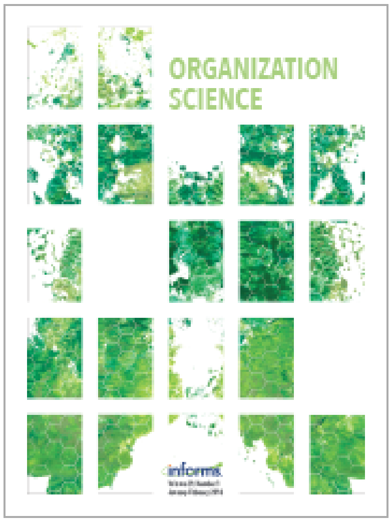


Organization Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

Anchored Differentiation: The Role of Temporal Distance in the Comparison and Evaluation of New Product Designs

Tian Heong Chan, Yonghoon G. Lee, HeeJung Jung

http://pubsonline.informs.org/journal/orsc

ORGANIZATION SCIENCE
Vol. 32, No. 6, November–December 2021, pp. 1523–1541
ISSN 1047-7039 (print), ISSN 1526-5455 (online)

Anchored Differentiation: The Role of Temporal Distance in the Comparison and Evaluation of New Product Designs

Tian Heong Chan,[a] Yonghoon G. Lee,[b] HeeJung Jung[c]

[a] Goizueta Business School, Emory University, Atlanta, Georgia 30322; [b] The Hong Kong University of Science and Technology, Clear Water Bay, Kowloon, Hong Kong; [c] Imperial College Business School, Imperial College London, London SW7 2AZ, United Kingdom

Contact: tian.chan@emory.edu, https://orcid.org/0000-0002-0286-1854 (THC); yglee@ust.hk, https://orcid.org/0000-0002-1558-9124 (YGL); hj.jung@imperial.ac.uk, https://orcid.org/0000-0001-5706-6308 (HJ)

Received: August 19, 2019
Revised: October 29, 2020
Accepted: January 8, 2020
Published Online in Articles in Advance: March 15, 2021

https://doi.org/10.1287/orsc.2021.1454

Abstract. A new design can be compared with its contemporaries or older designs. In this study, we argue that the temporal distance between the new design and its comparison play an important role in understanding how a new design's similarity with other designs contributes to its valuation. Construing the value of designs as a combination of their informational value and their expressive value, we propose the "anchored differentiation" hypothesis. Specifically, we argue that expressive value (which is enhanced by how much the new design appears different from others) is emphasized more than informational value (which is enhanced by how much the new design appears similar to others) compared with contemporary designs. Informational value, however, is emphasized more than expressive value when compared against designs from the past. Therefore, both difference from other contemporary designs (contemporary differentiation) and similarity to other past designs (past anchoring) help increase the value of a new design. We find consistent evidence for our theory across both a field study and an experimental study. Furthermore, we show that this is because temporal distance changes the relative emphasis on expressive and informational values. We discuss our contribution to the growing literature on optimal distinctiveness and design innovation by offering a dynamic perspective that helps resolve the tension between similarities and differences in evaluating new designs.

Funding: The authors gratefully acknowledge partial financial support by Goizueta Business School's Information Systems and Operation Management Department Area Fund.
Supplemental Material: The online appendixes are available at https://doi.org/10.1287/orsc.2021.1454.

Keywords: product design • design patents • innovation • optimal distinctiveness • mixed methods

1. Introduction

The design of a product—its visual form—is a key strategic resource. The initial award of $1 billion (USD) to Apple in 2012 for Samsung's patent infringement centered on design and attests to its economic relevance (*The Economist* 2012). Furthermore, winning design awards is associated with higher firm value (Xia et al. 2016), and both Silicon Valley firms and management consultancies are edging into design (Maeda 2015, Vanhemert 2015). Given design's importance, a fundamental concern to both academics and practitioners is to understand how the market compares and values new designs (Bloch 1995, Rindova and Petkova 2007). The comparison and valuation of new designs, however, like that of new products, services, or organizations, remain challenged by the dual difficulties of delineating reference boundaries to which designs should be compared (Cattani et al. 2017) and often opposing theories regarding how much new designs should appear similar or dissimilar to others in the set of references (Zhao et al. 2017).

The task's challenge is compounded as new designs arrive constantly to the market and introduce multiple boundaries of references based on temporal distance (Lo and Kennedy 2015, Anthony et al. 2016). In other words, a new design can be compared against contemporaries; alternatively, it can be compared with older designs that are introduced in the past. A new design can appear not only similar or different regardless of the reference set used, but also similar compared with one reference set yet different to another. This possibility raises the question of *how* different reference sets matter when evaluating designs. In the present paper, we develop a theory about how a new design's relationship to two temporal boundaries of reference—contemporaries versus past designs—affect its value. In doing so, we focus on two important sources of value that product design fulfills: informational value and expressive value. Design helps consumers not only learn and understand how the product works (Rindova and Petkova 2007) but also differentiate and express individuality (Hebdige 1979, Lynn and Harris 1997).

Research from different scholarly traditions suggests that the degree of similarity of a design to others exerts opposing forces on these value sources. On the one hand, designs similar to others diminish expressive value by failing to satisfy consumers' innate desire for distinctiveness (Lynn and Harris 1997, Irmak et al. 2010). On the other hand, they provide informational value by helping consumers learn and understand how products are used (Hargadon and Douglas 2001, Rindova and Petkova 2007, Eisenman 2013). Similar arguments form the core of the "optimal distinctiveness" hypothesis, which contends a need exists to strike a balance between similarities and differences. Evidence supporting this hypothesis has been found in automobile, corporate law market, music, gaming products, and mobile application markets (Paolella and Durand 2016; Askin and Mauskapf 2017; Liu et al. 2017; Zhao et al. 2017, 2018; Barlow et al. 2019).

Here, we advance, yet depart from, this hypothesis by suggesting that consumers weigh informational and expressive value differently when making comparisons against contemporaries vs. past designs. Specifically, we argue that expressive value is enhanced when a design differs from its contemporaries, because it helps consumers express themselves apart from one another more effectively. By contrast, informational value is enhanced when a new design appears similar with respect to past designs from which consumers have accumulated knowledge and experience. Taken together, we suggest a novel proposition that we call "anchored differentiation," whereby the point of optimal distinctiveness can be reached when new designs *anchor* on a stock of past designs while simultaneously *differentiating* themselves from contemporaries.

To test our theory, we conducted two studies: one based on field data and the other experimental. In the field study, we compiled a unique data set consisting of all design patents granted by the U.S. Patent and Trademark Office (USPTO) over the period 1977–2009. Design patents offer multiple empirical advantages. First, evaluating the similarity among designs is part of the examination process, and references of prior designs deemed most similar in visual concept are documented on the design patent itself (USPTO 2006). Thus, the list provides a basis to compute a *similarity score* against other designs (see Chan et al. 2018 for experimental validation for such a measure). Furthermore, design patents remain confidential until the day the patent is granted, whereupon its details are disseminated through the *Official Gazette* by the USPTO on the same day. This information shock unique to the design patent allowed us to capture the market's assessment of the design using the stock market reactions in the days after a design patent was granted. We find that two qualities of a design generate a more positive reaction from the market: (1) differentiating from contemporaries and (2) appearing similar with respect to past designs. We further find that contemporary differentiation becomes more valuable when the market evaluates the designs of more visible products. In contrast, past anchoring becomes more valuable when the market evaluates the designs of products with a longer technological lifespan.

We dive into our mechanisms more directly in a preregistered experimental study. We randomly assigned participants into groups in which we manipulated both the similarity and the temporal distance of a reference set. We then measured the effects of such manipulations on the expressive and informational values of the focal design. Consistent with expectations, we find first that differentiation increases subjects' perception of the expressive value of a focal design. More importantly, this increase is larger when the reference set is contemporary. We also find that similarity increases subjects' perception of informational value of a focal design, and this increase is larger when the reference set is in the past.

The present paper makes three important contributions. First, it contributes to the burgeoning conversation surrounding optimal distinctiveness, where multiple streams of literature are converging to provide a better understanding of how innovations are evaluated (Zhao et al. 2017). In particular, we join and advance the growing literature around the role of changing different reference points (Zhao et al. 2018, Barlow et al. 2019) by highlighting that the temporal distance of reference sets has an important implication to how optimal distinctiveness is achieved in a dynamic setting where new objects arrive constantly. Second, our work contributes to the literature examining how multiple dimensions add differently to the perception of value (Pontikes 2012, Cattani et al. 2017). By showing that expressive value and informational value weigh differently depending on the temporal distance of the references, our work suggests how firms can *orchestrate* similarities and differences across multiple boundaries to attain designs with both high expressive and high informational value. Finally, we contribute to the literature on innovation, where designs are contributing increasingly to product value. By advancing how the market evaluates new designs, the present work has implications for how these evaluative principles can shape the evolution of new designs (Rindova and Petkova 2007, Chan et al. 2018).

2. Theoretical Development

2.1. The Informational and Expressive Values of Design

The notion of design has multiple connotations (Ulrich 2011b). The defining characteristic of industrial design, however, is its role in shaping the physical form of a product (Bloch 1995, Krishnan and Ulrich 2001). Because the visual form of a product is one of the first things a consumer perceives, design is the basis for the cognitive processes of product comparison (Eisenman 2013).

Prior works have noted that design contributes to two sources of value—informational and expressive—that emerge from this comparison process (Rindova and Petkova 2007). Because many functional aspects of a product are not readily apparent, one fundamental purpose of product design is to inform consumers of the product's functionality (Rindova and Petkova 2007, Eisenman 2013). Indeed, the maxim "form follows function" (Sullivan 1896) embodies the design principle that physical shapes should inform or enhance an object's intended function. Gibson (1979) thus suggested that we should see product design not as mere physical attributes, but through the lens of a product's intended function; that is, in terms of *affordances* or what the product affords us to do. For example, a better way to describe a handle is not its diameter, but in terms of its "gripability" (Krippendorff and Butter 2007, p. 8). Because such understandings are established through experience and familiarity, designs that appear similar to other designs help deliver informational value (Rosch 1978, Veryzer and Hutchinson 1998, Krippendorff and Butter 2007, Hoegg and Alba 2011).

