, 2013; Veryzer and Hutchinson 1998). This research more innovative designs evoke negative consumer reactions, since novelty leads to uncertainty and tension. According to the processing fluency explanation, categorization and processing of typical designs is performed more efficiently, thereby leading to feelings of fluency, which in turn elicits positive affect and design evaluation (Reber et al. 2004). Accordingly, more innovative designs suffer lower evaluations and sales (Landwehr et al. 2011, 2013).

Thus, we offer H_1:

H_1: The greater the product design innovativeness, the lower the product's sales

Sociocognitive prespective (Rosa et al. 1999) supports the conclusion that more innovative designs suffer lower evaluation and sales, however, it also notes that product evaluations are dynamic and depend on category stability. It implies that in unstable product categories, highly innovative designs are considered acceptable, while in stable categories the range of acceptable design novelty diminishes and highly novel designs suffer lower evaluations and sales.

As noted before, category design variation reflects the stability of the category design, so that category design variation is lower for stable categories, and higher for unstable categories. Design innovativeness represents the distance of individual product design from the category prototype. Consequently, sociocognitive perspective suggests that category design variation moderates the effect of design innovativeness on sales. Namely, the effect of design innovativeness on sales is expected to be more positive for categories with higher design variation.

Thus, we offer H_2:

H_2: The greater the category design variation, the more positive is the effect of design innovativeness on sales

Brand prototypicality literature (Goedertier et al. 2015) suggests that highly innovative designs suffer lower evaluations and sales because they are characterized by high levels of risk and uncertainty. Brand prototypicality with regard to a product category design moderates the effect of design innovativeness on performance, reducing the perceived uncertainty about innovative designs and the purchase risk and increasing acceptance. Our measure of brand's share of design variation in the category is an inverse measure of brand prototypicality. More prototypical brands have products in its portfolio that are closer to the category prototype, which is reflected by lower value of brand's share of category design variation. Brands with low share of category design variation are considered low-risk brands in this framework, and will reduce the perceived risk associated with high design innovativeness. Brands that contribute more to the category design variation, on the opposite are considered high-risk, and exacerbate the negative effect of design innovativeness on sales. Accordingly, brand's share of design variation moderates the effect of design innovativeness on sales, and we expect negative interaction between brand's share of design variation and design innovativeness on sales.

Thus, we offer H_3:

H_3: The effect of design innovativeness on sales becomes more negative as brand's share of design variation in the category increases

2.3 Data and Method

2.3.1 Data

We chose US automotive industry as an empirical setting because design is important in this industry and has been studied before (Landwehr et al. 2011, 2013; Rubera 2014; Talke 2009, 2017). Moreover, existence of defined product categories with distinct design languages (such as coupe, SUV, minivan etc.) allows us to explore the effect of design variables across different categories.

Our data set consists of 38 brands and 748 car models sold in the U.S. passenger car market from 2000 to 2013, including overall 3503 model-year observations. We obtain sales data from Ward's Automotive Yearbook. From the portal Msn.com/autos we collect retail price, category, and car model-specific attributes, including performance, interior and exterior specifications (total of 196 specifications). We also collect front view pictures of each car model. We identify 634 new models (including 310 new generations of existing models). Car models are assigned to six product categories: passenger car, SUV, crossover, sport car, pickup and van. The description of the sample by the category is provided it Table 2. Table 3 represents definitions of the main constructs, measures, and data sources.

2.3.2 Measures

Design innovativeness. We operationalize design innovativeness in terms of shape and define design innovativeness of a car model is the degree of novelty in its shape compared to the established typical shape in the category c in the previous period. To obtain this deviation measure, we employ shape theory and landmark-based geometric morphometric analysis (Webster and Sheets 2010), which uses geometric coordinates instead of exact measurements. Following this methodology, we collect shape data from the digital photographs of cars' frontal views, which we collect from the website Msn.com/autos. We apply shape theory and morphometric methods to generate the typical shape of the category and quantify the design innovativeness as a distance between typical shape and each individual car model.

The key construct of a shape theory is the Kendall's (1977) definition of shape: "Shape is all the geometrical information that remains when location, scale, and rotational effects are filtered out from an object." In this framework, a product's design is a shape, which is represented by a configuration of landmarks marked on the product images. Landmarks are points of correspondence on each object that match between and within populations (Bookstein 1991, Dryden and Mardia 1998). Each landmark has to be present on every product; if it is not present it either has to be marked approximately or it cannot be used at all. The choice of landmarks is critical for the shape analysis, since the results directly depend on their quality of landmarks (Webster and Sheets 2010).

We follow previous research that has conceptualized car design as a shape to specify the landmarks. First of all, we draw on shape grammar literature (McCormack et al. 2004, Osborn et al. 2006, Osborn et al. 2008), which has been focused on developing so-called “design language” based key features that sufficiently describe the shape of the car with regard to product category (such as SUV, minivan, coupe etc.) and brand. According to Osborn et al. (2006, 2008) most relevant characteristics for an adequate definition of the car shape are the following: front wheels, rear wheels, front wheel well, rear wheel well, front fender, rear fender, front bumper, rear bumper, front windshield, rear windshield, grill, headlight, hood, roof, trunk, taillight, rocker, door, front side window, rear side window, door handle, ground, and belt line.

Next, we follow the work of Ranscombe et al. (2012) proposing a procedure that isolates the geometry in car images and visually decomposes the designs to identify the key aesthetic features and assess their influence on brand and category recognition. These features provide important input into our geometric morphometric representation of a car. Ranscombe et al. (2012) show front, side and rear images of car models with the different level of detailing to the participants and evaluate whether they were able the correctly identify the vehicle’s category and brand. The authors find that there were more correct responses based on front views and less correct responses with respect to side and rear views; the majority of responses using the side view of the car were incorrect. Ranscombe et al. (2012) conclude that frontal images of the cars with a certain level of detailing receive the greatest number of correct responses and provide the description of the design features that are most powerful in communicating vehicle brand and category.

Based on these studies, we focus on the front view of the car, and define 50 landmarks that fully describe the shape or the car and communicate the category and brand membership for the consumers. They include outline or the silhouette (the boundary created between the vehicle and space surrounding it), daylight opening (defined by the front windshields), and details such as headlamps, radiator grille etc. (Figure 1).

To build the measure of design innovativeness, we follow the procedure of geometric morphometric analysis described in the first paper. It implies building several geometric spaces. When we plot landmarks on the car photographs, we create a Euclidean *landmark space*, in which landmarks are represented by two coordinates (X, Y) in 2-dimensional space. However, the key feature of shape theory is that all comparisons of shapes are performed not between individual landmarks, but between so-called "configurations of landmarks", which represent shape as a whole. Configuration is defined as the full set of landmarks recorded for each object. Every configuration of K landmarks having M coordinates is represented by a single point in a space with $K \times M$ dimensions, which is called *configuration space*. Configuration space is a geometric space of $K \times M$ dimensions, which represents the set of all possible KMmatrices. We build the configuration space when we extract two-dimensional landmark coordinates for the analysis from a digital image of an object. In our sample, where car shape is represented by 50 2-dimensional landmarks, we create a 100-dimensional configuration space.

Next, we need to remove the effects of location, orientation, and size, following the definition of shape by Kendall (1977). The procedure called Procrustes superimposition is used to transform the configuration space removing position, size and rotation. It implies eliminating several dimensions of the configuration space and building a shape space. *Shape space* is the Non-Euclidean space of $K \times M$-4 dimensions in which configurations are plotted after scaling, translation, and rotation. In our case, the shape space of the car design includes 96 dimensions. In this space we work with pure differences on shape, filtering out all the irrelevant variation.

Superimposition procedure is described in detail in the Appendix 1, and includes following steps (Zelditch et al. 2012):

1. Center each configuration of landmarks at the origin by subtracting the coordinates of its centroid from the corresponding (X or Y) coordinates of each landmark.

2. Scale the landmark configurations to unit centroid size by dividing each coordinate of each landmark by the centroid size of that configuration.

3. Rotate the configurations to minimize the summed squared distances between homologous landmarks (over all landmarks) between the shapes. At this step, we build so-called "reference shape", or the average shape of the sample. The reference shape minimizes the average distances of all the shapes from the reference.

Following this procedure, we build the reference that represents the average car shape for each the category in each period. Prototypes are constructed by the consumers from an "average" of designs currently found on the market (Blijlevens et al. 2013). However, we need to take into account that more widely distributed and used products are perceived as more typical (Loken and Ward 1990, Meyvis and Janiszewski 2004). To make sure that our objective measure reflects the consumers' perception of typicality, we weight car models' contribution to the average shape according to the sales proportion in the year prior to introduction of the new model.

The surface of the shape space represents all the possible landmark configurations that can potentially represent shape of the object, and all existing shapes are represented as single points along the surface. The location of each individual object on the shape space depends on their distance from the reference that is placed in the center. This distance is called Procrustes distance.

Procrustes distance is the main measure of shape difference in geometric morphometrics. Procrusrustes distance between two shapes (landmark configurations) is a distance along the surface of the shape space after scaling, rotation and translation, which is analogous to Euclidean distance but in the curved non-Euclidean shape space. Average shape computed in the last step of the superimposition procedure is the shape whose sum of squared Procrustes distances to the other objects is minimal.

In sum, to build the measure of design innovativeness, we extract landmark coordinates from the product images, and apply superimposition procedure to remove the size, scale and rotational effects from the pictures. Next, we build the shape space and the typical shape of the car for each category. Procrustes distance to the mean category shape represents the measure of the design innovativeness of each car model. We measure design innovativeness of each car model every year it is present on the market, so that our design innovativeness measure varies in time, and as expected, in our sample it is decreasing over time as the product is longer present on the market.

Category design variation. We define category design variation as overall shape variety within a category. It indicates the range of shape space occupied and a magnitude of morphological variation within a category and is measured in terms of squared distances between forms, corresponding to a variance (Foote 1990,1993; Zelditch et al. 2012).

Measure of design variation represents shape variety within a car category, and is constructed using the design innovativeness measures of the car models in the category calculated before:

$$CDV_{ct} = \frac{\sum DI_i^2}{N-1} \tag{1}$$

Where DI is design innovativeness of car model i in category c in year t; N – number of models in category c in year t.

Brand's share of design variation. Brand's share of design variation is the contribution of all the products in the brand's portfolio to the overall category design variation. To obtain this measure, we partition overall category design variation into the contributions made by each subgroup, i.e. brand (Foote 1993).

The brand's share of design variation in the category is calculated as sum of the variance contributions of each individual product:

$$BSDV_{bct} = \frac{\sum_{\text{brand}} DI_i^2}{N{-}1} \tag{2}$$

Where DI is design innovativeness of brand's b model i in category c in year t; N - number of models in category c in year t.

Control variables. We control for marketing-mix variables, such as price and advertising. We obtain the data on manufacturer-suggested retail price (MSRP) from Msn Auto website. Advertising expenditure data are collected from TNS Media Intelligence that provides expenditure data across all major media. We include advertising spending variables on individual car model and on brand level. We also control for technological innovativeness of the car (based on Msn.com/auto data on car model performance in terms of horsepower and fuel economy). Number of previous generations of a car model can affect consumers' perception of a model quality and consequently sales; thus, we include it as another control variable. Finally, we control for year and country of origin fixed effects.

2.3.3 Model Specification

In our data, the repeated observations of sales over time are nested within car models, which are in turn nested within brands and categories. Multilevel mixed-effects modeling procedure allows to take this structure into account and explicitly model the group effects. Since car models can simultaneously be nested within two different higher-level categories, brands and car categories, we use a cross-classified three-level mixed model. We follow the procedure described by Singer (1998), and first estimate the unconditional means model that partitions the variance in sales into the variance associated with differences across categories (σ_c^2), the variance across brands (σ_b^2), the variance across car models (σ_m^2), and variance in the car model's sales over time (σ_e^2):

$$\begin{gathered}\text{Sales}_{tmbc} = Y_{tmbc} = \theta_{000} + \upsilon_{00c} + \upsilon_{00b} + r_{0mbc} + e_{tmbc}, \\ e_{tmbc} \sim N(0, \sigma_e^2), \quad r_{0mbc} \sim N(0, \sigma_m^2), \quad \upsilon_{00c} \sim N(0, \sigma_c^2), \quad \upsilon_{00b} \sim N(0, \sigma_b^2)\end{gathered} \tag{3}$$

where t, m, b, and c denote time, car model, brands, and categories; θ_{000} represents the grand mean of car model sales across brands and categories; e_{tmbc} is the time-level random error; r_{0mbc} is the random between-car modelresidual; υ_{00b} is the random between-brandsresidual; υ_{00c} is the random between-categoriesresidual.

To build the compact model presented above, at the first level we model car sales at each time period as a function of car model mean sales plus a random error:

$$\text{Level 1:} \quad \text{Sales}_{tmbc} = Y_{tmbc} = \pi_{0mbc} + e_{gmbc}, \quad e_{tmbc} \sim N(0, \sigma_e^2), \tag{4}$$

where t, m, b, and c denote time, car model, brands, and categories; π_{0mbc} is the mean sales of car model m in brand b in category c; e_{tmbc} is the time-level random error and represents variance acrosstime.

