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RESEARCH ARTICLE

What's the value of being different when everyone is? The effects of distinctiveness on performance in homogeneous versus heterogeneous categories

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***Research Summary*:** Is moderate distinctiveness optimal for performance? Answers to this question have been mixed, with both inverted U and U-shaped relationships being argued for and found in the literature. I show how nearly identical mechanisms driving the distinctiveness-performance relationship can yield both U-shaped and inverted U-shaped effects due to differences in relative strength, rather than their countervailing nature. Incorporating distinctiveness heterogeneity, I theorize a U-shaped effect in homogeneous categories that flattens into an inverted U in heterogeneous categories. Results combining a topic model of 69,188 organizational websites with survey data from 2,279 participants in the Dutch creative industries show a U-shaped effect in homogeneous categories, flattening and then disappearing in more heterogeneous categories. How distinctiveness affects performance thus depends entirely on how distinct others are.

***Managerial Summary*:** A core strategy recommendation is to be different from competitors. Recent work highlights the notion of optimal distinctiveness—being different enough to escape competition yet similar enough to be legitimate, thus yielding the highest performance. This article challenges the notion that one "optimal" level of distinctiveness exists and focuses on distinctiveness heterogeneity (representing variation in firm positions in a category) as a key contextual factor. Results from a sample of firms in the Dutch creative industries show that either being entirely different or entirely the same to competitors pays off when one's category is very homogeneous. However, being different loses its performance effects entirely when heterogeneity in firm positions is higher. Being different from competitors, therefore, no longer pays when others tend to be different, too.

KEYWORDS

categories, creative industries, heterogeneity, optimal distinctiveness, topic modeling

1 | INTRODUCTION

Scholars working at the intersection of strategic management and organization theory have long been interested in why firms differ and how these differences affect performance (Carroll, 1993; Deephouse, 1999; Zhao, Fisher, Lounsbury, & Miller, 2017; Zuckerman, 2016). A key idea in this stream of work is the existence of two countervailing forces, with isomorphic pressures pulling firms toward conformity by legitimizing a limited range of behavior (Deephouse, 1996; DiMaggio & Powell, 1983; Meyer & Rowan, 1977; Zuckerman, 1999) and with competitive pressures pushing firms to be different in the pursuit of competitive advantage (Baum & Mezias, 1992; Carroll, 1993; McNamara, Deephouse, & Luce, 2003)—leading to the recommendation that firms strategically balance these pressures by adopting moderately distinct positions to attain "optimal" distinctiveness (Deephouse, 1999; Navis & Glynn, 2011; Zhao et al., 2017).

Although some have found that moderate distinctiveness yields the highest performance (that is, an inverted U-shape: Deephouse, 1999; McNamara et al., 2003), others have found such distinctiveness to lead to the *worst* performance (i.e., a U-shape: Cennamo & Santalo, 2013; Jennings, Jennings, & Greenwood, 2009; Miller, Amore, Le Breton-Miller, Minichilli, & Quarato, 2018; Zott & Amit, 2007). These contradictory results challenge our understanding of distinctiveness and its implications for practice. Should firms aim for moderate distinctiveness or not? This article shows how both a U-shaped and an inverted U-shaped relationship can emerge from similar mechanisms, as the existence of countervailing forces is not a sufficient condition for either effect to emerge. Instead, what level of distinctiveness strikes the optimal balance between pressures to be similar or different depends crucially on what others in the firm's category do.

Recent work has called for a more comprehensive theory of optimal distinctiveness (Zhao et al., 2017). Addressing this call, I examine the effects of one salient contextual factor: distinctiveness heterogeneity. In heterogeneous categories, where many firms adopt distinctive positions, the distinctiveness of a focal firm has fundamentally different effects compared to homogeneous categories where being different is rare. My central prediction is that the performance effect of distinctiveness flattens and flips from a U-shape in homogeneous categories to an inverted U-shape in heterogeneous categories. To test my theory, I apply topic modeling (a methodology to discover the latent structure of large collections of texts) to over 69,000 organizational websites in the Dutch creative industries. Results show a strong U-shaped effect of distinctiveness on performance in homogeneous categories that flattens out in more average categories. However, contrary to expectations, distinctiveness has no effect in heterogeneous categories: being different no longer affects performance once many others are different, as well.

These results provide three key contributions to our understanding of optimal distinctiveness. First, although prior work has taken the countervailing mechanisms as unobserved, I offer a framework that explicates, harmonizes, and extends the seemingly contradictory arguments from prior work. Second, to date, the nature of categories in work on optimal distinctiveness has been kept remarkably fixed—leading to calls to incorporate how categories differ (Zhao et al., 2017). My framework offers a multilevel theory of distinctiveness to explain how incentives for differentiation and conformity shift depending on categorical context, thus supporting a more general yet more precise theory of optimal distinctiveness. Third, by relaxing the assumption that firms in categories cluster around the average (Vergne & Wry, 2014), I provide new insights with respect to the boundary conditions of the dominant conceptualization of distinctiveness as distance-from-the-average.