Yet design is not merely an exterior quality through which users access product functions; it also reflects the users' esthetic and symbolic choices (Rindova and Petkova 2007). The choice of what shoes to wear, for example, is a conscious display of the wearer's tastes (Hebdige 1979, Bellezza et al. 2014). People want to be somewhat distinct, and product designs offer a marker to express uniqueness (Lynn and Harris 1997, Tian et al. 2001, Irmak et al. 2010, Chan et al. 2012). Indeed, the market caters to such innate desires for individual uniqueness—this may explain why something as simple as a toaster comes in a wide variety of styles and shapes (Molotch 2003) or why the wardrobe of highly visible celebrities is comprised of uncommon designer dresses (Godart 2012). It follows, then, that dissimilar designs can help satisfy users' innate need for differentiation (Lynn and Harris 1997) and hence generate greater expressive value.

When juxtaposed, these two sources point to different predictions for the effect of design similarities on its value. An emphasis on informational value suggests that new designs should look similar to others, whereas an emphasis on expressive value suggests the opposite. Acknowledging these opposing forces, scholars have proposed that a balance of these two values—presumably achieved at a point where designs are neither too similar nor too different—yields the greatest outcome. Empirical support of this idea, which is often described as the optimal distinctiveness hypothesis, abounds. For example, Askin and Mauskapf (2017) showed that songs that differed from other songs, but were not *too* different, remain ranked by *Billboard* for a longer time. Liu et al. (2017) also documented an inverted U-shaped relation between typicality and the U.S. sales of automobiles.

However, such a conclusion may not be as straightforward as it appears. Cattani et al. (2017) and Zhao et al. (2017) stressed that audiences can make evaluative comparisons across multiple dimensions—an issue that Cattani et al. (2017, p. 67) described as "infinite dimensionality." The multidimensionality through which designs are comparable opens the possibility that a new design can be placed in multiple boundaries of references, leading, potentially, to different ways to grapple with the opposing implications of design similarities on value.

Specific to the innovation context is that because designs were introduced to the market at different points in time, we can distinguish a new design's similarity with respect to a *contemporary* reference group versus a *past* reference group. An important implication of considering the *temporal distance* between a new design and its possible comparisons is that what is similar vis-à-vis past designs may not be similar vis-à-vis contemporaries. For example, a new design can be similar to contemporaneous designs but dissimilar to designs introduced in the past. This might occur if designers collectively emulate a new inspiration, thereby creating a cohort of new designs similar to each other yet different from past designs. We might also observe the opposite outcome: a cohort of designs that differ from each other but are similar to past designs; such circumstances could arise if designers differentiate among themselves, while adhering closely to familiar, well-established looks.

Consider Table 1, which displays conceptual differences when the temporal distance between a new design and its comparison is considered. For conceptual simplicity, we consider a new design that can appear either similar or different to its contemporaries or past designs. This leads to four representative cases. The diagonal cases in Table 1, which we call the proto-cases, are unambiguously similar or different to both their contemporaries and past designs. In the off-diagonal cases, a balance is achieved between similarity and differences from multiple

Table 1. Comparing a New Design to Contemporary and Past Designs

		Past	
		Similar	Different
Contemporary	Similar	**Proto-typical**	**Trended differentiation**
	Different	**Anchored differentiation**	**Proto-atypical**

reference sets. By highlighting temporal distance, we can distinguish two cases. The first case is when a new design appears similar to its contemporaries but is dissimilar to its past designs. We call this *trended differentiation*, because the new design is differentiated from its predecessors while following the trending elements of its contemporaries. The second case is *anchored differentiation*, as the new design is differentiated from its contemporaries yet retains elements of past designs.

This conceptualization differs from existing work, which assumes that consumers are motivated to compare a new design against more *recent* designs. Hence, comparisons with temporally *near* objects universally gains greater weight than comparisons with temporally *distant* objects (Askin and Mauskapf 2017). Accordingly, this characterization overlooks a more fine-grained comparison that consumers can make for the similarities of a new design, that is, the off-diagonal cases.

Our distinction between trended and anchored differentiation is important because the value that consumers derive from design similarity depends on the relative emphasis consumers put on informational value (which enhances with similarity) compared with expressive value (which enhances with *dis*similarity). The key part of our theory is that the relative importance between the two value drivers changes when the comparison is made with contemporary designs versus when it is made with past designs.

First, when a new design is compared with contemporaries, we argue that consumers gain greater expressive value from those designs that appear different from their contemporaries, yet the extent to which consumers gain informational value from similarities across the designs is limited. Said differently, consumers are motivated to weigh the expressive value of the design *more* than its informational value when comparing a new design against its contemporaries.

Consumers derive expressive value from adopting designs capable of signaling their own uniqueness. The value of this signal is accentuated when a design differs from contemporary peers. Specific to fashion design, for example, is the notion of outfit clash (two celebrities awkwardly wearing the same outfit at the same occasion), the risk of which increases with designs similar to contemporary peers. Zuckerman (2016) illustrated another example in which a signal of admirable novelty (e.g., a never-before-seen tattoo) can turn into a signal of ridicule when two people attend the same social occasion with the same novel, but now undistinguished, tattoo. Furthermore, when designers are observed flocking toward the latest hot trend without giving their designs an individualistic spin, the market may perceive that the designers are unoriginal (Hemphill and Suk 2009). Overall, these ideas point to the greater emphasis on the expressive value that contemporaneously different designs afford.

Nevertheless, the expressive value gained from being dissimilar needs to be judged compared with the informational value from appearing similar to others. Here, we argue that informational value from similarities with contemporary designs is relatively limited. Newer designs are more relevant to consumers who are motivated to understand newer functionalities. This said, such designs might not afford customers sufficient exposure to accumulated knowledge and experience from use (Landwehr et al. 2013). Hence, informational value from being similar to contemporary designs is limited compared with the expressive value from being different from contemporary others.

The consequence of consumers placing greater weight on expressive value over informational value when evaluating a design against contemporary peers is that designs appearing similar to temporally close peers suffer from lower valuations. Hence, we state our first hypothesis.

Hypothesis 1. *The value of a design decreases as it becomes more similar in comparison with other contemporary designs.*

In contrast, when consumers compare a new design with its past designs, we argue that consumers are motivated to weigh the expressive value of the design *less* relative to the informational value. Consider first our argument that designs appearing different to the past yield little expressive value. Several works from different traditions support this argument. First, consumers are likely to be less concerned about looking similar (or different) from past designs in terms of expressing themselves, because the comparison designs may have retired from the marketplace. In fact, new designs reminiscent of older designs might even create expressive value. Recent research has suggested that adhering to traditional features can enhance a design's authenticity, helping consumers signal social status or distinction (Hahl 2016, Micheli and Gemser 2016). Indeed, the presence of fashion cycles in design innovation (Pesendorfer 1995) may indicate that consumers are at least not averse to new designs that resemble old ones. In this regard, the benefits of differences arising from enhanced expressive value may dissipate quickly as temporal distance increases.

Second, the informational value from similarities does not necessarily decline at the same rapid pace as expressive value with temporal distance. Because the informational value of design anchors on consumers' experience and understanding, designs adhering closely to existing features can enhance informational value. For example, Edison, by creating an electric lamp that resembled an existing kerosene lamp, won over consumers by clearly conveying the innovation's purpose and intended use (Hargadon and Douglas 2001). Indirectly supporting this idea is that increased familiarity with a design through repeated exposure tends to improve attraction (Alba and Hutchinson 1987, Landwehr et al. 2011).

When changes in the technology or underlying functionality of products are incremental, past designs offer a significant source of information on which consumers can draw to understand the new designs. Even if time or technological change renders some functional features useless, path dependency can make these features a useful signal of legitimacy to the extent that consumers believe such features define a certain style (Veryzer and Hutchinson 1998). The comfort of seeing a design that is legitimate and familiar may explain the phenomenon of skeuomorphism in design, for example, why electric cars retain ornamental cooling grilles when their batteries cool a different way.[1] This implies that older design features remain relevant as consumers' judge the new design, even if older designs themselves have passed on shelf space to new designs. Indeed, given that informational value is derived from experience, we might even expect that higher informational value is obtained from comparisons to prior references.

Nevertheless, we do not expect that informational value from past designs will linger forever. As temporal distance increases, informational value will eventually be reduced so much that temporally distant references will yield little value. One can argue that designs from the distant past are simply forgotten (Anderson et al. 1994); more fundamentally, however, consumers are less motivated to make these comparisons because they lose relevance to current product features.

As such, we predict that the informational value from similarities outweighs the expressive value from differences when the comparison designs are from the *recent* past (as opposed to the distant past). Thus, we present our second hypothesis.

Hypothesis 2. *The value of a design increases as it becomes more similar in comparison with other designs from the recent past.*

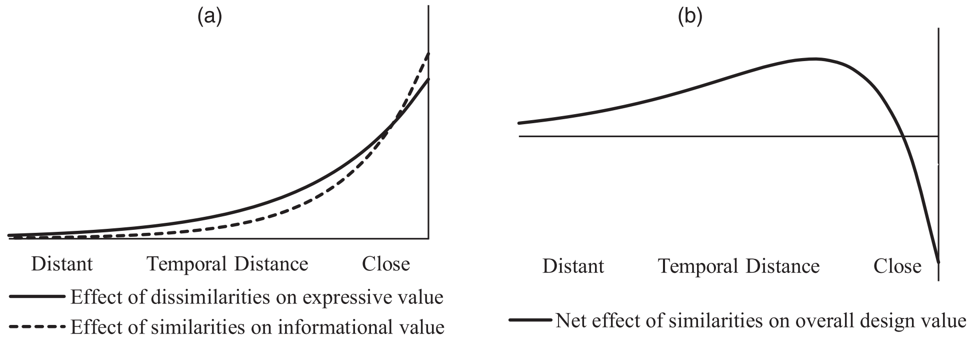
In sum, our hypotheses consider how consumers might weigh expressive value and informational value differently (afforded by how different or similar a design appears, respectively) depending on contemporaneous or near past comparisons. Combining our two hypotheses, we propose that *anchored differentiation* (i.e., lower left quadrant in Table 1) where new designs anchor on existing designs from the recent past yet differentiate from their contemporaries yield greater value than other cases. In other words, we should view new designs as situated within multiple references based on temporal distance, and particular locations endow designs with both informational and expressive value simultaneously.

Figure 1 summarizes the key arguments of our theory. In Figure 1(a), the solid line represents the extent to which design *similarities* generate informational value over the temporal distance between a new design and its comparisons. The dotted line depicts the extent to which design *dissimilarities* generate expressive value over the temporal distance between a new design and its comparisons. Figure 1(a) illustrates how we conceptualize the two curves would decay over time, using an exponential decay function. Although exponential decay functions are the simplest forms to illustrate our idea, we do not claim a priori knowledge of the exact form of decay. Indeed, informational value from comparisons with near-past designs may be higher than contemporary designs. If so, this would enhance our claim in Hypothesis 2 on the positive effects of similarities compared with designs in the recent past.