At the second level, 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:

$$\text{Level 2:} \quad \pi_{0mbc} = \beta_{00bc} + r_{0mbc}, \quad r_{0mbc} \sim N(0, \sigma_m^2), \tag{5}$$

where β_{00bc} is the mean sales of the car model in brand b and category c; and r_{0mbc} is the random between-car modelresidual. The between-car model variance σ_m^2 is assumed to be uniform across car models within each of the b brands and c categories.

Level 3 models variation between brands and within categories:

$$\text{Level 3:} \quad \beta_{00bc} = \theta_{000} + \upsilon_{00b} + \upsilon_{00c}, \quad \upsilon_{00b} \sim N(0, \sigma_b^2), \quad \upsilon_{00c} \sim N(0, \sigma_c^2), \tag{6}$$

where θ_{000} is grand mean of car model sales across brands and categories, υ_{00b} is the random between-brandsresidual, σ_b^2 is the between-brand variance, υ_{00c} is the random between-categoriesresidual, and σ_c^2 represents the between-categories variance.

The unconditional model allows us to estimate four components of the total variability in sales: at Level 1variance across car model generations (σ_e^2), at Level 2 – among car models within brands and categories (σ_m^2), and at Level 3 – among brands (σ_b^2) and among categories (σ_c^2). We use these results of unconditional model to make the decisions about the model specification and estimate the performance of the full conditional model.

Next, we add the design innovativeness variable at the first level, since it is measured yearly, and category- and brand-level predictors at the third level to estimate the full conditional model:

$$\begin{gathered} \mathbf{Sales}_{\boldsymbol{tmbc}} = \boldsymbol{\theta_{000}} + \boldsymbol{\theta_{100} DI_{tmbc}} + \boldsymbol{\theta_{001} CDV_{tbc}} + \\ + \boldsymbol{\theta_{002} BCDV_{tbc}} + \boldsymbol{\theta_{110}(CDV_{tbc} x DI_{tmbc})} + \\ + \boldsymbol{\theta_{120}(BCDV_{tbc} x DI_{tmbc})} + \boldsymbol{e_{tmbc}} + \boldsymbol{r_{0mbc}} + \boldsymbol{\upsilon_{00b}} + \boldsymbol{\upsilon_{00c}} \end{gathered} \tag{7}$$

Where DI is design innovativeness, CDV is category design variation; BSDV is brand's share of design variation. Independent variables in the model are centered at the grand mean.

2.4 Results

We run the unconditional means model using Stata *mixed* command to calculate the proportion of design innovativeness variance that occurs across car model generations, between car models, brands, and categories. We estimate the proportion of each level's variance in total variance as follows: $\sigma_e^2/(\sigma_e^2 + \sigma_m^2 + \sigma_b^2 + \sigma_c^2)$ is the proportion of variance across time; $\sigma_m^2/(\sigma_e^2+\sigma_m^2+\sigma_b^2+\sigma_c^2)$ is the proportion of variance between car models; $\sigma_b^2/(\sigma_e^2+\sigma_m^2+\sigma_b^2+\sigma_c^2)$ is the proportion of variance between brands; and $\sigma_c^2/(\sigma_e^2 + \sigma_m^2 + \sigma_b^2 + \sigma_c^2)$ is the proportion of variance between categories. This estimation allows us to test the nested structure of the model and determine whether there is significant variation across groups.

The variation in sales that occurs across time is 9%, between car models is 58%, between brands 15%, and 17% between car categories. The results are presented in Table 5. The likelihood test indicates that the full model has a better fit ($\Delta\chi^2(2) = 44.47$, $p < 0.001$); hence, we use the full model for hypotheses testing. To control for potential multicollinearity, we examine the variance inflation factors (VIFs) of the independent variables. Mean VIF is 2.20, and none of the VIFs is exceeding 2.75, indicating that the data are not affected by multicollinearity. Full conditional model explains 17% of total variance in car sales compared to unconditional model. It reduces variance on category level by 7%, on brand level by 75%, on the model level by 3%, and explains 17% of variation of car model sales across time.

2.4.1 Tests of hypotheses

Model-free evidence presented in Figure 4, provides initial support for Hypothesis 1 about negative effect of design innovativeness on sales, supporting the findings revealing consumers' preference for typicality (Landwehr et al. 2011, 2013). To test this Hypothesis, we estimate the main effects model. The results that are presented in Column 2 of Table 5 also support the negative effect of design innovativeness on sales ($b = -9695.33$, $p < 0.01$).

Next, we introduce interaction terms and test the moderation effects of category design variation and brand's share of design variation on the effect of design innovativeness on sales. Results presented in Column 3 of Table 5 reveal positive interaction effect between category design variation and design innovativeness ($b = 4128.308$, $p < 0.01$) in support of Hypothesis 2. Figure 5 depicting the interaction plot shows that more innovative designs suffer lower sales in the categories with low design variation, but in the categories with high design variation they are on the opposite more successful. Hypotheses 3 is also supported revealing negative interaction effect between brand's share of design variation and design innovativeness ($b = -8401.256$, $p < 0.01$). As Figure 6 shows, highly innovative designs introduced by brands with high share of design variation in the category suffer lower performance. Conversely, high innovativeness of designs introduced by more prototypical brands, which account for low design variation in the category, results in higher sales.

2.4.2 Robustness checks

We next report the results of additional analyses that examine the robustness of the results. First, we exclude cars priced over \$110000, which are unlikely to be in the consideration set of mainstream car shoppers (Liu et al. 2017). The results of main effects and interaction effects models, which are reported in Columns 2-3 of Table 6, do not change. In Tables 7 and 8 we report estimation results using two different samples: 1) excluding model-year observations after 2011, 2) excluding model-year observations before 2002. Again, the results reported in Columns 2-3 of Tables 7 and 8 are consistent with the main model results. Finally, we try modifying the sample by excluding sequentially each product category. The results do not change; we report in Table 9 the results of estimation with crossover category excluded.

2.5 General Discussion

To date, most of the research exploring design innovation has focused on its consequences in terms of sales. However, the studies exploring the effect of design innovativeness on sales have reported contradictory results ranging from strictly positive effect of design novelty (Talke at al. 2009, 2017) to consumer preference for typicality (Landwehr et al. 2011). Inconsistent results may be explained by existence of a boundary condition in form of design-related category- and brand-level moderator variables. Addressing this issue, we introduce the variables informed by the shape theory that describe distribution of existing designs on the market and brand's design profile with regard to the category. We contend that these two variables, design variation within a category and brand's share of design variation, affect consumers' perceptions and product design evaluations and thus moderate the effect of design innovativeness on sales.

Our findings, which are robust, demonstrate that category design variation positively moderates the effect of design innovativeness on sales, so that more novel designs are more successful in categories with high design variation. Brand's share of design variation negatively moderates the effect of design innovativeness on sales, exacerbating the risks associated with high innovativeness and thus worsening the performance in terms of sales. We conclude with a discussion of the paper's theoretical contributions, the managerial implications of the findings, and limitations and opportunities for future research.

2.5.1 Theoretical and Managerial Implications

First, we extend the design innovation literature by considering the role of category design variation and brand's share of design variation in the category. It allows to build a comprehensive framework illuminating boundary conditions and providing a deeper perspective on the relationship between design innovativeness and sales. Second, we integrate insights from evolutionary biology and shape theory and theoretical ideas from several streams of marketing literature (categorization and processing fluency theories, sociocognitive perspective of product markets, and brand prototypicality literature) to show that the variables coming from evolutionary biology and shape theory can be applied in the product design context to explain the effect of design innovativeness on sales.

Third, our results explain how the effects of product design innovativeness on sales vary depending on the level of category design variation and brand's share of design variation in the category. We find that category design variation positively moderates the effect of design innovativeness on sales. As depicted on Figure 5, more innovative designs are more successful in the categories with high design variation. Conversely, in the low design variation categories, products with more traditional designs are more successful.

We find a negative moderation effect of brand's share of design variation on relationship between design innovativeness and sales. This result, depicted on Figure 6, indicates that brands with a history of radical design products do not benefit from consecutive introductions of highly novel designs. Contrary to a belief that consumers may expect more innovative designs from these brands, traditional designs introduced by these brands achieve higher sales. We illustrate it with the example of Hummer, the brand consistently contributing a high share of category design variation. For example, Figure 3b shows, Hummer had the highest share of design variation in the SUV category in 2000 due to the high design innovativeness of its model H1. Figure 4 depicts the images of Hummer H1 and subsequent models H2 and H3 introduced in 2003 and 2006. We also report the design innovativeness measures of each model at the year of introduction and total sales. Each of H2 and H3 models is more typical than the previous Hummer models, and is more successful in terms of sales. Thus, in the portfolio of a brand with high share of design category variation, more traditional designs are more successful.

As Figure 6 indicates, sales of more innovative products are higher for the brands with low share of design variation. It implies that more traditional brands can benefit from the introduction of more eccentric designs, since higher prototypicality of these brands with respect to category design facilitates the acceptance of innovative designs reducing the perceived uncertainty and purchase risk.

These findings provide important implications for managerial practice. Managers may consider this study's insights as additional inputs making decisions about the design of new products, and offer the products with the optimal level of design innovativeness based on category conditions and brand's own position with regard to the category typical design.

2.5.2 Limitations and Opportunities for Further Research

This study has some limitations that present opportunities for further research. First, in this research, we focused on the automobile industry. Future research could try to replicate these findings in different product categories. Second, we consider the brand's share of design variation as a brand-level design variable that moderates the effect of design innovativeness on sales. This concept represents the brand prototypicality with respect to the category design. Another important variable on a brand level that further research could explore is brand-level design variation. This measure can be build analogous to category design variation, which represents design variety within a product category. Brand design variation then is the overall design variety within a brand product portfolio, reflecting the consistency of design across brand's product portfolio.

Finally, future research could consider other factors that can moderate the relationship between design innovativeness and sales. For example, number of products in the category can affect this relationship, since existing research suggests that an atypical appearance is advisable when there are many competing alternatives in the category (Creusen and Schmoormans 2005).

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Figures

Figure 1. Landmarks representing the car shape

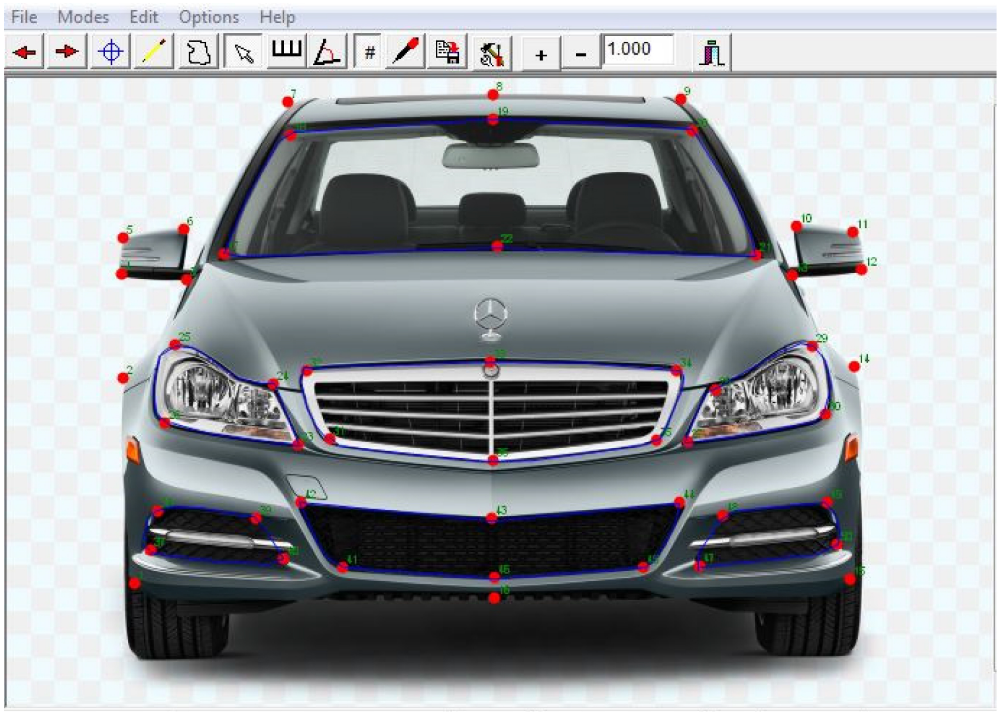
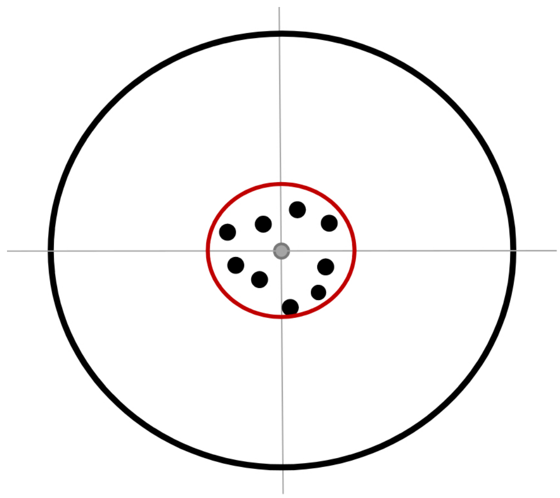