We theorize that the expressive value curve would intercept the y axis (when temporal distance is small) at a higher point than the information value curve. We also theorize that the expressive value curve would decay at a faster rate than the informational value curve, leading to informational value gaining greater weight as temporal distance increases. Here, we depart from existing theories in which the decay functions are implicitly assumed to be similar.

In Figure 1(b), we plotted the net effect of design similarities on value, which is the gap between the similarity effect from the informational curve and the difference effect from the expressive curve over the temporal distance of the comparison set. Our empirical

Figure 1. The Effect of Dissimilarities / Similarities with Increasing Temporal Distance



Notes. (a) Separate effects of dissimilarities and similarities on expressive and informational values. (b) Net effect of similarities on overall design value.

propositions are that the effects of similarities on the value of a new design would start out negative (compared with designs that are temporally close; Hypothesis 1 Hypothesis 2 Hypothesis 2) but turn positive (compared with designs from the recent past; Hypothesis 2).

It is important to reiterate that we do not assert that either of the value drivers work *exclusively* with one comparison set or the other. As different schools of thought have recognized, multiple drivers are at work when evaluating a new object, whether that is a new product (Hsu 2006), a new business venture or idea (Pontikes 2012, Berg 2016), a new organization (Stinchcombe 1965), or a new design. The key underlying mechanism of the hypothesis is that the relative weight between the expressive and informational value of a design shifts when consumers consider a new design versus its contemporary and near-past references. The difference in relative weight can then lead to a change in the net effect of similarities on value formalized in our hypotheses and as depicted in Figure 1(b) (see Haans 2019 for a similar approach to theorize combinatory nonlinear effects).

In the next sections, we further develop our theory by considering contingencies in which the relative weight between expressive and informational value might change. To this end, we focus on product visibility and technological lifespan, each of which enhances the weight of either expressive value or informational value. In this way, we provide theoretical boundary conditions to corroborate our main proposition of anchored differentiation.

2.2. Product Visibility and Technological Lifespan

Prior works have proposed that evaluative principles might be audience specific or attribute specific (Jensen et al. 2012). For example, Pontikes (2012) showed that *market makers*, who view uncertainty more positively, have a tendency to relax a general evaluative guide and use market labels differently. As such, market makers are more likely to evaluate atypical ventures positively. In a similar vein, Cattani et al. (2014) noted that peers and critics consider different aspects of candidates for consecration. For example, Ertug et al. (2016) developed a theory on audience-specificity in the context of contemporary arts, in which the audience distinguishes reputations based on the attributes of the source of a particular reputation signal, whether it is commercially oriented or artistically oriented.

These differences in audience evaluation suggest that the relative weights between informational value and expressive value may differ depending on the type of products that the market audience evaluates. In that regard, we propose two moderators to our hypotheses on anchored differentiation: product visibility and technological lifespan. We argue below that these attributes will enhance expressive value (moderating Hypothesis 1) and informational value (moderating Hypothesis 2).

First, not all products are highly visible. For example, Heffetz (2011) provided empirical evidence that particular products (e.g., jewelry, apparel, automobiles, furniture, silverware) are more visible than others (e.g., industrial goods, office equipment). Product visibility is a necessary condition for expressive value because the purpose of using a design to express one's own uniqueness inherently requires a public display. We would therefore expect consumers to pay greater attention to a design's uniqueness when the design is highly visible. This implies that the expressive value curve would shift upward, predominantly in comparison with contemporaries, because contemporary comparisons have the largest weight on expressive value. Although we would not observe a direct effect on expressive value independent of informational value, the preceding arguments suggest that consumers, when perceiving visible goods, would accentuate the cost to designs that appear similar with respect to other contemporary designs. We state this formally.

Hypothesis 3. *The negative effect of a design's similarity (with respect to contemporary designs) on its value will be enhanced for visible products.*

Second, a key argument for our second hypothesis (Hypothesis 2) on past anchoring is that information value gains greater weight when the knowledge and experience remain relevant, even as the temporal distance increases. The argument that consumers can rely on designs from the past to infer utility information assumes that product technologies are sufficiently long-lived. That is not always the case because the technological features of some products change slowly, whereas others change much more quickly (Eisenhardt and Tabrizi 1995, Brown and Eisenhardt 1997, Mendelson and Pillai 1999, Zhao et al. 2018). Fast technology evolution, or shorter technological lifespan, is more likely to make past design features obsolete and can dilute, in turn, the informational value that past design offers. Put differently, past designs serve as useful benchmarks for consumers insofar as they provide useful information to infer the value of the design. Thus, adhering to past designs might only be valuable when the technological basis of the product is sufficiently long-lived for such an inference to be useful.

In this regard, we expect that the informational value derived from older designs would continue to remain relevant if technologies are longer-lived than if they evolve quickly. As a result, we expect that consumers give more weight to the informational value of near-past designs for technologically stable products; therefore, consumers would draw greater value from the similarity of designs to the near past. We state this formally.

Hypothesis 4. *The positive effect of a design's similarities (with respect to near-past designs) on its value will be enhanced for products with technologically long lifespans.*

3. Field Study: Design Patents

The *design patent* is a special class of patent granted for "new, original, and ornamental design" (35 U.S.C. §171). Patent rights are limited specifically to the "visual characteristics" (USPTO 2006, p. 1) embodied in a product's design and *not* to the products themselves. Thus, the design patent's narrow scope isolates the product's visual characteristics; this allows us to focus on questions relating to the visual form of products. Considering that a product's visual form typically dominates its other aspects from the consumer's perspective (Bloch 1995, Ulrich 2011a), design patents are a context well suited to studying how products are understood and evaluated. Online Appendix A includes an example of a Herman Miller Aeron chair design patent.

3.1. Measuring the Value of a Design Patent

Recent developments in the patent valuation literature provide concrete guidance on how we can identify a patent's value. Particularly, Kogan et al. (2017) observed that the USPTO always issues patents each Tuesday. On the same day, it publishes the *Official Gazette*—a publication listing the patents issued and their details for the first time to the public. This information shock implies that the stock market's reaction to the announcement of a granted patent captures how the market values the newly granted design.

We follow the approach of Kogan et al. (2017) as follows. We first measure the three-day abnormal return r_j following a design patent j's grant announcement. This return, however, comprises both a signal from the announcement and also other unrelated factors (the noise). We remove the noise from r_j by measuring (1) the price variance for the firm f in the same year t (labelled $\sigma_{\varepsilon ft}$; or the amount of noise on a normal day for the firm-year) and (2) how much more volatile trading becomes on the days when a firm receives a patent (that is, the signal-to-noise ratio, labeled SNR). Assuming that a patent's value follows a normal distribution truncated at zero, and the signal-to-noise ratio is a constant, the patent's value V_j can then be derived as

$$V_j = \frac{M}{N}\left(SNR \times r_j + \sqrt{SNR} \times \sigma_{\varepsilon ft} \times \frac{\varnothing\left(-\sqrt{SNR} \times \frac{r_j}{\sigma_{\varepsilon ft}}\right)}{1 - \Phi\left(-\sqrt{SNR} \times \frac{r_j}{\sigma_{\varepsilon ft}}\right)} \right),$$

in which $\varnothing$ and Φ denote the probability density function and cumulative distribution function of a standard normal distribution, respectively, M the market capitalization of the firm, and N a count of the number of patents (if more than one) that are issued on the same day.

Beyond establishing a direct measure of value that is specific to the design, there are two other reasons we adopt this value measure. First, the measure provides an account of the design patent's value that is immediate—in other words, less contaminated by events unfolding in the future. Second, because the USPTO uniquely maintains the confidentiality of all pending design patents until the patent grant date (35 U.S.C. 122), the Tuesday on which a design patent is granted is the singular significant information event whereby the public first learns about the patent just granted.

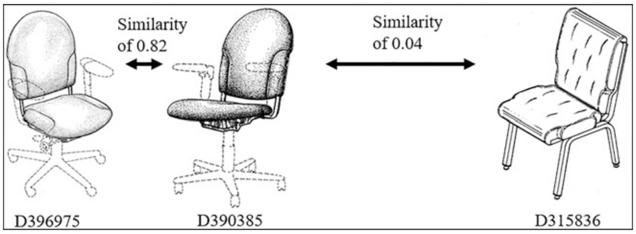
3.2. Measuring Similarity

For each design, our analysis requires us to measure its overall degree of similarity with respect to other contemporary designs and with respect to other near-past designs. The design patent is uniquely suited for our analysis, as the determination of similarity between designs is part of the patent examination process. Every design patent application undergoes a rigorous examination process to determine patentability. This process requires a patent examiner to search through prior patents to find those that are similar in terms of overall "visual impression" (USPTO 2006, p. 29) to the applicant's design. The examiner can reject an application if the resulting list contains a design that is substantially the same as the focal design. Otherwise, the examiner approves the application and documents the list of relevant patents found during the search process.

Hence, the list of patent references constitutes a documentary trail of human-evaluated visual similarity among designs. Chan et al. (2018) showed that measuring the *overlap* in the reference list of two designs is highly informative of similarity. The approach to measuring the similarity of any two design patents uses the Jaccard index, where we divided the number of overlaps in the reference lists by the total number of unique references the two designs made. If one of the designs references the other, we added to the Jaccard measure one over the size of the reference list of the citing design. Consider Figure 2. The design to the left and the design in the center have a large overlap in their reference list, sharing 23 references that appeared in both lists, among a total of 28 distinct references made by the two designs (but neither appears in the other's reference list). Therefore, the two chairs have a similarity score of 23/28 = 0.82. As another example, the pairwise similarity between the design in the center to the design on the right using the same approach is 0.04 (=1/24)—although the design in the center counts the design on the right as one of its 24 references, they share no overlaps in references.

In this way, we obtain an index of the similarity across all pairs of designs, regardless of whether they are granted to public or private firms. However, we constrain similarity comparisons to only designs of the same style.[2] We do this because similarity is generally evaluated within a specific categorical boundary, as cross-category comparisons are more difficult for consumers to make.[3] We use the similarity index to

Figure 2. Measure of Similarities Between Sample Designs



create the following measures for analysis. First, *SimContemporary* measures the focal design's sum similarity to other contemporary designs (in the same style) for which patents were granted within the last year (rolling 365-day window) of its grant date.[4] Second, we compute *SimNearPast* as the focal design's sum similarity to other designs (in the same style) for which patents were granted within the two years preceding the last year (rolling window of 1,095 to 366 days). The resulting measures of similarity vis-à-vis prior patents from different temporal distances incorporates the extent to which a new design is similar to others from a specific period, within the same style and regardless of whether those designs are created by private firms or by public firms.

We imposed in our empirical measures a hard boundary of what constitutes contemporary and near past based on rolling time windows. Nevertheless, our results are robust of using different temporal boundaries (see Online Appendix D) or using a continuous representation of temporal distance (see Online Appendix E).

3.3. Product Visibility and Technological Lifespan

We used established measures of product visibility and technological lifespan used in prior work. First, Heffetz (2011) considered product visibility empirically by surveying U.S. respondents to determine what kind of products are immediately noticed when meeting a new person living in a similar household.[5] Their results showed that product categories such as automobiles, clothing, furniture, jewelry, watches, tobacco products, and home recreational products (televisions/musical instruments/toys) topped the list in terms of visibility, outstripping other products such as books, food, and cell phones or consumption of services. We used their results to develop a binary measure of product visibility (denoted as *Visibility*, set to one if the industry is involved in making visible products and zero otherwise) at the three-digit Standard Industrial Classification (SIC) level.[6]

We used the approach by Bilir (2014) to develop a measure on the length of the technological lifespan of products (similarly at the three-digit SIC code level). The intuition is that the effective economic life of technology within an industry can be measured by the average lags in citations (i.e., the average time gap between a citing and a cited patent) of technological patents. Longer time lags indicate long technological life as technological innovations continue to be "re-used" by innovations far in the future, that is, they exhibit "lasting relevance" (Bilir 2014, p. 1991). We use Bilir's data on technology lifespan, at each three-digit SIC code level, and denote the measure as *TechLifespan*.[7] We present the *Visibility* and *TechLifespan* measures for the largest industries in our data in Online Appendix C.

3.4. Control Variables

To minimize the possibility of our results being biased due to heterogeneity in firms' abilities to generate and capture value from designs, all our models include firm-level fixed effects. We also created additional time-varying firm-level measures for assets (*logAssets*), firm age in years (*FirmAge*), and Research and Development expenditures (*logRandD*). All our models also include grant-year fixed effects to control for time-varying changes in design valuation.

In addition to including these controls for firm-level capability, we note that a firm whose design portfolio is highly concentrated (i.e., a specialist firm) might have some advantages regarding a particular style (Hsu 2006). The market might well infer value from such a focus, affecting the valuation of those firms' new designs (Tucker and Zhang 2011). Hence, we include a *FirmFocus* variable, which is a Herfindahl–Hirschman index (HHI)-based measure that captures the extent to which a firm's designs—over the preceding three years—are concentrated across styles.

Another reason similar designs are valued more is that firms may *cluster* around designs of higher inherent quality (Negro and Leung 2013, Zhao et al. 2018). To control for a design's inherent quality, we incorporate the control variable *logReferenceValue*; this term is the average value of designs (weighted by the degree of similarity), within the last three years, to which the focal design is similar.

At the style level, we count the total number of patents granted in the past three years (*logActivity*) as a measure of the style's overall patenting activity. We also include style fixed effects, a procedure that ensures that we compare the effect of similarity on value among designs of the same style. All our results are robust to controlling for additional features of the style, for example, the maturity of the style in years and the rate of growth or decline in activity.

3.5. Sample and Descriptive Statistics

Using patent data from the USPTO and stock price data from the Center for Research in Securities Prices (CRSP), we assigned a value to each design patent granted to publicly listed firms in the United States between 1977 and 2009. This methodology required that we match companies in the USPTO patent data to the firms issuing securities in the CRSP data. For that purpose, we used the matching results from the National Bureau of Economic Research (NBER) Patent Data Project (Hall et al. 2005), which covers patents from 1976 to 2006. For the 2007–2009 data, we used the name-matching algorithm of Bessen (2008) to match names from the two databases. We followed this with a close visual inspection of all approximate name matches to ensure accuracy. Using this procedure, we matched and identified the market value of 57,113 patents granted from 1977 to 2009. After removing designs from new styles, where one of our key independent variables, *logSimNearPast*, is undefined, our final sample consisted of 54,156 patents granted between 1978 and 2009. Table 2 reports the summary statistics of our variables, and Table 3 presents their correlations.

4. Results of the Field Study

We estimate our models using generalized least squares (GLS) with standard errors clustered at the firm level. To enable the interpretation of the linear terms as

Table 2. Summary Statistics of Variables (N = 54,156 observations)

Variable	Description	Mean (standard deviation)
logValue	Log of the value of a design patent estimated from three-day abnormal stock returns, in millions of 1983 USD	1.07 (1.45)
logSimContemporary	Log of the sum of similarity to designs in the same style and granted within the past year (a rolling window of the past 365 days)	0.64 (0.63)
logSimNearPast	Log of the sum of similarity to designs in the same style and granted within a rolling window of 1,095 to 366 days (three years excluding the past year)	0.55 (0.51)
Visible	A binary measure that is one if the designed product is classified as a visible good (based on Heffetz 2011) and zero otherwise.	0.20 (0.40)
TechLifespan	The technological lifespan of the designed product, established using the average of utility patent citation lags in years in each industry (Bilir 2014)	9.46 (0.71)
logActivity	Log of the total number of patents granted within the style over the past three years	3.62 (1.63)
logAssets	Log of the assets of the firm that was granted the patent, in millions of 1983 USD	8.08 (1.95)
logRandD	Log of the Research and Development expenditures of the firm that was granted the patent, in millions of 1983 US dollars	2.08 (7.17)
FirmAge	Age of the firm that was granted the patent	25.9 (12.6)
FirmFocus	HHI for the degree of concentration of the firm's designs across styles over the past three years	0.27 (0.28)
logReferenceValue	Average (weighted by the degree of similarity) of the value of designs—patented within the past three years—to which the focal design is similar	1.39 (1.04)

the effect at the mean when we include moderating variables, we demean variables with interactions before including them in the regression model. These variables have the suffix *(dm)*. In Table 4, we present the results from the GLS models. Models 1–3 aim to test Hypotheses 1 and 2. Models 1 and 2 test Hypothesis 1 and Hypothesis 2 separately (i.e., including either *logSimContemporary* or *logSimNearPast*, but not both), whereas model 3 tests Hypothesis 1 and Hypothesis 2 jointly in a single model. We find strong statistical support for both hypotheses across all models. In other words, temporal distance matters to how similarity contributes to design value. It follows that temporal distance should help distinguish between similarity's expressive and informational values.

Focusing on model 3, the coefficient for *logSimContemporary* is negative (−0.09) and statistically significant ($p < 0.001$). Given the log-log setting, this result implies that a 1% increase in similarity with respect to contemporaneously released designs reduces value by 0.09%. Put differently, an increase of one standard deviation in a design's similarity (with respect to its contemporaries; that is, a 63% increase) corresponds to a decrease of about 5.7% in value: viz., $0.09 \times 63\% = 5.7\%$. Thus, in support of Hypothesis 1, we find that the negative effect of similarity (compared with contemporaneous peers) is large and statistically significant.

Also, the coefficient for *logSimNearPast* is positive (0.09) and significant ($p < 0.001$), which implies that a 1% increase in similarity—with respect to designs granted in the past three years (but not in the previous year)—results in an 0.09% increase in value. In this context, therefore, an increase of one standard deviation (51%) in a design's similarity corresponds to an increase of about 4.5% ($0.09 \times 51\% = 4.5\%$) in value. This result is evidence of similarity's positive effect vis-à-vis designs introduced in the near past, which supports Hypothesis 2.

Suppose we consider a design to be highly similar (dissimilar) if its degree of similarity—as measured by *logSimContemporary* or *logSimNearPast*—is one standard deviation above (below) the mean. We then can posit counterfactuals to assess the value of designs that exhibit various combinations of similarity with respect to the near past and to the current cohort (see Figure 3(a)). With this approach, designs that are highly similar to past designs and to contemporary designs (proto-typical) result in a net value effect of −1.2%; that is, the negative effect of being similar to contemporary designs (5.7%) more than offsets the positive effect of being similar to past designs (4.5%). At the other extreme, designs that differ under any temporal comparison (proto-atypical) lead to a net value effect of 1.2%. In this case, the costs of being different to past designs offsets *most* of the benefit due to being unique to contemporaries. The worst case is that of trended differentiation, because these designs fail to leverage the positive effect of similarity vis-à-vis past designs and still suffer from being similar to the contemporaries; here the total penalty is −10.2%. Finally, the best case is anchored differentiation, which simultaneously achieves both high informational and expressive value; such designs command a value premium of 10.2%. Overall, we find that proto-typical or proto-atypical designs are not highly valued. For the designs between the two extremes (those in the middle), we find that superior value is achieved only by those that are similar to designs of the near past *and* different from contemporaries.

We do not claim, however, that being similar to very old references would yield significant positive value. Model 4 in Table 4 provides evidence that the positive effects of similarity dissipates over time by relying on a nonparametric decomposition of our key variables. Namely, we define more fine-grained similarity variables that represent temporal distance of one, two, three, and four or more years. The regression results are consistent with those derived under model 3. Figure 3(b) plots the corresponding coefficients for *logSim* from model 5, but this graph clearly shows the importance of considering temporal distance. Within a given style, similarity with respect to designs in the far past (three years or more) have a

Table 3. Correlation Matrix (N = 54,156 observations)

	Variable	1	2	3	4	5	6	7	8	9	10
1	*logValue*	1.00									
2	*logSimContemporary*	0.08	1.00								
3	*logSimNearPast*	0.11	0.56	1.00							
4	*Visible*	−0.12	0.08	0.09	1.00						
5	*TechLifespan*	−0.14	0.06	0.04	0.43	1.00					
6	*logActivity*	0.13	0.46	0.54	0.15	0.07	1.00				
7	*logAssets*	0.56	0.10	0.11	−0.20	−0.26	0.11	1.00			
8	*logRandD*	0.26	0.01	0.02	−0.31	−0.33	−0.06	0.53	1.00		
9	*FirmAge*	0.20	0.05	0.02	−0.10	0.11	0.09	0.40	0.15	1.00	
10	*FirmFocus*	−0.17	0.02	0.00	0.11	0.13	0.06	−0.49	−0.33	−0.36	1.00
11	*logReferenceValue*	0.53	0.11	0.13	−0.11	−0.10	0.18	0.29	0.16	0.07	−0.01