Figure 2. Shape space boundaries: range of design innovativeness

(a) Shape space with low design variation



(b) Shape space with high design variation

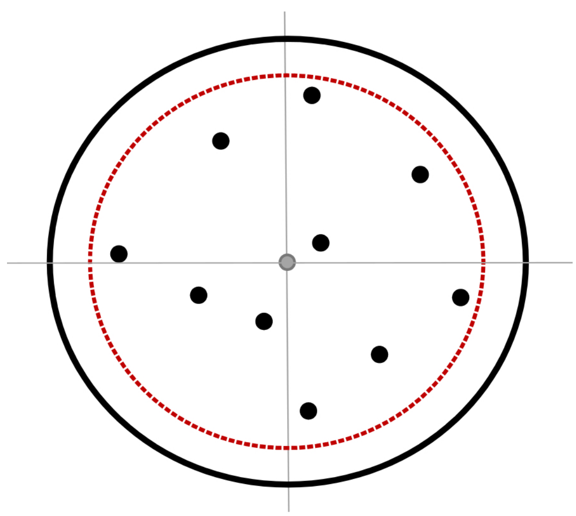
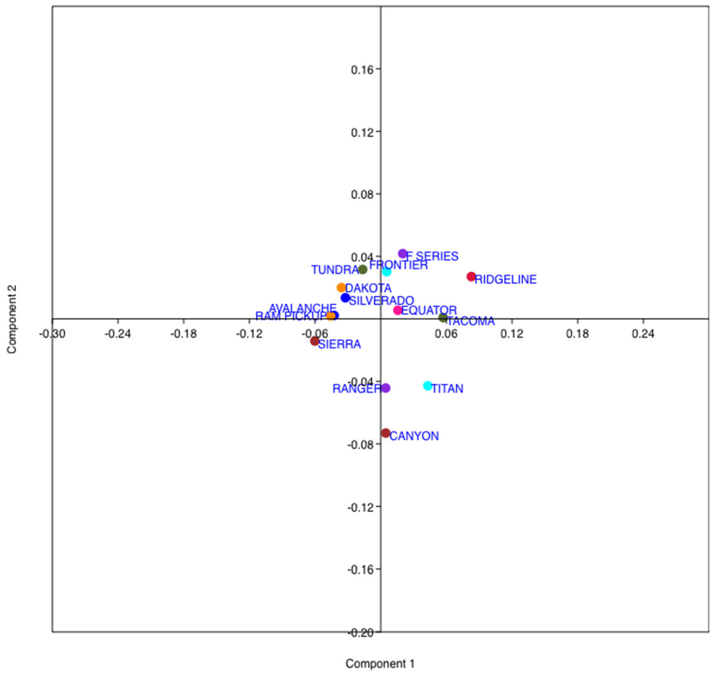


Figure 3. Examples of categories with low and high design variation

(a) Pickup 2011: low design variation



(b) SUV 2000: high design variation

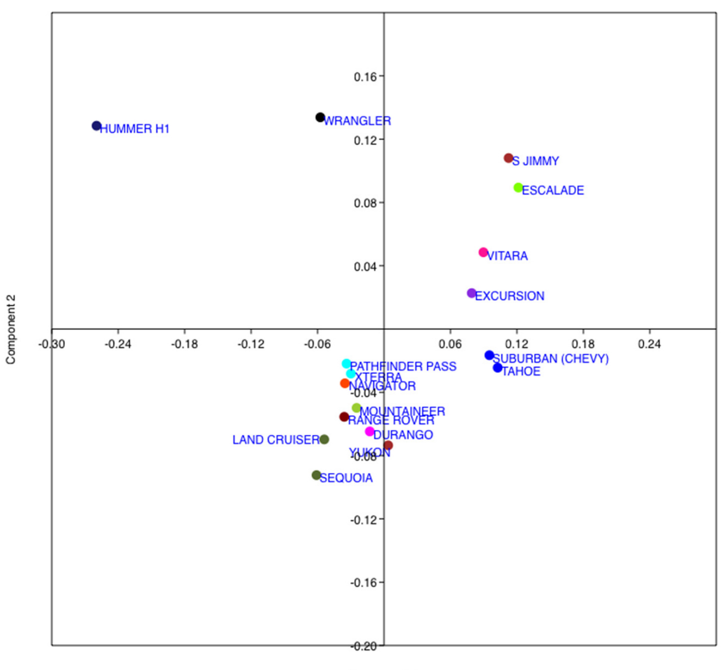
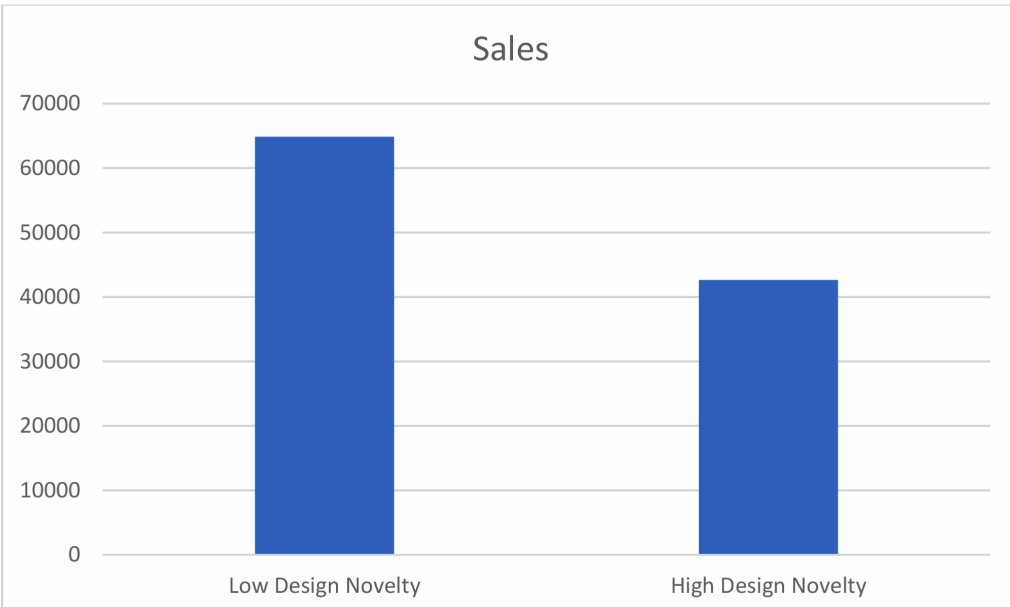


Figure 4. Model-free impact of design innovativeness on sales



$$t(3360) = 7.6448, \quad P < 0.0000$$

Figure 5. Interaction effect between design innovativeness and category design variation

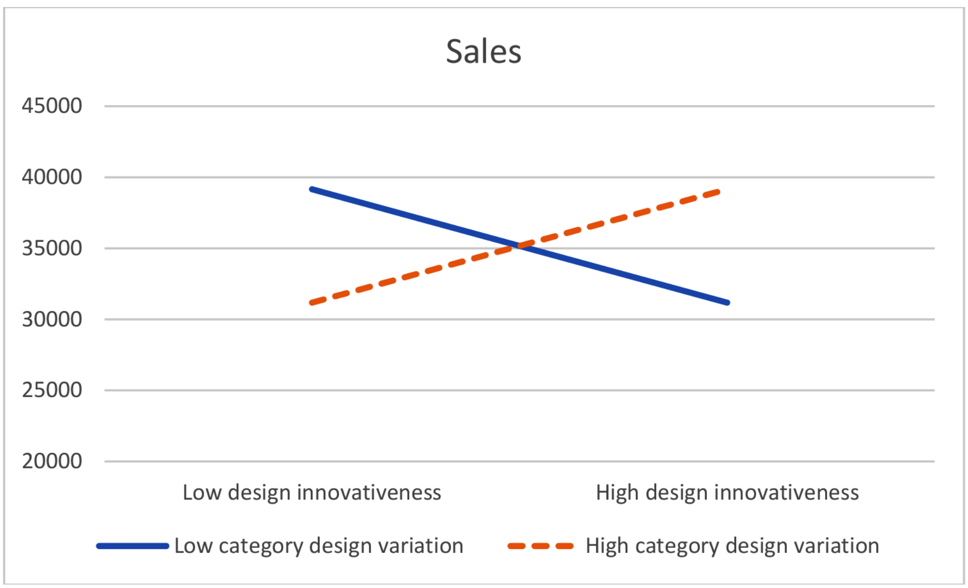


Figure 6. Interaction effect between design innovativeness and brand's share of design variation

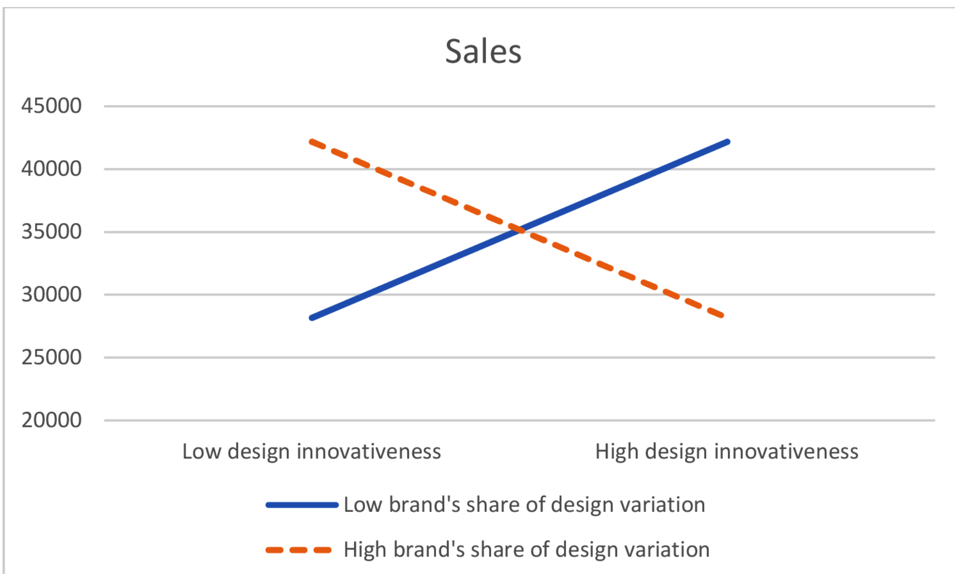


Figure 7. Sales of Hummer models

	Hummer H1	Hummer H2	Hummer H3
			
Year of introduction	2000	2003	2006
Design innovativeness	0.297	0.179	0.116
Total sales	4421	16455	166622
Average sales per year on the market	491	3291	23803

Tables

Table 1. Literature review

Reference	**Independent Variables**	**Dependent Variable**	**Main findings**	**Context**	**Sample size**
Talke et al. (2009)	Design newness	Sales	Positive impact of design newness on sales	German car market	157 car models
Landwehr et al. (2011)	Design prototypicality	Sales	Positive impact of design typicality on sales	German car market	28 car models
Landwehr et al. (2013)	Design prototypicality	3. Aesthetic liking 4. Sales	Initial positive impact of design typicality that is reversed in the long run	German car market	28 car models
Mugge and Dahl (2013)	Design newness	Consumer evaluations	Negative impact of design newness for radical innovations; No effect for incremental innovations	Lab experiment	130 participants
Rubera (2014)	Design innovativeness	Sales	Negative impact of design innovativeness on initial sales status; Positive impact on sales growth	US car market US motorcycle market	520 new car models
Liu et al. (2017)	4. Segment Prototypicality 5. Brand Consistency 6. Cross-segment mimicry	Market share	Inverted U-shape relationship between prototypicality and market share	US car market	202 car models
Talke et al. (2017)	Design newness	Sales	Positive impact of newness on sales	German car market	109 car models
Our Study	**1. Design innovativeness (DI)** **2. Category design variation (CDV)** **3. Brand's share of design variation (BSDV)**	**Sales**	**1. Negative impact of DI on sales** **2. Positive interaction between DI and CDV** **3. Negative interaction between DI and BSDV**	**US car market**	**746 car models, including 623 new models (310 new generations)**

Table 2. Sample description

Category	**Number of brands**	**Number of car models (including new generations of the same model)**	**MSRP range, USD**
Passenger car	32	379	8895 – 213200
Crossover	32	129	16325 – 146000
Pickup	14	39	20131 – 54145
Sport	16	46	21287 – 440000
SUV	26	112	18680 – 139771
Van	18	43	20980 – 47510