Table 4. GLS Models Estimating the Effects of Similarity on *logValue* (N = 54,156 observations)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
logSimContemporary(dm)	−0.07***(0.02)		−0.09***(0.02)	−0.09***(0.02)	−0.09***(0.02)	−0.09***(0.02)
logSimNearPast(dm)		0.05***(0.01)	0.09***(0.02)		0.09***(0.02)	0.09***(0.02)
logSimPast1Yr				0.08***(0.02)		
logSimPast2Yr				0.04 (0.03)		
logSimPast3Yr				0.00 (0.02)		
logSimPast4Yr+				−0.00 (0.01)		
Visible(dm) × *logSimContemporary(dm)*					−0.13** (0.04)	−0.15**(0.05)
Visible(dm) × *logSimNearPast(dm)*						0.07 (0.05)
TechLifespan(dm) × *logSimContemporary(dm)*						0.00 (0.02)
TechLifespan(dm) × *logSimNearPast(dm)*					0.06** (0.02)	0.04* (0.02)
Control variables						
Visible(dm)			Absorbed in firm fixed effects			
TechLifespan(dm)			Absorbed in firm fixed effects			
logActivity	−0.06***(0.02)	−0.09***(0.02)	−0.08***(0.02)	−0.07***(0.02)	−0.08***(0.02)	−0.07***(0.02)
logFirmAssets	0.52***(0.06)	0.52***(0.06)	0.52***(0.06)	0.52***(0.06)	0.52***(0.06)	0.52***(0.06)
logRandD	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)
FirmAge	−0.01 (0.01)	−0.01 (0.01)	−0.01 (0.01)	−0.01 (0.01)	−0.01 (0.01)	−0.01 (0.01)
FirmFocus	0.18* (0.08)	0.18* (0.08)	0.18* (0.08)	0.18* (0.08)	0.17* (0.08)	0.17* (0.08)
logReferenceValue	0.09***(0.01)	0.09***(0.01)	0.09***(0.01)	0.09***(0.01)	0.09***(0.01)	0.09***(0.01)
Grant-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Within-R^2	0.069	0.068	0.071	0.071	0.072	0.073
F	38.2	30.1	33.5	26.0	32.8	31.5

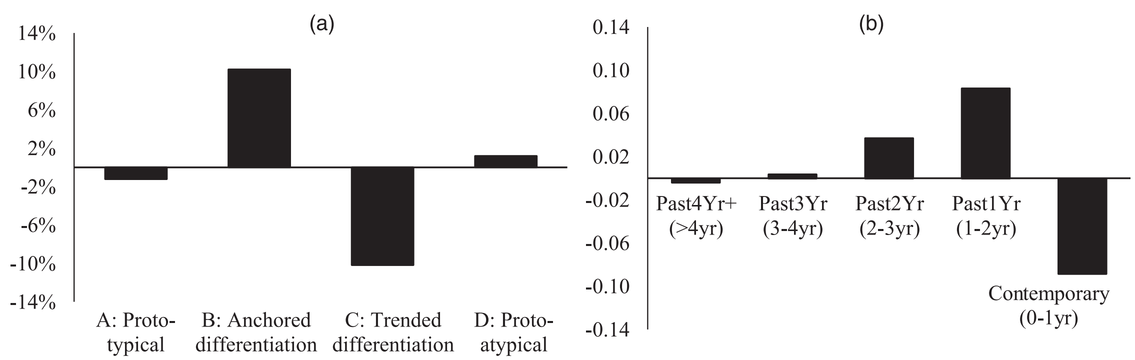
Notes. Standard errors (in parentheses) are clustered by firm. (dm) refers to demeaned.
$*p < 0.05$; $**p < 0.01$; $***p < 0.001$.

sparse effect on the focal design's value. Yet we can also see that the positive effect increases as the temporal distance is reduced (until, but excluding, contemporaries). We conclude that designs from the near past are relevant benchmarks for evaluating the focal design, which leads to similarity having a positive effect. At the same time, however, similarity with respect to contemporaries continues to have a negative effect on value.

4.1. Moderating Hypotheses

Models 5 and 6 represent models considering interactions with product visibility and technological lifespan. Model 5 is our full model with all necessary interactions included. As a test of Hypothesis 3, the model includes the interaction term *Visible(dm)* × *logSimContemporary(dm)*. Although the linear effect of *logSimContemporary(dm)* remains negative and statistically significant as before (as this is the overall mean effect), we observe that the coefficient for the interaction term is –0.13 ($p < 0.01$). This shows that visible products accentuate the expressive value of designs, meaning that an additional value premium (discount) is placed on designs that are contemporaneously different (similar) from others in the market. As a test of Hypothesis 4, the model also includes the interaction term *TechLifespan(dm)* × *logSimNearPast(dm)*.

Figure 3. A Graphical Representation of Our Regression Results



Notes. (a) Effect of different combinations of similarity and temporal distance on design value. (b) Partial effects of log similarity (with temporal distance) on log value.

We note that the linear effect of *logSimNearPast(dm)* remains positive and statistically significant. Also, the coefficient for the interaction term is 0.06 ($p <$ 0.01), which confirms that products with technological lifespans have a systematically stronger positive effect of similarity with respect to designs from the near past. This provides indirect evidence of the informational value designs afford. Stated opposite, products with short technological lifespans do not enjoy as positive of an effect of similarity as do other products. Finally, in model 6, we consider if product visibility might interact with near-past similarity, whereas technological lifespan might interact with contemporaneous similarity. We do not find statistical evidence of these further interactions while all our insights remain robust.

4.2. Robustness Checks

To assess the robustness of our results, we conducted several additional analyses. First, our main model excluded observations involving designs from newly formed styles, because their similarity with respect to past designs is undefined. Table 5, model 7, includes designs with new styles so that we can examine their value implications and see whether our key results are robust to their inclusion. To identify the value effect of designs falling into new styles, we created an indicator variable, *InNewStyle*, that is set to one for designs subsumed by a style that has existed for fewer than 365 days and to zero otherwise. Because designs in a new style by definition have no reference group in either the near or distant past, in this model we set the value of *logSimNearPast* to zero. Under this setup, *InNewStyle* captures the value effect of being part of a new style against being part of an existing style, but with *logSimNearPast* held at zero. The coefficient for *InNewStyle* in model A1 is −0.07 ($p < 0.10$), which reflects a discount of 7% for designs in new styles over those in existing styles. Thus, consistent with the literature (Zuckerman 1999, Lo and Kennedy 2015), we find that designs so novel as to define new styles suffer an additional value discount.

Second, we assessed whether a design's similarity beyond its own style boundary impacts our results. To test for this possibility, we ran a regression in model 8 incorporating the variables *logResidualSimNearPast* and *logResidualSimContemporary*, which measures the sum similarity of a design to designs that are outside of the style but are at a common temporal distance as defined by *NearPast* and *Contemporary*, respectively. The coefficients for these variables are not statistically significant, and our results are robust to controlling for their effects. This finding implies that cross-style similarity has a weaker effect on value than does within-style similarity; it also underscores the importance of considering style boundaries when assessing the effect of similarity on a design's value.

Third, we test whether our results are driven by firms building on their own past designs. To this end, we break down *logSimNearPast* into *logSimNearPast(OwnFirm)*, which reflects the degree to which a new design is similar to past designs of the firm, and

Table 5. Robustness to Full Sample, Cross-Style Similarity, and Separate Controls of Ecological Effects

Variables	Model 7 Full sample	Model 8 Residual similarity	Model 9 Own firm similarity
logSimContemporary(dm)	−0.09***(0.02)	−0.09***(0.02)	−0.09***(0.02)
logSimNearPast(dm)	0.09***(0.02)	0.09***(0.02)	
logSimNearPast(OwnFirm)			0.05* (0.02)
logSimNearPast(OtherFirm)			0.08** (0.03)
InNewStyle	−0.07+ (0.04)		
logResidualSimContemporary		−0.06 (0.04)	
logResidualSimNearPast		0.05 (0.03)	
Control variables			
logActivity	−0.08***(0.02)	−0.08***(0.02)	−0.07***(0.02)
logFirmAssets	0.53***(0.07)	0.52***(0.06)	0.52***(0.06)
logRandD	−0.00 (0.01)	−0.00 (0.00)	−0.00 (0.00)
FirmAge	−0.01 (0.01)	−0.01 (0.01)	−0.01 (0.01)
FirmFocus	0.16* (0.07)	0.17* (0.08)	0.18* (0.08)
logReferenceValue	0.09***(0.01)	0.09***(0.01)	0.09***(0.01)
Grant-year fixed effects	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Within-R^2	0.075	0.071	0.071
F	30.0	28.6	29.8
N	57,113	54,156	54,156

Note. Standard errors (in parentheses) are clustered by firm.
$^{+}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

logSimNearPast(OtherFirm), which reflects the degree to which a new design is similar to the past designs of other firms. Model 9 in Table 5 reports the result of an analysis in which we replaced *logSimNearPast* by these two variables. Here, we see that *logSimNearPast(OwnFirm)* indeed carries a positive effect on the value of a new design (at 0.05; $p < 0.05$). However, we note that so does *logSimNearPast(OtherFirm)* (at 0.08; $p < 0.01$). Hence, both the focal firm and other firm's past designs contribute to the positive effects of similarity. Thus, the results are consistent with the notion that the market perceives similarity more broadly to derive informational value, as opposed to making interpretations regarding a firm's brand or capabilities.

In addition, we share further robustness checks in the appendix, where we included designer fixed effects, replaced the dependent variables with abnormal returns using the Fama–French–Carhart four-factor model (Xia et al. 2016) and used alternative cutoff points (ranging from 6 to 14 months) that defines the split between contemporary and near past (see Online Appendix D). We also used continuous time models that defines a fuzzier split between the two periods (see Online Appendix E).

5. Experimental Study: Expressive and Informational Value

In the field study, we provided clear empirical evidence of our theory of anchored differentiation by focusing on the design's overall value as an outcome variable. Yet, our conclusions rather rest on the assumptions that design similarities on value is exogenous conditional on the covariates, and that individual consumers perceive informational and expressive values as a function of product design similarity and temporal distance. Thus, we conducted an experimental study—where we asked individual consumer subjects about their perceptions of each informational and expressive value separately—to examine directly the underlying mechanism behind our theoretical model presented in Figure 1.[8]

To this end, we designed a 2 × 2 between-subject experiment with four experimental conditions whereby consumer subjects were asked to evaluate a focal design against a set of reference designs. Subjects were assigned randomly to conditions whereby the reference designs were either similar or dissimilar to the focal design (similarity condition) and were either listed as contemporary or past (temporal distance condition). To better build causal inference, the focal product design that is evaluated by consumer subjects remained the same across experimental conditions.

Based on our theoretical model in Figure 1, we expect that consumers will gain greater expressive value when a new design appears dissimilar to the reference designs. More importantly, our theory suggests that the positive effects of dissimilarity on expressive value depends on temporal distance, such that the positive effects become smaller as temporal distance increases. Hence, we predict that the positive effect of dissimilarity will be stronger in the contemporary condition than in the past condition. By contrast, consumers gain greater informational value when a new design appears similar to the reference designs. The amount of informational value gained may depend on temporal distance as well. Because we argue that consumers would continue to glean useful informational value based on similarities to past designs, informational value is not expected to dissipate as quickly—and may even increase—with temporal distance.

5.1. Respondents and Recruitment

We recruited 400 people online via the Prolific platform, where researchers can hire large, diverse, and highly qualified consumer subject pools (Peer et al. 2017). Potential subjects were limited to those between 20 and 75 years of age and were recruited through an advertisement indicating a job "[t]o express your preferences for different kinds of lawnmower product designs." Respondents were given further instructions to evaluate the new garden tool as potential consumers. Respondents were told that the task would take approximately nine minutes and that they would be compensated $1.60 after the task's completion.

To ensure that subjects paid close attention to the prompts and vignettes used throughout the study, we followed previous studies using online respondents (Mason and Suri 2012, Hahl 2016, Younkin and Kashkooli 2020) to include screening tools throughout the experiments. Specifically, we excluded subjects who (1) did not pass any of the attention or manipulation checks or (2) stayed for less than four minutes. The final sample thus included 340 respondents. Respondents' average age was 28.77 (SD = 9.72); 41.5% of the respondents were female; and 54.4% had previous experience buying garden tools. The demographics of those who failed the screening tests and were thus excluded from the analysis were not statistically different from those who passed all the screening tests.

5.2. Procedure and Manipulation

The experimental study used a 2 × 2 between-subject design with random assignment. Specifically, we manipulated the reference design's similarity to the focal design (i.e., similar versus dissimilar). We also manipulated the reference designs' temporal distance to the focal design (i.e., past versus contemporary).

We picked the lawnmower as the product design in our manipulation for two reasons. First, lawnmowers are among products that are design patented (there are 84 lawnmower designs in our design patent data).

Second, lawnmowers are neither highly visible nor unique in their technological life span.[9] In our experiment, we had five lawnmower designs: one focal and four reference designs, which were further broken down to two similar (denoted designs A and B) and two dissimilar designs (denoted designs C and D) that would be compared with the focal design. All five lawnmowers had similar quality reviews and were also moderately priced ($280–$390). To ensure successful manipulation of similarity, we separately sourced 196 consumer respondents from Prolific who would evaluate the similarity of the four reference designs to the focal design. Respondents assessed design similarity by answering "How much do you agree that the product design A is similar to the focal design" with a seven-point scale (1 = *strongly disagree*; 7 = *strongly agree*) such that higher scores represented greater perceived similarity between the focal and the reference design. Indicating successful manipulation, similarity score between the focal design and design A (mean = 5.13, SD = 1.42) is higher than similarity scores between the focal design and design C (mean = 1.69, SD = 0.98, $t(196) = 28.2$, $p = 0.000$) and design D (mean = 1.92, SD = 1.16, $t(196) = 24.5$, $p = 0.000$). Similarity score between the focal design and design B (mean = 5.42, SD = 1.24) is also higher than similarity scores between the focal design and design C ($t(196) = 31.4$, $p = 0.000$) and design D ($t(196) = 28.2$, $p = 0.000$).

Subjects were told they would see a series of lawnmowers (two reference product designs and the focal design) that were being introduced in the gardening magazine *English Garden*. As potential consumers, they were told they would evaluate a new product named "Swift RM18 Lawnmower," the focal product used in our experiment. We manipulated the reference designs' introductory date, such that respondents were randomly assigned to either past or contemporary conditions. Respondents in the past condition received a gardening magazine cover published in Spring 2018 with the following instruction:

> *"The English Garden" is a monthly magazine that covers the latest garden designs and introduces a wide range of gardening products and gardening projects, and landscape design specialists gardening designers, all while advertising gardening tools. Your task is to read part of the Spring 2018 issue from two years ago and part of the most recent Spring 2020 issue. As a potential consumer, you'll review gardening tools (lawn mowers) that were advertised either two years ago (Spring 2018) or more recently (Spring 2020), respectively. Please first read the cover page of the 2-year-old Spring 2018 issue.*

Meanwhile, respondents in the contemporary condition received the following description about their project with a magazine cover published in Spring 2020:

> *"The English Garden" is a monthly magazine that covers the latest garden designs and introduces a wide range of gardening products and gardening projects, and landscape design specialists gardening designers, all while advertising gardening tools. Your task is to read part of the Spring 2020 issue and, as a potential consumer, review the gardening products (lawn mowers) that are advertised in the magazine. Please first take a look at the cover page of the Spring 2020 issue.*

Next, we manipulated the similarity of the reference designs (relative to the focal design). After receiving their issue of *English Garden*, respondents in the similar condition saw two lawn mowers (designs A and B) similar in design to the focal design, which would be introduced later. Respondents in the dissimilar condition saw two lawn mowers (designs C and D) dissimilar in design to the focal design, which again would be introduced later. Each design was issued with a clear image, as well as a brief description of each product, including dimensions, key materials, package contents, and product names. We did not specify the producers for each product given producers frequently provide clues regarding products' reputation and quality, which can influence respondents' perception of informational or expressive values. Table 6 presents a summary of the different conditions in the experimental design.

After having a set of two reference designs (i.e., similarity/dissimilarity manipulation), all respondents were given a copy of *English Garden* whose cover page was dated Spring 2020. Respondents were then asked to review the focal design, the Swift RM18. Respondents were asked about the information and expressive values. They were also asked a series of questions, including manipulation checks (years of introduction of each product in the experiment), an attention check, and basic demographic questions, which included gender, age, and garden tool purchase experiences.

5.3. Dependent Variable

Respondents reported on their evaluation of expressive value and informational value for the Swift RM18 by answering how much they agree that "the Swift RM18 is unique" (expressive value) and "the functionality and affordance (i.e., the quality or property of products that defines their possible uses) of the Swift RM18 are easily understood" (informational value). Responses were assessed using a seven-point scale (1 = *strongly disagree*; 7 = *strongly agree*), such that higher scores represented a greater perceived value of the focal product.

6. Results of the Experimental Study

We submitted each of the expressive and informational value scores to a 2 (reference product similarity: similar versus dissimilar) × 2 (reference product time:

Table 6. Summary of Experimental Design and Respondent Characteristics by Condition

	Condition 1. Past similar	Condition 2. Past dissimilar	Condition 3. Contemporary similar	Condition 4. Contemporary dissimilar
Manipulation: A focal product "Swift RM18" that was introduced in the present-day issue (2020) is compared with two other…	…similar products (Designs A and B) that were introduced in the past issue (2018)	…dissimilar products (Designs C and D) that were introduced in the past issue (2018)	…similar products (Designs A and B) that were introduced in the same issue (2020)	…dissimilar products (Designs C and D) that were introduced in the same issue (2020)
Age, years	27.6	29.0	28.7	28.8
Female %	59	54	51	64
Garden tool purchase experience %	43	57	45	53
European nationality %	90	80	89	89
Number of respondents	70	82	84	104

past versus contemporary) analysis of variance (ANOVA).[10]

First, we were interested in the effect of similarity between reference products and the focal product on each of the expressive and informational values. As predicted, we find a significant and negative effect on expressive value when the reference set is similar to the focal product. The expressive value was greater for respondents in the dissimilar condition (n = 186, mean = 5.80, SD = 1.24) than for respondents in the similar condition (n = 154, mean = 5.21, SD = 1.75; F = 5.45, p = 0.001). Conversely, informational value was greater for respondents in the similar condition (n = 154, mean = 5.64, SD = 1.44) than for respondents in the dissimilar condition (n = 186, mean = 5.30, SD = 1.20; F = 5.07, p = 0.025).

We then tested whether the temporal distance with the referenced design (past versus contemporary) moderated the effect of similarity when perceiving expressive values. Our test revealed a significant interaction between similarity and temporal distance in predicting perceived expressive value (F = 5.26, p = 0.022). To further examine the nature of this interaction, we compared the difference in scores of expressive values within each of the contemporary versus the past condition. Within the contemporary condition, the expressive value in the dissimilar condition (mean = 5.80, SD = 1.17) was greater than the score in the similar condition (mean = 4.88, SD = 1.38; F = 18.0, p = 0.000). By contrast, in the past condition, the expressive value for the dissimilar condition was not significantly different from the score in the similar condition (p = 0.463). Together, we confirm that the effect of similarity on the expressive value mainly exists when the product is compared with other contemporary designs.

Finally, we conducted the same moderation test but when perceiving informational values. Our test revealed a significant interaction between similarity and temporal distance in predicting informational value (F = 4.67, p = 0.031). Then, we compared the difference in scores of informational values within each of the contemporary versus the past conditions. In the contemporary condition, the informational value for the similar condition was not significantly different from the informational value for the dissimilar condition (p = 0.947). However, in the past condition, the informational value score in the similar condition (mean = 5.90, SD = 1.79) was greater than the score in the dissimilar condition (mean = 5.27, SD = 1.17; F = 8.82, p = 0.003). Together, we confirm that the effect of similarity on the informational value mainly exists when the product is compared with other past products (see Table 7 for a summary of results).

Based on the findings reported in Table 7, we further plot the net effect of similarity on informational value in Figure 4(a). We also plot the net effect of dissimilarity on expressive value (by removing the negative signs of the effects shared in Table 7). These results support our theoretical model—dissimilarity with contemporary designs enhances the value of a new design through higher expressive value, whereas similarity with past designs enhances the value of a new design through higher informational value.

Although we depict informational value arising from similarities would decay with temporal distance (Figure 1(a)), our experimental results indicate that design similarities can have a stronger effect when reference designs are from the past, rather than contemporary. Such a finding is consistent to—and even reinforces—the notion that the temporal distance of reference sets is an important dimension to consider.

Finally, if we take an overall value of design as the sum of expressive and information values (equivalently, plotting the gap between the similarity effect from the informational curve and the dissimilarity effect from the expressive curve), we would see the pattern shown in Figure 4(b), which is consistently observed in our field study—the effects of similarity

Table 7. Effect of Similarity Within Each Temporal Distance Conditions

	Dependent variable: *Expressive Value*		Dependent variable: *Informational Value*	
	Past	Contemporary	Past	Contemporary
Similar	mean = 5.63, SD = 2.04	mean = 4.88 SD = 1.38	mean = 5.90 SD = 1.79	mean = 5.42 SD = 1.03
Dissimilar	mean = 5.80, SD = 1.34	mean = 5.80 SD = 1.17	mean = 5.27 SD = 1.17	mean = 5.40 SD = 1.22
Net effect of similarity[a]	−0.18 (0.24)	−0.92***(0.22)	0.63** (0.21)	0.01 (0.19)

Note. SD, standard deviation.
[a]Net effect of similarity = mean of the similarity condition – mean in dissimilarity condition. Numbers in parentheses are the standard errors of the estimate of the net effect.
***p < 0.001 and **p < 0.01: Mean difference is significant (based on the F test).