Table 3. Variable description and data sources

Variable	**Definition / Measure**	**Data source**
Sales of the car model	Total sales of car model i in year t	Ward's Auto Yearbook
Design innovativeness of the car model	Degree of novelty in the shape of car model i. Measured as a Procrustes distance from the typical shape in category c in the previous period $(t-1)$	Frontal pictures of car models from MSN Autos
Category design variation	Indicates overall shape variety within a category: $$DV_{ct} = \frac{\sum DI_i^2}{N{-}1}$$ Where DI is design innovativeness of car model i in category c in year t; N – number of models in category c in year t	Frontal pictures of car models from MSN Autos
Brand's share of design variation	The relative contribution of the brand to design variation: $$BDV_{bct} = \frac{\sum_{\text{brand}} DI_i^2}{N{-}1}$$ Where DI is design innovativeness of brand's b model i in category c in year t; N – number of models in category c in year t	Frontal pictures of car models from MSN Autos
Control variables		
Car model price	Manufacturer's Suggested Retail Price of car model i in year t	MSN Autos
Technological innovativeness of the car model	Degree of novelty in the technological performance of the of car model i. Measured as a distance from the average performance in the category in terms of horsepower and fuel economy	MSN Autos
Previous generations	Number of previous generations of a car model i	MSN Autos
Brand-level advertising expenditures	Total advertising expenditures of brand b in year t	TNS Media Intelligence
Model-level advertising expenditures	Total advertising expenditures of brand b on the promotion of car model in year t	TNS Media Intelligence

Table 4. Descriptive statistics and correlation matrix

Variable	**Mean**	**SD**	**Min**	**Max**		**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Variable	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9
1. Sales	54792.2	86341.01	1.000	928607	1								
2. Design innovativeness	0.103	0.037	0.042	0.297	-0.080^{***}	1							
3. Category design variation	0.012	0.003	0.006	0.022	-0.077^{***}	0.292^{***}	1						
4. Brand's share of design variation	0.0008	0.0009	0	0.007	0.054^{***}	0.470^{***}	0.534^{***}	1					
5. Technological innovativeness	0	93.420	-217.571	382.862	-0.059^{***}	0.043^{***}	0.011^{***}	0.039^{**}	1				
6. Previous generations	0.432	0.683	0	4.000	0.144^{***}	-0.116^{***}	-0.226^{***}	-0.113^{***}	0.106^{***}	1			
7. MSRP	41365.89	30445.62	8895.000	440000	-0.166^{***}	0.095^{***}	0.201^{***}	0.141^{***}	0.686^{***}	0.130^{***}	1		
8. Model advertising	24877.42	43554.06	0	451065.4	0.473^{***}	-0.148^{***}	-0.097^{***}	-0.059^{***}	-0.020^{**}	0.120^{***}	-0.112^{***}	1	
9. Brand advertising	398741.3	349136.9	0	1390533	0.442^{***}	0.005	0.057^{**}	0.216^{***}	-0.082^{***}	0.004	-0.158^{***}	0.2^{***}	1

$^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Table 5. Effect of design variables on sales: cross-classified mixed model results

	Unconditional means model	Conditional model: main effects	Conditional model: interaction effects
Intercept	47261.01 (16695.8)***	47714.56 (18606.78)***	50477.86 (18621.46)***
Fixed effects			
Design innovativeness (H1)		-9695.33 (2172.947)***	-8048.951 (2301.308)***
Category design variation		7033.775 (1765.631)***	5931.173 (1879.125)***
Brand's share of design variation		-1751.317 (1492.055)	1958.126 (1655.373)
Category design variation × Design innovativeness (H2)			4128.308 (1350.451)***
Brand's share of design variation × Design innovativeness (H3)			-8401.256 (1186.621)***
Control variables			
Technological innovativeness		17.10939 (19.04673)	16.931 (19.55)
Previous generations		28259.72 (5212.026)***	28963.44 (5454.296)***
MSRP		-0.019 (0.078)	-0.017 (0.086)
Model advertising		0.159 (0.0169)***	0.156 (0.0169)***
Brand advertising		0.029 (0.006)***	0.028 (0.006)***
Year fixed effects		Yes	Yes
Country of origin fixed effects		Yes	Yes
Random effects			
e_{tmbc}	7.23×10^8 $(1.95 \times 10^7)^{**}$	5.89×10^8 $(1.64 \times 10^7)^{**}$	5.89×10^8 $(1.64 \times 10^7)^{**}$
r_{0mbc} (model)	4.75×10^9 $(2.64 \times 10^8)^{**}$	4.31×10^9 $(2.44 \times 10^8)^{**}$	4.6×10^9 $(2.65 \times 10^8)^{**}$
υ_{00b} (brand)	1.2×10^9 $(3.35 \times 10^8)^{**}$	2.9×10^8 $(1.27 \times 10^8)^{**}$	3.01×10^8 $(1.36 \times 10^8)^{**}$
υ_{00c} (category)	1.39×10^9 $(8.81 \times 10^8)^{**}$	1.35×10^9 $(8.54 \times 10^8)^{**}$	1.31×10^9 $(8.38 \times 10^8)^{**}$

Standard errors in parentheses.
$^{*}\,p < 0.1$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$

Table 6. Robustness check: excluding cars priced over \$110,000

	Unconditional means model	Conditional model: main effects	Conditional model: interaction effects
Intercept	47655.11 (16630.83)***	48867.08 (18823.36)***	52108.03 (18800.21)***
Fixed effects			
Design innovativeness (H1)		−9751.626 (2285.3)***	−8137.866 (2396.4)***
Category design variation (H2)		7035.631 (1861.743)***	6335.372 (1958.619)***
Brand's share of design variation (H3)		−1852.584 (1557.178)	1699.591 (1694.471)
Category design variation × Design innovativeness (H4)			4766.807 (1466.135)***
Brand's share of design variation × Design innovativeness (H5)			−9779.498 (1286.704)***
Control variables			
Technological innovativeness		18.324 (22.626)	13.761 (22.901)
Previous generations		29135.69 (5354.408)***	29792.29 (5596.169)***
MSRP		−0.01 (0.153)	−0.01 (0.156)
Model advertising		0.159 (0.017)***	0.155 (0.017)***
Brand advertising		0.03 (0.006)***	0.028 (0.006)***
Year fixed effects		Yes	Yes
Country of origin fixed effects		Yes	Yes
Random effects			
e_{tmbc}	7.52×10^8 $(2.07 \times 10^7)^{**}$	6.11×10^8 $(1.73 \times 10^7)^{**}$	6.04×10^8 $(1.74 \times 10^7)^{**}$
r_{0mbc} (model)	4.85×10^9 $(2.73 \times 10^8)^{**}$	4.41×10^9 $(2.53 \times 10^8)^{**}$	4.73×10^9 $(2.77 \times 10^8)^{**}$
v_{00b} (brand)	1.22×10^9 $(4.42 \times 10^8)^{**}$	3.02×10^8 $(1.34 \times 10^8)^{**}$	3.06×10^8 $(1.41 \times 10^8)^{**}$
v_{00c} (category)	1.37×10^9 $(8.71 \times 10^8)^{**}$	1.33×10^9 $(8.5 \times 10^8)^{**}$	1.28×10^9 $(8.28 \times 10^8)^{**}$

Standard errors in parentheses.
$^{*}\, p < 0.1$, $^{**}\, p < 0.05$, $^{***}\, p < 0.01$

Table 7. Robustness check: excluding model-years after 2011

	Unconditional means model	Conditional model: main effects	Conditional model: interaction effects
Intercept	45326.04 (15076.98)***	50174.49 (17055.1)***	52536.16 (16739.59)***
Fixed effects			
Design innovativeness (H1)		−10176.8 (2318.459)***	−8131.299 (2415.097)***
Category design variation (H2)		8135.591 (2007.989)***	6718.759 (2109.263)***
Brand's share of design variation (H3)		−1525.272 (1609.505)	3525.382 (1796.074)*
Category design variation × Design innovativeness (H4)			5748.118 (1471.33)***
Brand's share of design variation × Design innovativeness (H5)			−10415.83 (1261.495)***
Control variables			
Technological innovativeness		9.618 (21.417)	9.074 (21.744)
Previous generations		24850.24 (5454.091)***	25358.89 (5630.277)***
MSRP		−0.019 (0.088)	−0.004 (0.095)
Model advertising		0.159 (0.019)***	0.155 (0.019)***
Brand advertising		0.034 (0.006)***	0.032 (0.006)***
Year fixed effects		Yes	Yes
Country of origin fixed effects		Yes	Yes
Random effects			
e_{tmbc}	7.75×10^8 $(2.28 \times 10^7)^{**}$	6.33×10^8 $(1.93 \times 10^7)^{**}$	6.23×10^8 $(1.93 \times 10^7)^{**}$
r_{0mbc} (model)	4.52×10^9 $(2.69 \times 10^8)^{**}$	4.08×10^9 $(2.64 \times 10^8)^{**}$	4.28×10^9 $(2.61 \times 10^8)^{**}$
υ_{00b} (brand)	1.01×10^9 $(2.93 \times 10^8)^{**}$	1.99×10^8 $(1.1 \times 10^8)^{**}$	1.95×10^8 $(1.14 \times 10^8)^{**}$
υ_{00c} (category)	1.11×10^9 $(7.19 \times 10^8)^{**}$	1.1×10^9 $(7.1 \times 10^8)^{**}$	1.01×10^9 $(6.64 \times 10^8)^{**}$

Standard errors in parentheses.
$^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Table 8. Robustness check: excluding model-years before 2002

	Unconditional means model	Conditional model: main effects	Conditional model: interaction effects
Intercept	46797.94 (16297.32)***	40883.46 (18464.58)***	43653.84 (18534.31)**
Fixed effects			
Design innovativeness (H1)		-8929.419 (2216.638)***	-6920.809 (2348.323)***
Category design variation (H2)		8212.929 (1818.731)***	7519.727 (1945.625)***
Brand's share of design variation (H3)		-614.8582 (1535.65)	3190.525 (1706.066)*
Category design variation $\times$ Design innovativeness (H4)			4576.864 (1381.511)***
Brand's share of design variation $\times$ Design innovativeness (H5)			-8714.303 (1230.336)***
Control variables			
Technological innovativeness		10.185 (19.489)	8.581 (20.04)
Previous generations		28185.03 (5151.91)***	28976.93 (5396.347)***
MSRP		-0.02 (0.08)	-0.002 (0.088)
Model advertising		0.181 (0.017)***	0.178 (0.018)***
Brand advertising		0.035 (0.006)***	0.033 (0.006)***
Year fixed effects		Yes	Yes
Country of origin fixed effects		Yes	Yes
Random effects			
e_{tmbc}	6.89×10^8 $(1.97 \times 10^7)^{**}$	5.76×10^8 $(1.66 \times 10^7)^{**}$	5.75×10^8 $(1.69 \times 10^7)^{**}$
r_{0mbc} (model)	4.73×10^9 $(2.65 \times 10^8)^{**}$	4.2×10^9 $(2.39 \times 10^8)^{**}$	4.5×10^9 $(2.61 \times 10^8)^{**}$
v_{00b} (brand)	1.18×10^9 $(3.30 \times 10^8)^{**}$	2.58×10^8 $(1.2 \times 10^8)^{**}$	2.59×10^8 $(1.26 \times 10^8)^{**}$
v_{00c} (category)	1.32×10^9 $(8.37 \times 10^8)^{**}$	1.37×10^9 $(8.63 \times 10^8)^{**}$	1.34×10^9 $(8.54 \times 10^8)^{**}$

Standard errors in parentheses.
$^{*}\,p < 0.1$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$

Table 9. Robustness check: excluding crossover category

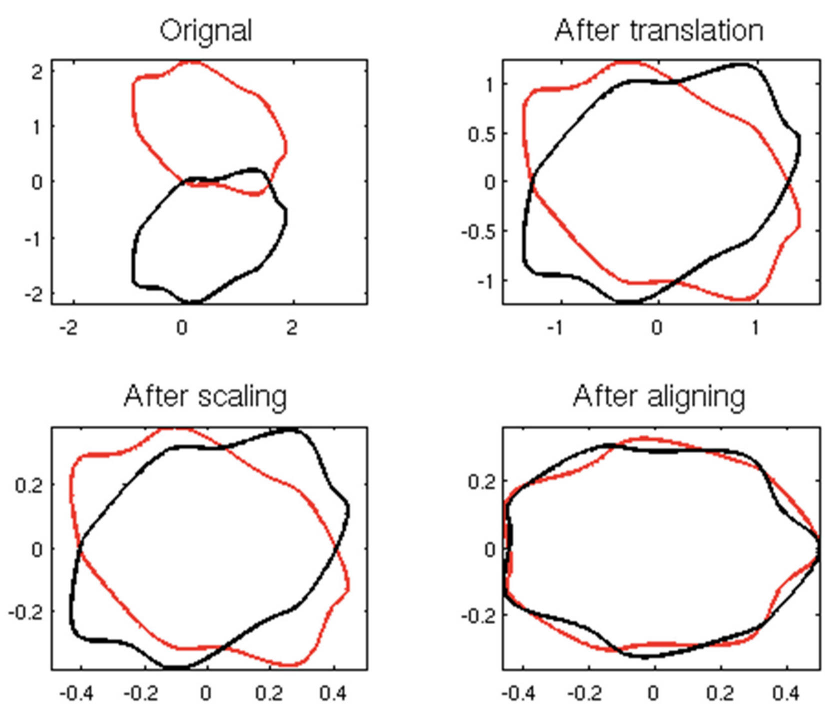
	Unconditional means model	Conditional model: main effects	Conditional model: interaction effects
Intercept	48641.85 (20061.75)***	53114.08 (21299.8)***	56042.22 (21094.62)**
Fixed effects			
Design innovativeness (H1)		−9922.194 (2442.558)***	−7717.337 (2561.665)***
Category design variation (H2)		6160.841 (1872.556)***	4855.516 (1997.774)***
Brand's share of design variation (H3)		−866.2313 (1603.684)	3238.237 (1786.484)*
Category design variation × Design innovativeness (H4)			3876.481 (1434.254)***
Brand's share of design variation × Design innovativeness (H5)			−8582.945 (1271.316)***
Control variables			
Technological innovativeness		28.342 (21.586)	27.695 (22.135)
Previous generations		30420.69 (6145.29)***	31357.26 (6413.994)***
MSRP		−0.036 (0.085)	−0.022 (0.092)
Model advertising		0.167 (0.019)***	0.164 (0.019)***
Brand advertising		0.032 (0.006)***	0.03 (0.006)***
Year fixed effects		Yes	Yes
Country of origin fixed effects		Yes	Yes
Random effects			
e_{tmbc}	7.94×10^8 $(2.34 \times 10^7)^{**}$	6.4×10^8 $(1.95 \times 10^7)^{**}$	6.38×10^8 $(1.98 \times 10^7)^{**}$
r_{0mbc} (model)	5.45×10^9 $(3.33 \times 10^8)^{**}$	4.94×10^9 $(3.06 \times 10^8)^{**}$	5.27×10^9 $(3.34 \times 10^8)^{**}$
υ_{00b} (brand)	1.26×10^9 $(3.72 \times 10^8)^{**}$	2.47×10^8 $(1.45 \times 10^8)^{**}$	2.52×10^8 $(1.54 \times 10^8)^{**}$
υ_{00c} (category)	1.73×10^9 $(1.19 \times 10^9)^{**}$	1.58×10^9 $(1.09 \times 10^9)^{**}$	1.49×10^9 $(1.04 \times 10^9)^{**}$

Standard errors in parentheses.
$^{*}\, p < 0.1$, $^{**}\, p < 0.05$, $^{***}\, p < 0.01$

Appendix 1. Superimposition Procedure

Procrustes superimposition aligns shapes and minimizes differences between them to ensure that only real shape differences are measured:

1. Translation: centers all shapes at the origin (0,0)
2. Scaling of all shapes to the same size
3. Aligning: rotates each shape around the origin until the sum of squared distances among them is minimized (similar to least-squares fit of a regression line)
4. Ensures that the differences in shape are minimized



To center all shapes at the origin $(0,0)$, 2-dimensional coordinates (X,Y) of all the landmarks are averaged:

$$X_C = \frac{1}{K}\sum_{j=1}^{K} X_j$$

$$Y_C = \frac{1}{K}\sum_{j=1}^{K} Y_j$$

Then the centered configuration matrix XC by subtracting the centroid coordinate from the corresponding coordinate of each landmark:

$$XC = \begin{bmatrix} (X_1 - X_C) & (Y_1 - Y_C) \\ (X_2 - X_C) & (Y_2 - Y_C) \\ \vdots & \vdots \\ (X_K - X_C) & (Y_K - Y_C) \end{bmatrix}$$

Next, we rescale each shape so that its centroid size is one. The formula for centroid size is:

$$CS(X) = \sqrt{\sum_{i=1}^{K}\sum_{j=1}^{M}(X_{ij} - C_j)^2}$$

Dividing each coordinate of the centered shape by its centroid size produces the pre-shape space where the surface of a hypersphere centered on the origin, and the sum of all squared landmark coordinates is one:

$$\sum_{i=1}^{K}\sum_{j=1}^{M}(X_{ij})^2 = 1$$

Next step is to rotate each shape around the origin until the sum of squared distances among them is minimized. The sum of the squared Euclidean distances between the K landmarks of the rotated target and the reference is:

$$D^2 = \sum_{j=1}^{k}\left[\left(X_{Rj} - \left(X_{Tj}\cos\theta - Y_{Tj}\sin\theta\right)\right)^2 + \left(Y_{Rj} - (X_{Tj}\sin\theta + Y_{Tj}\cos\theta)\right)^2\right]$$

where (X_{Rj}, Y_{Rj}) are the coordinates of the landmark in the reference. To minimize this squared distance as a function of θ, we take the derivative with respect to θ and

$$-\sum_{j=1}^{K}\left[\begin{array}{c} 2(X_{Rj}-(X_{Tj}\cos\theta - Y_{Tj}\sin\theta))(-X_{Tj}\sin\theta - Y_{Tj}\cos\theta) \\ \\ +2(Y_{Rj}-(X_{Tj}\sin\theta + Y_{Tj}\cos\theta))(X_{Tj}\cos\theta - Y_{Tj}\sin\theta) \end{array}\right] = 0$$

and solve for θ:

$$\theta = \text{arctangent}\left(\frac{\sum_{j=1}^{K} Y_{Rj}X_{Tj} - X_{Rj}Y_{Tj}}{\sum_{j=1}^{K} X_{Rj}X_{Tj} + Y_{Rj}Y_{Tj}}\right)$$

which gives the angle by which to rotate the target to minimize its distance from the reference.

Chapter 3

CATEGORY- AND BRAND-LEVEL DESIGN INNOVATIVENESS: CONCEPT AND EFFECT ON PERFORMANCE[1]

3.1 Introduction

Despite the growing evidence of importance of product design and design innovation, research exploring design innovativeness and its effect on performance is still limited and provides contradicting results. Since innovativeness-performance effect can vary significantly depending on how innovativeness is conceptualized, first of all we review relevant literature to clarify the concept of design innovativeness. We conceptualize design innovativeness as a construct that exists at two levels: category level and brand level, arguing for relevance of previously overlooked brand-level design innovativeness.

Building on the habituation-tedium theory and processing fluency arguments, we propose and evaluate differential effects of category-level and brand-level design innovativeness, as well as their interaction effect, on new product performance in terms of sales. Since the effect of design novelty changes with the level of exposure (Tellis 1997), it is important to disentangle the short- and long-term effect of design innovativeness. We employ growth

[1]Best Paper Award based on Doctoral Work at the EMAC Annual Conference, Groningen, Netherlands, 2017.

curve analysis, which allows to estimate the effect of design category-level and brand-level design innovativeness, as well as their interaction effect, on initial sales status and sales growth rates. We employ geometric morphometric analysis, which is used in evolutionary biology to quantify shape and shape variation, to develop an objective measure of design innovativeness. To test out hypotheses, we analyze car sales data in the US from 1995 to 2007 using cross-classified 3-level growth model.

We find that category-level design innovativeness negatively affects initial sales status but positively affects sales growth rates. Brand-level design innovativeness has positive effect on initial sales status and no effect on sales growth. We also find support for the negative interaction effect of category- and brand-level design innovativeness on initial sales status and no significant effect on sales growth.

In sum, in this research we conceptualize design innovativeness as a construct that exists at two levels, define category- and brand-level design innovativeness, and reveal their differential effects on sales' evolution over time. Since our measure of design innovativeness is calculated yearly, we run supplementary analysis confirming that, as expected, both category-level and brand-level design innovativeness measures decrease with time. With this study we also address a need for a deeper integration between brand and innovation management exploring the under-researched interrelationship between branding and innovations (Brexendorf et al. 2015). From managerial perspective, this analysis can provide guidance on styling of new products, and suggest when new products should look similar or different to the products on the market and brand's own product portfolio.

3.2 Theoretical Framework

Design innovation involves changes in the in the external appearance of the product, as opposed to technological innovation that involves changes in the functionalities of the product (Dell'Era and Verganti 2007, Rubera and Droge 2013). To the extent that aesthetic liking affects consumers' purchase decisions, design innovativeness is expected to affect new product performance in terms of sales (Landwehr et al. 2013). However, research exploring the effect of design innovativeness on sales is limited, moreover, existing empirical studies report contradicting results. Talke et al. (2009) find positive impact of design innovativeness on sales right after the introduction that persists in strength over time. Rubera (2014) reveals that design innovativeness, on the opposite, diminishes initial sales' status but increases sales' growth rate. These studies also reach contradicting conclusions about the interaction effect of design and technological innovativeness: while Talke et al. (2009) report no significant results, Rubera (2014) finds and negative interaction effect on initial sales' status and positive interaction effect on sales' growth rates.

Innovativeness-performance effect can vary significantly depending on how innovativeness is conceptualized (Szymanski et al. 2007), accordingly clearly defining and measuring the design innovativeness construct is important to reconcile the contradictions. Innovativeness is most frequently used as a measure of the degree of newness of an innovation; however, it is important to clarify from whose perspective this degree of newness is viewed and what is new (Garcia and Calantone 2002).

Most of existing studies focus on evaluating design innovativeness with regard to a product category or segment typical design (Mugge and Dahl 2013, Rubera 2014) or typical design segment (Landwehr 2011, 2013; Talke et al. 2009), where ssegments are the subgroups of the same product category (e.g. economy and luxury segments of sedan product category in Landwehr (2011)). However, design affects also so-called brand categorization, i.e., how a product is perceived as a new member of a particular brand family (Kreuzbauer and Malter 2005). On practice it means that a product may be seen as more typical within a product category and brand product portfolio: new model of Volvo SUV can look more or less like Volvo and more or less like SUV. This view implies that the design innovativeness of a product can be determined using two reference points by comparing its appearance with those of competing products on category level, and with present portfolio of the firm on a brand level. In the design innovation literature, two recent papers, Liu at al. (2017) and Talke (2017), open up the discussion of brand-level design typicality and introduce two related variables: brand consistency and design newness with respect to brand category.

Based on these arguments, we define design innovativeness is the degree of novelty in a product's external appearance that can be represented as a degree of deviation from typical external appearance of a product in a category (category-level design innovativeness), and as a degree of deviation from typical brand design (brand-level design innovativeness). On each of these two levels the key managerial decision is to strive for differentiation or similarity in design, which can have different effects on new product performance. Importantly, existing design literature has described so-called "shape grammar" methodology that allows to create new product designs with desired levels of innovativeness on both product category and brand levels (Orsborn et al. 2008, McCormack et al. 2004). However, no previous studies provide the guidance on the optimal innovativeness values.

Existing literature has explored the effects of design innovativeness on consumer evaluation and sales, but mostly focused only on product category-level or brand-level relationships in isolation. On product category level, design innovation is shown to have either positive or negative effect on consumer evaluation and liking, depending on degree of design newness, also referred to as design innovativeness, novelty or atypicality (Mugge and Dahl, 2013).

Consumer research on novelty has revealed the attraction of novelty that facilitates learning (Hekkert et al. 2003), as well as preference for typicality – innovative products that are incongruent with consumer expectations for product category suffer lower evaluation and preference (Landwehr et al. 2013, 2011; Noseworthy and Trudel 2011). On a brand level, distinctive product design is considered a key component of brand strategy, since brands can profit from easy-to-identify product design (Herm and Moller 2014, Townsend et al. 2013). However, deviation of the prior brand styles or simultaneous use of different styles can also be viable brand design strategies since deviation from prior products can help draw attention to the product (Person et al. 2008).

First, we review relevant literature exploring the evolution of consumer attitude toward innovative designs. Overall, it suggests inverted u-shape relationship between liking of novel stimuli and exposure level. According to processing fluency and mere exposure theory, more innovative stimuli initially evoke negative consumer reactions (Veryzer 1999), but repeated exposure increases processing fluency resulting in more positive evaluations and increased liking of atypical objects (Zajonc 1980, Landwehr et al. 2013). However, at higher levels of exposure consumers are likely to discount the fluency signal and express decreased liking (Landwehr et al., 2013). Habituation-tedium theory (Berlyne 1970, Sawyer 1981, Tellis 1997) explains the inverted U-shape relationship between consumer liking of novel stimuli and exposure by the combination of two factors – habituation and tedium – that mediates consumer response (Figure 1). First encounter of innovative stimuli leads to uncertainty and tension, leading to lower evaluation of a novel products; with additional exposures, this uncertainty is being reduced, increasing familiarity and liking (habituation process). Repetitive exposure, however, causes boredom and decreased liking (the process of tedium).At the first stage, which is called “wearin”, habituation process is stronger, while tedium is strong later on during so-called “wearout” stage (Tellis 1997).