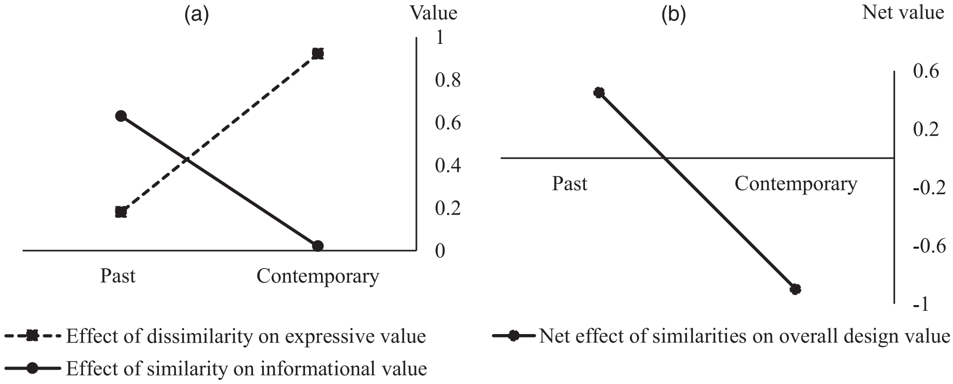
on design value starts out negative when comparing against contemporary designs, but becomes more positive as temporal distance increases, such that both contemporary differentiation and past similarity increases design value.

7. Discussion

Our findings from both the field study and the experimental study confirm that design similarity can serve as an important means by which people judge and evaluate the value of new designs. Construing the value of a design as a composite of the expressive value and the informational value the design conveys, we develop a theory that incorporates the idea that these two sources of value are weighted differentially based on the temporal distance between the new designs and their comparisons. This leads to our hypothesis of anchored differentiation. We argue that, on one hand, consumers would weigh expressive value more relative to informational value when comparing a new design against its contemporaneous peers. On the other hand, consumers would weigh informational value more relative to expressive value when comparing a new design against designs from the past. We find strong empirical evidence supporting our theory—designs benefit from increased valuation from both contemporaneous differentiation (appearing different with respect to contemporaries), as well as past anchoring (appearing similar with respect to past designs). Further supporting our theory, we find that designs of highly visible products benefit even more from contemporaneous differentiation, whereas designs of products with long technological lifespans benefit even more from past anchoring.

Our approach advances the emerging literature examining optimal distinctiveness. Consistent with the optimal differentiation hypothesis, we find that the extremes—designs that are proto-typical or proto-atypical—yield low value. We broaden the optimal distinctiveness hypothesis, however, as we uncover temporal distance as an important dimension of reference sets. This leads to two ways in which middle ground can be accomplished. On one hand, new designs can mix common elements from the past while trying to differentiate from contemporaries, a phenomenon we term anchored differentiation. On the other hand, new designs can deviate from past designs while adopting common elements of other contemporary designs, which we term trended differentiation. Our theory and supporting evidence show that the case of anchored differentiation yields the highest value, whereas the case of trended differentiation yields the lowest value. By extending optimal distinctiveness with a dynamic perspective, our

Figure 4. The Effect of Dissimilarities / Similarities with Increasing Temporal Distance



Notes. (a) Effect of dissimilarity on expressive value, and the effect of similarity on informational value. (b) Effect of design similarities on overall design value.

work joins a recent call to advance the literature on optimal distinctiveness in the context of a dynamic environment (Zhao et al. 2018) and provides a finer-grained understanding on how optimal distinctiveness can be accomplished by designs leveraging familiar themes yet differentiating from contemporary competition.

Our work also adds to, yet departs from, the prior literature on strategic balance by explicitly engaging with audiences' evaluations rather than pressure from appearing legitimate while avoiding competition (Deephouse 1999). Our work highlights that, in the context of product designs, consumer audiences evaluate based on the dual criteria of expressive and information value. More importantly, these value criteria yield different evaluative outcomes when the reference set comes from either contemporary comparisons or near past comparisons.

Our work also has implications for the design innovation literature. We show that past designs offer a valuable anchor on which designers should base their new works. An important nuance is that designers should also maintain a strong awareness of what competitors are currently doing and innovate in distinct ways. Otherwise, the risk is designers will generate proto-typical designs that do not enhance value. In fact, such an approach may even destroy value, especially if designers slavishly follow new trends without individual innovations. In short, designers must be vigilant in search of high-value designs—success depends on staying deviant to competitors' choices while keeping near-past anchors. Additionally, our work suggests that designers working on products that are highly visible (which feature higher expressive value) or with short technological lifespans (which feature more rapid decay of informational value) should focus even more on differentiation. The heightened value pressures on differentiating in these kinds of products is consistent with anecdotal and empirical evidence of greater variety and more rapid churn of designs in both the fashion and high-tech industries (Godart 2012, Chan et al. 2018).

Although our primary objective is to uncover how similarities and differences determine the value of new designs, our theoretical framework can be adapted easily to examine an array of contexts, such as new products, ventures, or organizations. For example, new business ideas may benefit from keeping key components of existing businesses while differentiating themselves from competing contemporaries. Nevertheless, the extent to which our anchored differentiation hypothesis is appropriate depends on the extent to which informational value and expressive value show opposing forces. For example, in a pure form of abstract art, where informational value is limited, we expect that expressive value could dominate over all temporal distances.[3]

Acknowledgments

The authors benefited greatly from the constructive comments from senior editor Gino Cattani and two anonymous reviewers. The authors also thank David Clough, Özgecan Koçak, Jürgen Mihm, Celia Moore, Giacomo Negro, Nelson Phillips, Michelle Rogan, and Anand Swaminathan who provided valuable suggestions. The authors appreciate the feedback from seminar participants at the National University of Singapore and the Global Entrepreneurship and Innovation Research Conference co-hosted by the University of Virginia Darden School of Business, the University of Cambridge Judge Business School, and the University of Hong Kong's Faculty of Business and Economics. Remaining errors are our own.

Endnotes

[1] See http://www.bbc.com/future/story/20171023-the-useless-design-features-in-modern-products.

[2] A style is a cluster consisting of visually similar designs (Zhao et al. 2018). Style data (from Chan et al. 2018) is available at www.stylesinproductdesign.com. A pseudocode to obtain styles given similarity between designs is attached in Online Appendix C.

[3] Experimental validation conducted by Chan et al. (2018) established the usability of the similarity/style information (DiMaggio et al. 2013, Cattani et al. 2017). Specifically, the algorithm-generated styles are similar to what humans would do—that is, styles correlate with how humans would categorize designs based on visual similarity, and they do not appear different from human-generated categories in the eyes of an independent evaluator. The styles are also coherent in the sense that most human observers would concur that the designs therein are sufficiently similar to form a valid style.

[4] We use *sum* similarity (and, in the regression, we control for the *log* of the number of designs in the list of reference) to account for the effect by which an increasing number of designs mechanically result in increased sums. All our results are robust to the alternative of defining via *average* similarity. Also, in the regression, we reduce the effect of outliers by including the log form of these variables (more precisely, log + 1 to preclude dividing by zero). All logged variables are marked hereafter with a *log* prefix.

[5] The question from their survey reads: "Imagine that you meet a new person who lives in a household similar to yours. Imagine that their household is not different from other similar households, except that they like to, and do, spend more than average on [jewelry and watches]. Would you notice this about them, and if so, for how long would you have to have known them, to notice it?" with "[jewelry and watches]" replaced each time with other products or services.

[6] SIC codes of visible products include jewelry and silverware (SIC 391), apparel (230), shoes (302 / 310), eyeglasses (385), watches and clocks (387), automobiles (371, 375), furniture (250), household audiovisual (365), and games and toys (394). We label all other industries as producing less visible goods—they include a variety of industrial/consumer products (e.g., chemicals, 280; medical products, 283; electrical equipment, 360; tires, 301).

[7] Specifically, we developed the measure by taking all the citation lags of all technology patents that were granted during the period 1976–1990, where the *citing* patent was granted between 1976 and 2006. An average of those lags is then taken at the (three-digit) SIC level. The data are at https://www.aeaweb.org/aer/data/10407/20120668_data.zip. For about 20% of designs, which the authors lumped into "other industries," we follow the same approach to generate finer-grained measures.

[8] The experiment is preregistered at https://aspredicted.org/.

[9] Lawnmower designs are mostly patented by industries categorized as nonvisible (80%) and their average technological life span is about 9.7 years. Both numbers are close to the overall average in our design patent data.

[10] The gender, age, and experience of gardening tool purchase of respondents did not differ across the two experimental conditions, indicating that the randomization was effective. Including or excluding these controls did not change the results; as such, we report the results from the analyses without such a control variable.

References

Alba JW, Hutchinson JW (1987) Dimensions of consumer expertise. *J. Consumer Res.* 13(4):411.

Anderson MC, Bjork RA, Bjork EL (1994) Remembering can cause forgetting: Retrieval dynamics in long-term memory. *J. Experiment. Psych. Learning Memory Cognition* 20(5):1063–1087.

Anthony C, Nelson AJ, Tripsas M (2016) "Who are you? . . . I really wanna know": Product meaning and competitive positioning in the nascent synthesizer industry. *Strategy Sci.* 1(3):161–183.

Askin N, Mauskapf M (2017) What makes popular culture popular? Product features and optimal differentiation in music. *Amer. Sociol. Rev.* 82(5):910–944.

Barlow MA, Verhaal JC, Angus RW (2019) Optimal distinctiveness, strategic categorization, and product market entry on the Google Play app platform. *Strategic Management J.* 40(8):1219–1242.

Bellezza S, Gino F, Keinan A (2014) The red sneakers effect: Inferring status and competence from signals of nonconformity. *J. Consumer Res.* 41(1):35–54.

Berg JM (2016) Balancing on the creative highwire: Forecasting the success of novel ideas in organizations. *Admin. Sci. Quart.* 61(3): 433–468.

Bessen J (2008) The value of U.S. patents by owner and patent characteristics. *Res. Policy* 37(5):932–945.