3.2.1 Hypotheses

Since habituation and tedium work differently depending on exposure characteristics (Tellis 1997), we expect differences in the shape of liking curve depending on whether design innovativeness is assessed on category or brand level (Figure 2). According to Barsalou (1985), perceived typicality depends on the frequency of instantiation as a member of category. Weight of single product in brand portfolio is higher than within a product category. Since brands are organized as categories (Boush 1993, Joiner, 2007), higher frequency of instantiation will facilitate acceptance of innovative design as a typical brand category member. Accordingly, on brand level both habituation and tedium occur sooner, leading to immediate liking (wearin stage can be very fast or skipped) and earlier peak.

At the same time, weight of single product in a product category is much lower. In this case both frequency of exposure as a category member and attention are lower, so that more exposure is required for habituation, but also tedium occurs much later. This effect is expected to be more pronounced for products with more innovative designs, which are likely to reach their sales peak later as they go through a consumers' sensemaking process that is required to insure their acceptability as a category member (Rosa et al., 1999). As aesthetic liking affects consumers' purchase decisions, so that design-related variables have impact on sales (Landwehr et al. 2011, 2013), we expect negative impact of category-level design innovativeness on initial sales and positive impact on sales growth.

H1a: Increased Category-level design innovativeness has negative impact on initial sales

H1b: Increased Category-level design innovativeness has positive impact on sales growth

As noted before, on brand level both habituation and tedium occur sooner, leading to fast wearin or immediate liking, but also fast wearout of novelty effect. Moreover, designs highly innovative on brand level provide less uncertainty to the consumers, as brand category membership is assigned by being labeled with brand name (Joiner 2007). Accordingly, we propose positive impact of brand-level design innovativeness on initial sales and negative impact on sales growth.

H2a: Increased Brand-level design innovativeness has positive impact on initial sales

H2b: Increased Brand-level design innovativeness has negative impact on sales growth

We expect negative interaction effect of category- and brand-level design innovativeness on both initial sales status and sales growth, since novelty on both levels leads to higher uncertainty and tension. Products highly innovative on both levels need more exposure for habituation, leading to slow and weak wearin. Moreover, sensemaking process will require deeper processing that results in negative affective response (Bornstein and D'Agostino 1992) and increases wearout.

H3a: There is a negative interaction effect between category- and brand-level design innovativeness on initial sales

H3b: There is a negative interaction effect between category- and brand-level design innovativeness on sales growth

3.3 Data and Method

3.3.1 Data

We use US automotive industry as an empirical setting because of existence of defined product categories in form of bodystyles (coupe, SUV, minivan etc.) and importance of brand distinctive design. Our sample consists of car models sold in the US from 1996 to 2007, total of 3530 model-year observations. We identify 671 car models (including new generations of existing models) introduced by 37 brands, and assigned to nine categories in terms of bodystyle. We provide the sample description in Table 2.

Sales data is collected from Ward's Auto Yearbook. Advertising expenditure data are collected from TNS Media Intelligence that provides expenditure data across all major media. We include advertising spending variables on individual car model and on brand level. From the portal Msn.com/autos we collect bodystyle, performance, technology, interior and exterior specifications of each car model. We also collect the pictures of each car model (front view).

3.3.2 Measures

Design innovativeness. Design is defined as the form or shape of a product, and shape analysis is appropriate to analyze product appearance and explore similarity between products in design studies (Ranscombe et al. 2012, McCormack et al. 2004). Accordingly, we operationalize *category-level design innovativeness* as a deviation of product's shape from a typical shape in the category. *Brand-level design innovativeness* is represented by deviation from the typical shape among brand family products. To obtain this deviation measure, we employ geometric morphometric approach, which offers a methodology to quantify shape and shape variation (Webster and Sheets 2010). This methodology uses geometric coordinates instead of exact measurements, so that data can be easily collected from digital images. Moreover, size variation in picture, scale and rotational effects are mathematically removed from the analysis. In this framework shape is a configuration of landmarks and curves representing a product, which are marked on the product images.

We collect shape data from the digital photographs of cars' frontal views, which we collect from the website Msn.com/autos. We follow existing design studies (McCormack et al. 2004, Osborn et al. 2006, Ranscombe et al. 2012) to choose the landmarks that reflect elements essential for vehicle brand and category representation. Based on these studies, we focus on the front view of the car, and define 50 landmarks that fully describe the shape or the car and communicate the category and brand membership for the consumers (Figure 3). We apply shape theory and morphometric methods to generate the typical shape of the category and quantify the design innovativeness as a distance between typical shape and each individual car model.

Shape theory defines shape as all the geometrical information that remains when location, scale, and rotational effects are filtered out from an object (Kendall 1977). First, we plot landmarks on the car photographs; landmarks are represented by two coordinates (X, Y) in 2-dimensional space. Next, we need to remove from the shape data the effects of location, orientation, and size, following the Kendall's (1977) definition of shape. To transform the data accordingly, we use so-called Procrustes superimposition procedure, which is described in detail in the Appendix 1, and includes following steps (Zelditch et al. 2012):

1. Center each configuration of landmarks at the origin by subtracting the coordinates of its centroid from the corresponding (X or Y) coordinates of each landmark.

2. Scale the landmark configurations to unit centroid size by dividing each coordinate of each landmark by the centroid size of that configuration.

3. Rotate the configurations to minimize the summed squared distances between homologous landmarks (over all landmarks) between the shapes. At this step, we build so-called "reference shape", or the average shape of the sample that minimizes the average distances of all the shapes from the reference.

After Procrustes superimposition, the configuration space is transformed removing position, size and rotation, eliminating several dimensions in the process and resulting in a shape space. *Shape space* is the Non-Euclidean space in which configurations are plotted after scaling, translation, and rotation. For a shape represented by configuration of K landmarks having M coordinates, shape space has $K \times M$-4 dimensions. The shape space of the car shape sample consists of 96 dimensions. The surface of the shape space represents all the possible landmark configurations that can potentially represent shape of the object, and all existing shapes are represented as single points along the surface. The location of each individual object on the shape space depends on their distance from the reference located in the center, which is called Procrustes distance.

We build two reference shapes, one representing the average car shape for each category in each period, second – average shape of each brand in each period. Since perceived typicality depends on frequency of exposure (Meyvis and Janiszewski, 2004), we use all models existing on the market in category (in the brand's portfolio) with a weight according to the sales proportion in the year prior to introduction of the new model.

Next, we estimate so-called Procrustes distance, the main measure of shapes difference in morphometrics that represents to the measure of design innovativeness. Procrustes distance between two shapes (landmark configurations) is a distance along the surface of the shape space after scaling, rotation and translation. It is analogous to Euclidean distance but in the curved non-Euclidean shape space.

In sum, to build the measures of design innovativeness, we apply superimposition procedure to remove the size, scale and rotational effects from the pictures. Next, we build the shape space and the typical shape of the car for each category. Procrustes distance to the reference shape of the category represents the measure of category-level design innovativeness of each car model. We repeat the procedure to build the average shape for each brand and calculate Procrustes distance to the average brand shape to build the measure of brand-level design innovativeness of each car model.

Control variables. We control for marketing-mix variables, such as price and advertising. Advertising expenditures on model level are accumulated since the year of model introduction (according to TNS Media Intelligence), We control for brand's advertising expenditures as a cumulative variable that accounts for the brand expenditures since the year of a new model introduction. To build advertising expenditures variables, we use a depreciation factor of 1/6 every year to account for the diminishing effect of advertising expenditures on sales (Rubera 2014). We also control for technological innovativeness of the car (based on Msn.com/auto data on car model performance in terms of horsepower and fuel economy). Finally, we control for previous brand innovativeness. Table 3 provides the description of the variables and data sources.

3.3.3 Model Specification

We employ multilevel mixed-effects modeling procedure, where the repeated observations of sales over time are nested within car models, which are in turn nested within brands and categories. Since car models can simultaneously be nested within two different higher-level categories, brands and car categories, we use a cross-classified three-level growth model.

First, we estimate the unconditional means model where we partition the variance in sales into the variance associated with differences across categories (σ_c^2), the variance across brands (σ_b^2), the variance across models (σ_m^2), and variance across time (σ_e^2):

$$\text{Sales}_{tmbc} = Y_{tmbc} = \theta_{000} + \upsilon_{00c} + \upsilon_{00b} + r_{0mbc} + e_{tmbc},$$
$$e_{tmbc} \sim N(0, \sigma_e^2), \quad r_{0mbc} \sim N(0, \sigma_m^2), \quad \upsilon_{00c} \sim N(0, \sigma_c^2), \quad \upsilon_{00b} \sim N(0, \sigma_b^2)$$

where t, m, b, and c denote time, car model, brands, and categories; θ_{000} represents the grand mean of car model sales across brands and categories; e_{tmbc} is the time-level random error;

r_{0mbc} is the random between-car modelresidual; υ_{00b} is the random between-brandsresidual; υ_{00c} is the random between-categoriesresidual.

To build the compact model presented above, at the first level we model car sales at each time period as a function of car model mean sales plus a random error:

$$\text{Level 1:} \quad \text{Sales}_{tmbc} = Y_{tmbc} = \pi_{0mbc} + e_{tmbc}, \quad e_{tmbc} \sim N(0, \sigma_e^2),$$

where t, m, b, and c denote time, car model, brands, and categories; π_{0mbc} is the mean sales of car model m in brand b in category c; e_{tmbc} is the time-level random error and represents variance acrosstime.

At the second level, 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:

$$\text{Level 2:} \quad \pi_{0mbc} = \beta_{00bc} + r_{0mbc}, \quad r_{0mbc} \sim N(0, \sigma_m^2),$$

where β_{00bc} is the mean sales of the car model in brand b and category c; and r_{0mbc} is the random between-car modelresidual. The between-car model variance σ_m^2 is assumed to be uniform across car models within each of the b brands and c categories.

Level 3 models variation between brands and within categories:

$$\text{Level 3:} \quad \beta_{00bc} = \theta_{000} + \upsilon_{00b} + \upsilon_{00c}, \quad \upsilon_{00b} \sim N(0, \sigma_b^2), \quad \upsilon_{00c} \sim N(0, \sigma_c^2),$$

where θ_{000} is grand mean of car model sales across brands and categories, υ_{00b} is the random between-brandsresidual, σ_b^2 is the between-brand variance, υ_{00c} is the random between-categoriesresidual, and σ_c^2 represents the between-categories variance.

The total variability in the outcome Y_{tmbc} includes four components: at Level 1variance across time (σ_e^2), at Level 2 – among car models within brands and categories (σ_m^2), and at Level 3 – among brands (σ_b^2) and among categories (σ_c^2). We estimate the proportion of each level's variance in total variance as follows: $\sigma_e^2/(\sigma_e^2+\sigma_m^2+\sigma_b^2+\sigma_c^2)$ is the proportion of variance across time; $\sigma_m^2/(\sigma_e^2+\sigma_m^2+\sigma_b^2+\sigma_c^2)$ is the proportion of variance between car models; $\sigma_b^2/(\sigma_e^2+\sigma_m^2+\sigma_b^2+\sigma_c^2)$ is the proportion of variance between brands; and $\sigma_c^2/(\sigma_e^2+\sigma_m^2+\sigma_b^2+\sigma_c^2)$ is the proportion of variance between categories.

Next, we introduce the time variable representing the number of years since the car model was introduced, and estimate unconditional growth model:

$$\text{Sales}_{tmbc} = \theta_{000} + \theta_{100}\text{Time}_{tmbc} + \theta_{200}\text{Time}^2_{tmbc} + \upsilon_{00c} + \upsilon_{00b} + r_{0mbc} + r_{1mbc}\text{Time}_{tmbc} + e_{tmbc}$$

If we represent the model above by levels, 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}).

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

The Level 2 equation simultaneously partitions the three estimates into sample averages and error components:

$$\begin{aligned}\text{Level 2:}\quad & \pi_{0mbc} = \beta_{00bc} + r_{0mbc}, \quad r_{0mbc} \sim N(0, \sigma^2_{m0})\\ & \pi_{1mbc} = \beta_{10bc} + r_{1mbc,} r_{1mbc} \sim N(0, \sigma^2_{m1})\\ & \pi_{2mbc} = \beta_{20bc}\end{aligned}$$

At Level 3, the fixed effect coefficients θ_{000}, θ_{100} and θ_{200} represent the grand mean initial status, grand mean growth rate, and grand mean acceleration; υ_{00b} and υ_{00c} capture the random effects of brand and category.

$$\begin{aligned}\text{Level 3:}\quad & \beta_{00bc} = \theta_{000c} + \upsilon_{00b} + \upsilon_{00c}, \quad \upsilon_{00b} \sim N(0, \sigma_b^2), \quad \upsilon_{00c} \sim N(0, \sigma_c^2),\\ & \beta_{10bc} = \theta_{100}\\ & \beta_{20bc} = \theta_{200}\end{aligned}$$

Finally, we estimate a **conditional growth model**:

$$\mathbf{Sales}_{tmbc} = \boldsymbol{\theta}_{000} + \boldsymbol{\theta}_{300}\boldsymbol{CI}_{mbc} + \boldsymbol{\theta}_{400}\boldsymbol{BI}_{mbc} + \boldsymbol{\theta}_{500}(\boldsymbol{CI}_{mbc}\boldsymbol{x}\boldsymbol{BI}_{mbc}) + \boldsymbol{\theta}_{100}\text{Time}_{mbc} +$$

$$\boldsymbol{\theta}_{600}(\boldsymbol{CI}_{mbc}\boldsymbol{x}\mathbf{Time}_{mbc}) + \boldsymbol{\theta}_{700}(\boldsymbol{BI}_{mbc}\boldsymbol{x}\mathbf{Time}_{mbc}) + \boldsymbol{\theta}_{800}(\boldsymbol{CI}_{mbc}\boldsymbol{x}\boldsymbol{BI}_{mbc}\boldsymbol{x}\mathbf{Time}_{mbc}) +$$

$$+\boldsymbol{\theta}_{200}\mathbf{TIME}^{2}_{mbc} + \boldsymbol{e}_{tmbc} + \boldsymbol{r}_{0mbc} + \boldsymbol{r}_{1mbc}\mathbf{Time}_{tmbc} + \boldsymbol{\upsilon}_{00c} + \boldsymbol{\upsilon}_{00b}$$

To build this model, we add our measures of design innovativeness on the first level, since they are calculated yearly:

Level 1:

$$\text{Sales}_{tmbc} = \pi_{0mbc} + \pi_{1mbc}\text{Time}_{tmbc} + \pi_{2mbc}\text{Time}^2_{tmbc} + \pi_{3mbc}CI_{tmbc} +$$

$$+\pi_{4mbc}BI_{tmbc} + \pi_{5mbc}(CI_{tmbc}xBI_{tmbc}) + \pi_{6mbc}(CI_{tmbc}x\text{Time}_{tmbc}) +$$

$$+\pi_{7mbc}(BI_{tmbc}x\text{Time}_{tmbc}) + +\pi_{8mbc}(CI_{tmbc}xBI_{tmbc}x\text{Time}_{tmbc}) + e_{tmbc},$$

Level 2:

$$\pi_{0mbc} = \beta_{00bc} + r_{0mbc}, \quad r_{0mbc} \sim N(0, \sigma^2_{m0})$$

$$\pi_{1mbc} = \beta_{10bc} + r_{1mbc}, \quad r_{1mbc} \sim N(0, \sigma^2_{m1})$$

$$\pi_{(2-8)mbc} = \beta_{(2-8)0bc}$$

Level 3:

$$\beta_{00bc} = \theta_{000} + \upsilon_{00b} + \upsilon_{00c}, \quad \upsilon_{00b} \sim N(0, \sigma^2_b), \quad \upsilon_{00c} \sim N(0, \sigma^2_c),$$

$$\beta_{10bc} = \theta_{100},$$

$$\beta_{(2-8)0bc} = \theta_{(2-8)00}$$

Where CI is the category-level design innovativeness, BI is brand-level design innovativeness; e_{tmbc}, r_{0mbc}, υ_{00c}, and υ_{00b} are random effects. Coefficients θ_{300}, θ_{400} and θ_{500} represent effects on initial sales status; θ_{600}, θ_{700} and θ_{800} – effects on sales growth rates; θ_{200} – growth rate acceleration.

3.4 Results

First, we run the unconditional means model using Stata *mixed* command to calculate the proportion of sales variance that occurs across time, between car models, brands, and categories. The results are presented in Table 4. The variance in sales that occurs across time is 16.2%; between car models is 58%; between brands 17.3%; between car categories 7.5%.

Since variation between categories is less than 10%, we fit nested model with only brand as a third level group variable, excluding the category level. However, the likelihood test indicates that the cross-classified three-level model has a better fit ($\chi^2(3) = 278.84$, $p < 0.001$). Accordingly, we continue the analysis using the initial cross-classified model with both brand and category on the third hierarchical level. The results of unconditional growth model, also reported in Table 4, show that car sales grow with time, but a decreasing rate. Figure 4 depicts car sales growth curve. The full conditional model explains 58% of variance in sales, including 59% of the variance on category level, 82% on brand level, 37% on model level, and 22% of the variance in car model sales across time.

The full conditional model (Table 4) supports hypotheses H1a and H1b, showing that category-level design innovativeness negatively affects initial sales status and positively affects sales growth rates. Hypothesis H2a is supported revealing the positive effect of brand-level design innovativeness on initial sales status. However, its negative effect on sales growth rates is not supported (the coefficient is negative but not significant). We find support for the negative interaction effect of category- and brand-level design innovativeness on initial sales (H3a), while H3b predicting negative interaction effect on sales growth rates is not supported, as the coefficient is negative but not statistically significant.

3.4.1 Additional analysis

Since our measure of design innovativeness is calculated yearly, we run supplementary analysis to explore the trajectory of design innovativeness change over time. We apply multilevel mixed-effects modeling procedure to estimate the growth model of design innovativeness:

$$DI_{tmbc} = \theta_{000} + \theta_{100}\mathrm{Time}_{tmbc} + \theta_{200}\mathrm{Time}^2_{tmbc} + \upsilon_{00c} + \upsilon_{00b} + r_{0mbc} + r_{1mbc}\mathrm{Time}_{tmbc} + e_{tmbc}$$

As expected, both category-level and brand-level design innovativeness measures decrease with time (coefficients of time are negative and significant). We represent the growth curves of category- and brand-level design innovativeness on Figure 4. On average, brand-level design innovativeness is lower probably reflecting the effort of brands to strive for consistency and strong brand family resemblance in product portfolios (Herm and Moller 2014).

3.5 General Discussion

Past design innovation research exploring the effect of design innovativeness on performance has been focused on design novelty with regard to product category or segment of a product category. However, since brands are also organized as categories (Boush 1993, Joiner 2007), consumers perceive design novelty not only with respect to a product category, but also with respect to the products in brand portfolio. Accordingly, design innovativeness can be defined on two levels, product category level and brand level. Brand consistency level in design is an important component of brand strategy (Herm and Moller 2014, Townsend et al. 2013). To date, however, the literature exploring the effect of brand-level design innovativeness is very limited.

Addressing this gap, we define design innovativeness as a concept existing on two levels, and explore category- and brand-level design innovativeness on performance. To build the comprehensive framework of design innovativeness and its effect on sales, we draw on categorization (Barsalou 1985, Boush 1993, Joiner, 2007) and habituation-tedium theories (Tellis 1997). We conclude with a discussion of the paper's theoretical contributions, the managerial implications of the findings, and limitations and opportunities for future research.

The paper's findings contribute to the literature in marketing that explores design innovation. Namely, we extend the literature on brand-level design innovativeness (Liu at al. 2017, Talke 2017), by exploring the effect of brand-level design innovativeness and its interaction with category-level design innovativeness on sales evolution. Since the effect of design novelty changes with the level of exposure (Tellis 1997), it is important to disentangle the short- and long-term effect of design innovativeness. We employ growth curve analysis, which allows to estimate the effects of design category-level and brand-level design innovativeness, as well as their interaction effect, on initial sales status and sales growth rates.

We find that category-level design innovativeness negatively affects initial sales status but positively affects sales growth rates. It implies that initially consumer prefer more typical designs, however, more innovative designs are more successful in the long run. The results show that brand-level design innovativeness has positive effect on initial sales status. However, its negative effect on sales growth rates is not supported. Overall, it suggests that the deviation from brand design can be a rewarding strategy. Importantly, on practice, brands often strive for consistency in the product portfolio, while the opposite strategy may be more beneficial. For example, Person et al. (2008) explains that the deviation from prior products can help draw attention to the product and thus improve its performance. We also find support for the negative interaction effect of category- and brand-level design innovativeness on initial sales.

These findings generate useful implications for business practice. Managers can use them as a guidance on styling of new products, suggesting whether new products should look similar or different to the products on the market and brand's own product portfolio, depending on their short- and long-term goals.

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Figures

Figure 1. Inverted U-shape relationship between liking of novel stimuli and exposure

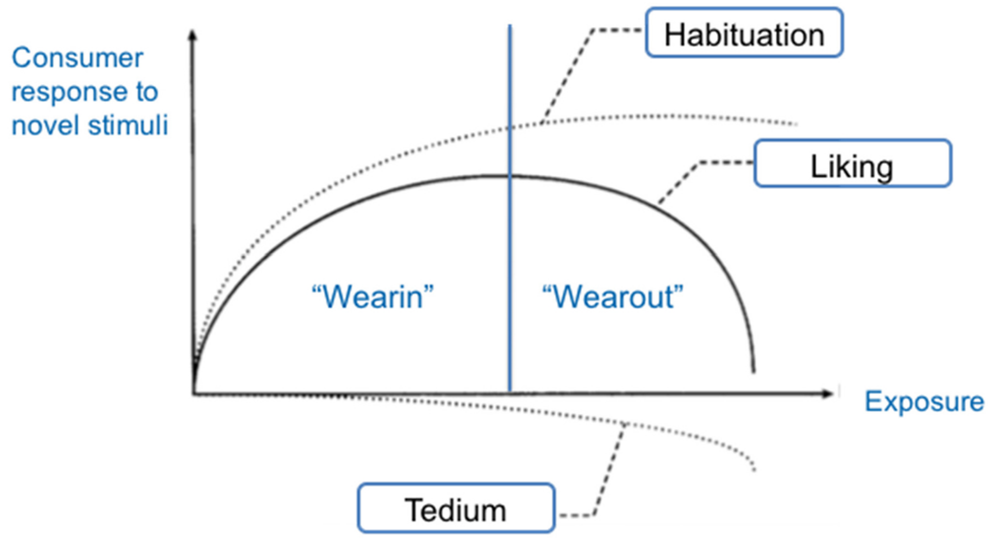


Figure 2. Idealized liking curves of innovative designs on brand and category level

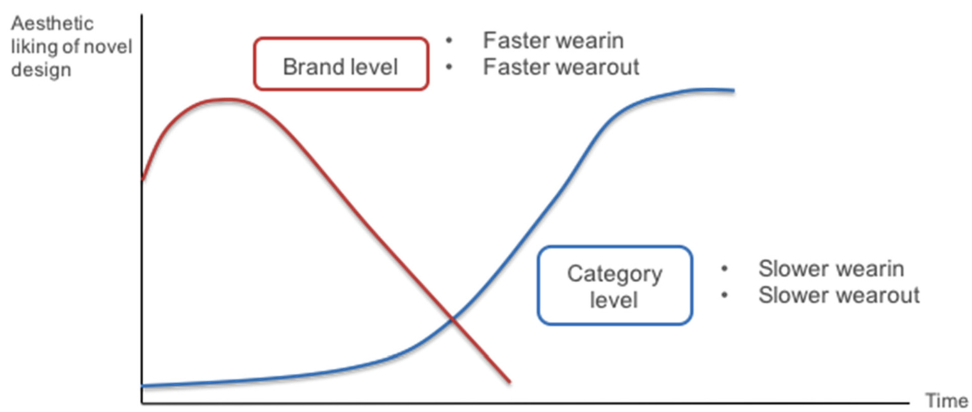


Figure 3. Landmarks representing the car shape

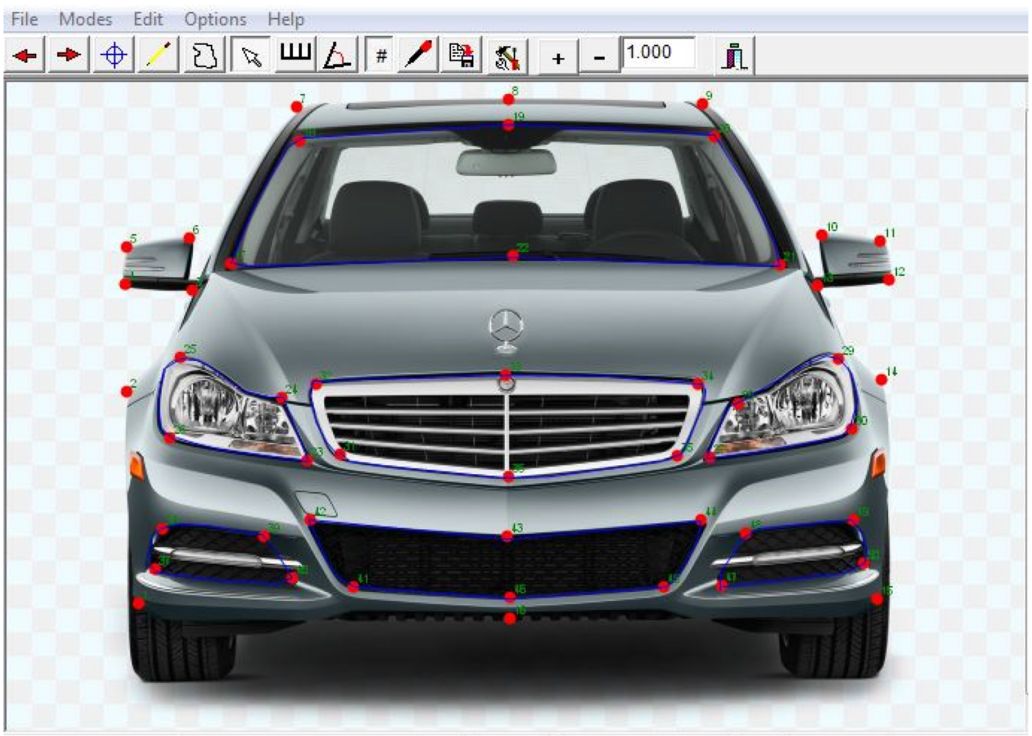
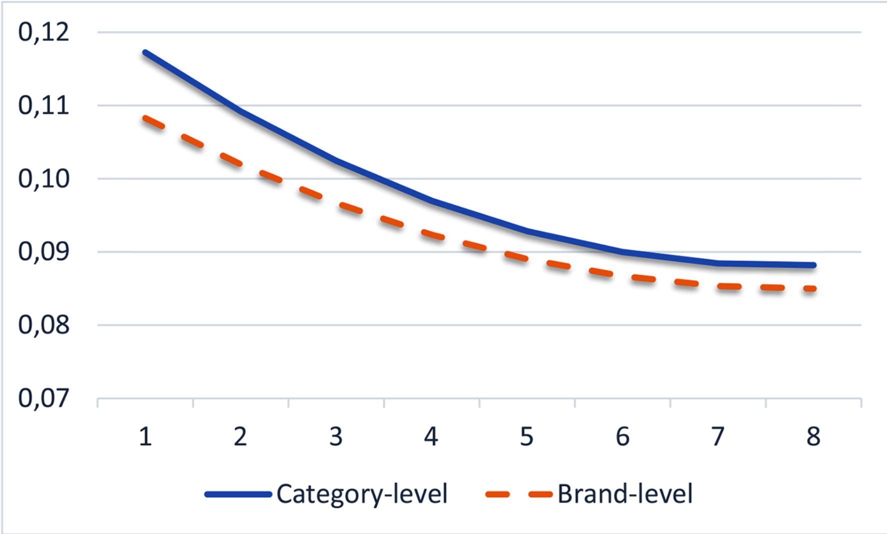