Bilir LK (2014) Patent laws, product life-cycle lengths, and multinational activity. *Amer. Econom. Rev.* 104(7):1979–2013.

Bloch P (1995) Seeking the ideal form: Product design and consumer response. *J. Marketing* 59(3):16–29.

Brown S, Eisenhardt K (1997) The art of continuous change: Linking complexity theory and time-paced evolution in relentlessly shifting organizations. *Admin. Sci. Quart.* 42(1):1–34.

Cattani G, Ferriani S, Allison PD (2014) Insiders, outsiders, and the struggle for consecration in cultural fields: A core-periphery perspective. *Amer. Sociol. Rev.* 79(2):258–281.

Cattani G, Porac JF, Thomas H (2017) Categories and competition. *Strategic Management J.* 38:64–92.

Chan C, Berger J, Van Boven L (2012) Identifiable but not identical: Combining social identity and uniqueness motives in choice. *J. Consumer Res.* 39(3):561–573.

Chan TH, Mihm J, Sosa ME (2018) On styles in product design: An analysis of US design patents. *Management Sci.* 64(3):1230–1249.

Deephouse DL (1999) To be different, or to be the same? It's a question (and theory) of strategic balance. *Strategic Management J.* 20(2):147–166.

DiMaggio P, Nag M, Blei D (2013) Exploiting affinities between topic modeling and the sociological perspective on culture: Application to newspaper coverage of U.S. government arts funding. *Poetics* 41(6):570–606.

Eisenhardt K, Tabrizi B (1995) Accelerating adaptive processes: Product innovation in the global computer industry. *Admin. Sci. Quart.* 40(1):84–110.

Eisenman M (2013) Understanding aesthetic innovation in the context of technological evolution. *Acad. Management Rev.* 38(3):332–351.

Ertug G, Yogev T, Lee Y, Hedström P (2016) The art of representation: How audience-specific reputations affect success in the contemporary art field. *Acad. Management J.* 59(1):113–134.

Gibson JJ (1979) *The Ecological Approach to Visual Perception* (Houghton Mifflin, Boston, MA).

Godart F (2012) *Unveiling Fashion: Business Culture, and Identity in the Most Glamorous Industry* (Palgrave Macmillan, London).

Haans R (2019) What's the value of being different when everyone is? The effects of distinctiveness on performance in homogeneous vs. heterogeneous categories. *Strategic Management J.* (40):3–27.

Hahl O (2016) Turning back the clock in baseball: The increased prominence of extrinsic rewards and demand for authenticity. *Organ. Sci.* 27(4):929–953.

Hall BH, Jaffe AB, Trajtenberg M (2005) Market value and patent citations. *RAND J. Econom.* 36(1):16–38.

Hargadon AB, Douglas Y (2001) When innovations meet institutions: Edison and the design of the electric light. *Admin. Sci. Quart.* 46(3):476–501.

Hebdige D (1979) *Subculture: The Meaning of Style* (Routledge, London).

Heffetz O (2011) A test of conspicuous consumption: Visibility and income elasticities. *Rev. Econom. Statist.* XCIII(4):1101–1117.

Hemphill CS, Suk J (2009) The law, culture, and economics of fashion. *Stanford Law Rev.* 61(5):1147–1199.

Hoegg J, Alba JW (2011) Seeing is believing (too much): The influence of product form on perceptions of functional performance. *J. Production Innovation Management* 28(3):346–359.

Hsu G (2006) Jacks of all trades and masters of none: Audiences' reactions to spanning genres in feature film production. *Admin. Sci. Quart.* 51(3):420–450.

Irmak C, Vallen B, Sen S (2010) You like what I like, but I don't like what you like: Uniqueness motivations in product preferences. *J. Consumer Res.* 37(3):443–455.

Jensen M, Kim H, Kim BK, Barnett ML, Pollock TG, eds. (2012) *Meeting Expectations: A Role-Theoretic Perspective on Reputation* (Oxford Handbook of Corporate Reputation, Oxford, UK), 141–159.

Kogan L, Papanikolaou D, Seru A, Stoffman N (2017) Technological innovation, resource allocation, and growth. *Quart. J. Econom.* 132(2):665–712.

Krippendorff K, Butter R (2007) Semantics: Meanings and contexts of artifacts. Schifferstein HNJ, Hekkert P, eds. *Production Exp.* (Elsevier, New York), 353–376.

Krishnan V, Ulrich K (2001) Product development decisions: A review of the literature. *Management Sci.* 47(1):1–21.

Landwehr JR, Labroo AA, Herrmann A (2011) Gut liking for the ordinary: Incorporating design fluency improves automobile sales forecasts. *Marketing Sci.* 30(3):416–429.

Landwehr JR, Wentzel D, Herrmann A (2013) Product design for the long run: Consumer responses to typical and atypicai designs at different stages of exposure. *J. Marketing* 77(5):92–107.

Liu Y, Li KJ, Chen HA, Balachander S (2017) The effects of products' aesthetic design on demand and marketing-mix effectiveness: The role of segment prototypicality and brand consistency. *J. Marketing* 81(1):83–102.

Lo JYC, Kennedy MT (2015) Approval in nanotechnology patents: Micro and macro factors that affect reactions to category blending. *Organ. Sci.* 26(1):119–139.

Lynn M, Harris J (1997) The desire for unique consumer products: A new individual differences scale. *Psych. Marketing* 14(6):601–616.

Maeda J (2015) Have designers killed the engineering star? Interview by Emily Chang. *Bloomsburg Business*, retrieved June 7, 2015, http://www.bloomberg.com/news/videos/2015-05-19/the-growing-importance-of-designers-in-silicon-valley.

Mason W, Suri S (2012) Conducting behavioral research on Amazon's Mechanical Turk. *Behav. Res. Methods* 44(1):1–23.

Mendelson H, Pillai RR (1999) Industry clockspeed: Measurement and operational implications. *Manufacturing Service Oper. Management* 1(1):1–20.

Micheli P, Gemser G (2016) Signaling strategies for innovative design: A study on design tradition and expert attention. *J. Production Innovation Management* 33(5):613–627.

Molotch H (2003) *Where Stuff Comes From: How Toasters, Toilets, Cars, Computers and Many Other Things Come to Be as They Are* (Routledge, New York).

Negro G, Leung MD (2013) "Actual" and perceptual effects of category spanning. *Organ. Sci.* 24(3):684–696.

Paolella L, Durand R (2016) Category spanning, evaluation, and performance: Revised theory and test on the corporate law market. *Acad. Management J.* 59(1):330–351.

Peer E, Brandimarte L, Samat S, Acquisti A (2017) Beyond the Turk: Alternative platforms for crowdsourcing behavioral research. *J. Experiment. Soc. Psych.* 70:153–163.

Pesendorfer W (1995) Design innovation and fashion cycles. *Amer. Econom. Rev.* 85(4):771–792.

Pontikes EG (2012) Two sides of the same coin: how ambiguous classification affects multiple audiences' evaluations. *Admin. Sci. Quart.* 57(1):81–118.

Rindova VP, Petkova AP (2007) When is a new thing a good thing? Technological change, product form design, and perceptions of value for product innovations. *Organ. Sci.* 18(2):217–232.

Rosch E (1978) Principles of categorization. Rosch E, Lloyd BB, eds. *Cogn. Categ.* (Lawrence Erlbaum Associates, Hilsdale, NJ), 27–48.

Stinchcombe AL (1965) Social structure and organizations. March JG, ed. *Handbook of Organization* (Routledge, New York), 142–193.

Sullivan LH (1896) The tall office building artistically considered. *Lippincott's Mag.* 57(3):406.

The Economist (2012) Apple v Samsung: iPhone, uCopy, iSue. *The Economist* (September 1), https://www.economist.com/leaders/2012/09/01/iphone-ucopy-isue.

Tian KT, Bearden WO, Hunter GL (2001) Consumers' need for uniqueness: Scale development and validation. *J. Consumer Res.* 28(1):50–66.

Tucker C, Zhang J (2011) How does popularity information affect choices? A field experiment. *Management Sci.* 57(5):828–842.

Ulrich K (2011a) *Design: Creation of Artifacts in Society* (University of Pennsylvania, Philadelphia).

Ulrich K (2011b) Design is everything? *J. Production Innovation Management* 28(3):394–398.

USPTO (2006) *Design Patents (Chapter 1500). Man. Pat. Examining Proced* (U.S. Patent and Trademark Office, Alexandria, VA), 1501–1562.

Vanhemert K (2015) Consulting giant McKinsey buys itself a top design firm. *WIRED.com*, Retrieved June 17, 2019, https://www.wired.com/2015/05/consulting-giant-mckinsey-bought-top-design-firm/.

Veryzer RW, Hutchinson JW (1998) The influence of unity and prototypicality. *J. Consumer Res.* 24(4):374–385.

Xia Y, Singhal VR, Zhang GP (2016) Product design awards and the market value of the firm. *Production Oper. Management* 25(6): 1038–1055.

Younkin P, Kashkooli K (2020) Stay true to your roots? Category distance, hierarchy, and the performance of new entrants in the music industry. *Organ. Sci.* 31(3):604–627.

Zhao EY, Fisher G, Lounsbury M, Miller D (2017) Optimal distinctiveness: Broadening the interface between institutional theory and strategic management. *Strategic Management J.* 38: 93–113.

Zhao EY, Ishihara M, Jennings PD, Lounsbury M (2018) Optimal distinctiveness in the console video game industry: An exemplar-based model of proto-category evolution. *Organ. Sci.* 29(4): 558–611.

Zuckerman EW (1999) The categorical imperative: Securities analysts and the illegitimacy discount. *Amer. J. Sociol.* 104(5): 1398–1438.

Zuckerman EW (2016) Optimal distinctiveness revisited: An integrative framework for understanding the balance between differentiation and conformity in individual and organizational identities. Pratt MG, et al. eds. *Oxford Handb. Organ. identity* (Oxford University Press, Oxford, UK), 183–199.

Tian Chan is an assistant professor in information systems and operations management at Goizueta Business School, Emory University. He received his PhD from INSEAD. His research focuses on innovation management, innovation teams, and intellectual property, with emphasis on new product and service development.

Yonghoon G. Lee is an assistant professor in the Department of Management at Hong Kong University of Science and Technology. He received his PhD from INSEAD. His research focuses on network, social status, and social evaluation with particular emphasis on the careers of creative professionals.

HeeJung Jung is an assistant professor in the Department of Management and Entrepreneurship at Imperial College London. She received her PhD from INSEAD. Her research focuses on nonregulatory drivers that affect diversity and equality in organizations with an emphasis on entrepreneurial, top echelon, and innovative teams.