Figure 4. Car sales growth curve

Years on the market

Figure 5. Design innovativeness growth trajectory



Years on the market

Tables

Table 1. Literature review

Reference	**Concept**	**Level of novelty analysis**	**Measure**	**Dependent Variable**	**Context**	**Sample size**
Landwehr et al. (2011)	Design prototypicality	Segment	Euclidean distance from average shape (picture morphing)	Sales	German car market	28 car models
Landwehr et al. (2013)	Design prototypicality	Segment	Euclidean distance from average shape (picture morphing)	5. Aesthetic liking 6. Sales	German car market	28 car models
Mugge and Dahl (2013)	Design newness	Product category	Manipulation: 3D line drawings of products with a high or low level of design newness	Consumer evaluations	Lab experiment	130 participants
Rubera (2014)	Design innovativeness	Product category	Rating based on expert reviews (1-5)	Sales	US car market US motorcycle market	520 new car models
Liu et al. (2017)	5. Segment Prototypicality 6. Brand Consistency 7. Cross-segment mimicry	Segment Brand	Euclidean distance from average shape (picture morphing)	Market share	US car market	202 car models
Talke et al. (2009)	Design newness	Segment	Rating based on survey (1-7)	Sales	German car market	157 car models
Talke et al. (2017)	Design newness	Segment Brand Previous generation	Rating based on survey (1-7)	Sales	German car market	109 car models
Our Study	**Design innovativeness**	Product category Brand	**Procrustes distance from the typical shape in product category in the period prior to the product introduction**	**Sales**	**US car market**	**671 car models (3530 model-year observations)**

Table 2. Sample description

Category	**Number of brands**	**Number of car models**	**MSRP range, USD**
Coupe	29	91	12255 – 191700
SUV	35	134	9889 – 139771
Convertible	19	41	17469 – 440000
Sedan	34	204	9809 – 181500
Hatchback	18	39	8895 – 42240
Wagon	20	42	12424 – 85400
Crossover	14	20	17195 – 50135
Van	22	59	15931 – 87400
Truck	15	41	12063 – 54145

Table 3. Variable description and data sources

Variable	**Definition / Measure**	**Data source**
Sales of the car model	Total sales of car model i in year t	Ward's Auto Yearbook
Category-level design innovativeness of the car model	Degree of novelty in the shape of car model i with regard to the product category. Measured as a Procrustes distance from the typical shape in category c in the previous period $(t-1)$	Frontal pictures of car models from MSN Autos
Brand-level design innovativeness of the car model	Degree of novelty in the shape of car model i with regard to brand portfolio. Measured as a Procrustes distance from the typical shape of the brand c in the previous period $(t-1)$	Frontal pictures of car models from MSN Autos
Control variables		
Car model price	Manufacturer's Suggested Retail Price of car model i in year t	MSN Autos
Technological innovativeness of the car model	Degree of novelty in the technological performance of the of car model i. Measured as a distance from the average performance in the category in terms of horsepower and fuel economy	MSN Autos
Brand-level advertising expenditures	Total advertising expenditures of brand b in year t	TNS Media Intelligence
Model-level advertising expenditures	Total advertising expenditures of brand b on the promotion of car model i accumulated since the year of model introduction	TNS Media Intelligence
Previous brand design innovativeness (category-level)	Average category-level design innovativeness of the car models in the portfolio of brand b in the previous period $(t-1)$	Frontal pictures of car models from MSN Autos
Previous brand design innovativeness (brand-level)	Average brand-level design innovativeness of the car models in the portfolio of brand b in the previous period $(t-1)$	Frontal pictures of car models from MSN Autos

Table 4. Cross-classified growth model results

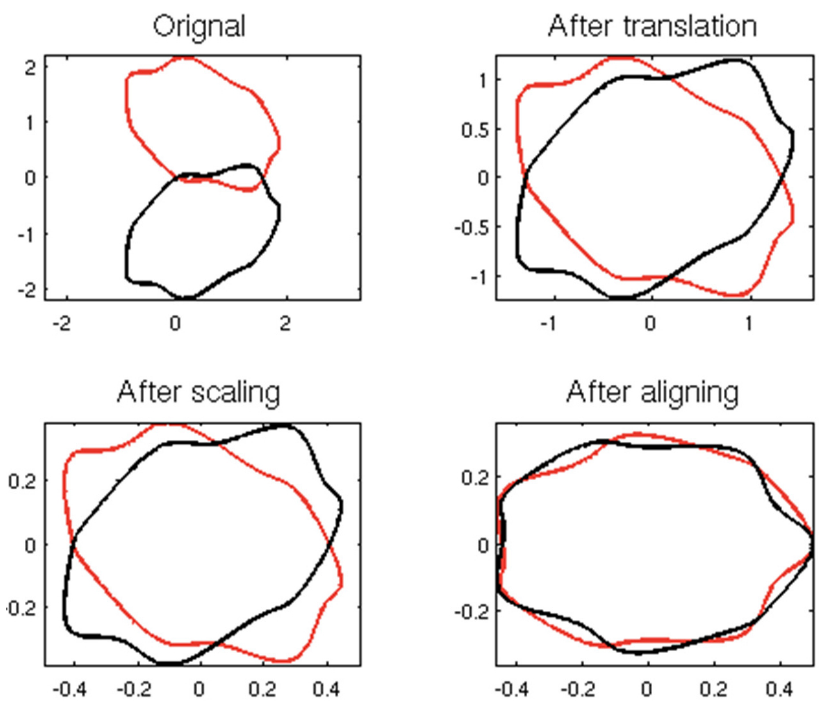
	Unconditional model	Unconditional growth model	Conditional growth main model	Conditional growth full model
Intercept	49848.46 (11006.61)***	48349.28 (10638.89)***	60540.45 (10607.14)***	59078.31 (10497.93)***
Fixed effects: Initial status				
Time		3011.111 (753.86)***	−1473.309 (1711.538)	−1351.198 (1712.716)
Time^2		−581.215 (83.412)***	−398.9699 (219.26)*	−374.367 (219.911)*
Category-level design innovativeness (H1a)			−15659.75 (2458.279)***	−16981.31 (2659.291)***
Brand-level design innovativeness (H2a)			5219.028 (1951.037)***	7968.466 (2222.021)***
Category-level DI × Brand-level DI (H3a)				−4486.844 (1289.695)**
Fixed effects: Growth rate				
Category-level design innovativeness × Time (H1b)			2068.709 (492.3271)***	2926.19 (662.696)***
Brand-level design Innovativeness × Time (H2b)			−116.922 (801.0602)	−117.5473 (801.037)
Category-level DI × Brand-level DI × Time (H3b)				−705.75 (602.001)
Control variables				
Price			−0.053 (0.096)	−0.06 (0.095)
Model-level advertising expenditures			0.336 (0.037)***	0.33 (0.037)***
Brand-level advertising expenditures			0.027 (0.003)***	0.026 (0.003)***
Technological innovativeness			−11783.94 (4736.441)**	−10852.22 (4724.094)**
Previous brand design innovativeness (category-level)			9300.962 (4459.195)**	8966.386 (4510.262)**
Previous brand design innovativeness (brand-level)			−8311.214 (5514)	−6925.196 (5622.251)
Random effects				
r_{1mbc} (time)		8316.292 (488.496)**	6255.405 (733.1772)**	6331.063 (742.741)**
e_{tmbc}	37374.72 (494.97)**	31551.01 (455.7039)**	34475.54 (801.7372)**	34332.97 (799.864)**
r_{0mbc} (model)	71289.22 (2189.21)**	74052.58 (2311.642)**	45205.44 (2592.003)**	45084.1 (2583.131)**
υ_{00b} (brand)	38614.21 (5194.63)**	38630.94 (5183.486)**	16745.33 (4293.107)**	16213.6 (4277.979)**
υ_{00c} (category)	25429.69 (7026.34)**	23803.75 (6738.174)**	12996.4 (5013.047)**	12664.86 (4958.835)**

Standard errors in parentheses.
$^{*}\,p < 0.1$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$

Appendix 1. Superimposition Procedure

Procrustes superimposition aligns shapes and minimizes differences between them to ensure that only real shape differences are measured:

1. Translation: centers all shapes at the origin (0,0)
2. Scaling of all shapes to the same size
3. Aligning: rotates each shape around the origin until the sum of squared distances among them is minimized (similar to least-squares fit of a regression line)
4. Ensures that the differences in shape are minimized



To center all shapes at the origin $(0,0)$, 2-dimensional coordinates (X, Y) of all the landmarks are averaged:

$$X_C = \frac{1}{K} \sum_{j=1}^{K} X_j$$

$$Y_C = \frac{1}{K}\sum_{j=1}^{K} Y_j$$

Then the centered configuration matrix XC by subtracting the centroid coordinate from the corresponding coordinate of each landmark:

$$XC = \begin{bmatrix} (X_1 - X_C) & (Y_1 - Y_C) \\ (X_2 - X_C) & (Y_2 - Y_C) \\ \vdots & \vdots \\ (X_K - X_C) & (Y_K - Y_C) \end{bmatrix}$$

Next, we rescale each shape so that its centroid size is one. The formula for centroid size is:

$$CS(X) = \sqrt{\sum_{i=1}^{K}\sum_{j=1}^{M}(X_{ij} - C_j)^2}$$

Dividing each coordinate of the centered shape by its centroid size produces the pre-shape space where the surface of a hypersphere centered on the origin, and the sum of all squared landmark coordinates is one:

$$\sum_{i=1}^{K}\sum_{j=1}^{M}(X_{ij})^2 = 1$$

Next step is to rotate each shape around the origin until the sum of squared distances among them is minimized. The sum of the squared Euclidean distances between the K landmarks of the rotated target and the reference is:

$$D^2 = \sum_{j=1}^{k}\left[\big(X_{Rj} - \big(X_{Tj}\cos\theta - Y_{Tj}\sin\theta\big)\big)^2 + \big(Y_{Rj} - (X_{Tj}\sin\theta + Y_{Tj}\cos\theta)\big)^2\right]$$

where (X_{Rj}, Y_{Rj}) are the coordinates of the landmark in the reference. To minimize this squared distance as a function of θ, we take the derivative with respect to θ and set it equal to zero:

$$-\sum_{j=1}^{K}\left[\begin{array}{c} 2(X_{Rj}-(X_{Tj}\cos\theta - Y_{Tj}\sin\theta))(-X_{Tj}\sin\theta - Y_{Tj}\cos\theta) \\ +2(Y_{Rj}-(X_{Tj}\sin\theta + Y_{Tj}\cos\theta))(X_{Tj}\cos\theta - Y_{Tj}\sin\theta) \end{array}\right] = 0$$

and solve for θ:

$$\theta = \text{arctangent}\left(\frac{\sum_{j=1}^{K} Y_{Rj}X_{Tj} - X_{Rj}Y_{Tj}}{\sum_{j=1}^{K} X_{Rj}X_{Tj} + Y_{Rj}Y_{Tj}}\right)$$

which gives the angle by which to rotate the target to minimize its distance from the reference.