2 | THEORY AND HYPOTHESES

The question of whether firms should strive to be different or the same compared to others in their market category has seen significant theoretical and empirical exploration. On the one hand, "being the same" via alignment with the norms in the category prevents the firm from falling outside the range of acceptable behavior and thus facing legitimacy challenges (Deephouse, 1999; DiMaggio & Powell, 1983). On the other hand, "being different" enables the escape of competition by staking out a position with greater potential for sustained superior performance (Baum & Mezias, 1992; Porter, 1991)—leading to the proposition that moderately distinctive positions enable a strategic balance between these countervailing pressures (Deephouse, 1999) and, in turn, optimal performance (Zhao et al., 2017; Zuckerman, 2016). Several studies find support for moderate distinctiveness yielding the highest performance, compared to either strong conformity or deviation (Deephouse, 1999; McNamara et al., 2003; Roberts & Amit, 2003).

In spite of its intuitive appeal, other work suggests that moderately distinct firms may be unable to sufficiently reduce competition while also suffering from a lack of focus, insufficient demand, and blurred positions in the minds of stakeholders (Jennings et al., 2009; Zott & Amit, 2007)—such that distinctiveness may be beneficial only when taken to very high levels. Thus, moderate distinctiveness may actually lead to worse performance than either conformity or deviation. For instance, Cennamo and Santalo (2013) find such a U-shaped effect, with moderate distinctiveness yielding the worst performance for platforms. In similar spirit, Jennings et al. (2009) show how new law firms have the lowest levels of productivity when incorporating employment systems that deviate moderately from industry norms, with either strong conformity or high deviation leading to greater productivity. Zott and Amit (2007) found that attempts to balance between efficiency and novelty in business model design adversely affect performance.

These inconsistent results may lead one to conclude that little progress has been made in determining whether or not firms should aim for moderately distinct positions. However, there is strong agreement in work developing both U-shaped and inverted U-shaped effects on the importance of two key forces that push and pull firms toward conformity and differentiation, and most studies make reference to both forces (see, for instance, Deephouse, 1999; Jennings et al., 2009; McNamara et al., 2003; Porac, Thomas, Wilson, Paton, & Kanfer, 1995). Indeed, these mechanisms determine whether a U-shaped or inverted U-shaped relationship manifests itself, making it crucial to be explicit about their nature (Haans, Pieters, & He, 2016).

Complicating matters, however, the two mechanisms are typically unobserved to the researcher. As a result, significantly less agreement exists on their *exact* nature. Although few are explicit about this matter, to start, some exceptions exist. For instance, Deephouse (1999) assumes that distinctiveness linearly reduces both competition and legitimacy. In contrast, Jennings et al. (2009, p. 344) theorize that that "the benefits associated with either of the more extreme positions will increasingly outweigh the costs." Conversely, McNamara et al. (2003, p. 170) anticipate "diminishing returns to both conformity to obtain legitimacy and differentiation to reduce rivalry." These different assumptions about the nature of the mechanisms matter, as they jointly and simultaneously determine whether a U-shaped or inverted U-shaped effect manifests itself, more so as even small differences in mechanisms can yield widely different curvilinear relationships (Haans et al., 2016). Because of this, I first synthesize prior work addressing each of these two mechanisms central to the literature on optimal distinctiveness—legitimacy and competition—to make explicit how, on average, they appear to be a function of distinctiveness.

2.1 | The effect of distinctiveness on legitimacy

Because work on distinctiveness is concerned with similarity among firms, most work builds on the prototype view of categories (Durand & Paolella, 2013; Rosch, 1975) in developing theory. In this view, prototypical firms—those that are representative of and central to the category—are of crucial importance to the existence of categories. Because distinctiveness entails deviation from the conventional, normal strategies in a category (Deephouse, 1996, 1999), the prototypical firm is often taken to be the most-average member of the category. Thus, distinctiveness predominantly entails differentiation vis-à-vis average positions (Vergne & Wry, 2014, p. 72).[1] By providing information about the central tendencies of a category, the average aids the categorization process (Porac et al., 1995) and a consequence of isomorphism to this central position is that the firm is more likely to be judged as legitimate—desirable, proper, or appropriate—by the firm's external environment (Deephouse, 1996; DiMaggio & Powell, 1983; Meyer & Rowan, 1977). Such legitimacy aids performance, allowing the attainment of higher-quality resources on better terms than for less-legitimate positions (Deephouse, 1999; Lounsbury & Glynn, 2001; Navis & Glynn, 2011).

Firms have some leeway to position themselves, however, due to the existence of a "range of acceptability" (Deephouse, 1999, p. 152) around the prototypical behavior of the category. Ambiguity and uncertainty make the choice of the most appropriate position unclear (Deephouse, 1996), such that firms can differentiate themselves within this range without immediate loss of legitimacy (Navis & Glynn, 2011). Nevertheless, positioning that does fall outside this range triggers difficulties in audiences' sense making by calling into question what the firm does, why it does it, and how it should be valued (Durand, Rao, & Monin, 2007)—rapidly jeopardizing the firm's external standing and thus resulting in a "sharp discipline" (White, 1981, p. 526) by threatening the fundamental act of cross-offering comparison sustaining the market. Nevertheless, once the firm moves from being a peripheral (close to or just beyond the edge of the range of acceptability) to a "non-player" (positioned too far outside the range; Zuckerman, 1999, p. 1402), further loss of legitimacy is likely not as dramatic given that the firm is no longer considered by audience members, to start. Put differently, distinctiveness first substantially harms legitimacy, but this slows down after a certain threshold.

[1]This conceptualization is different from the prototype as the most salient category member, which tends to be an extreme case or outlier (Vergne & Wry, 2014), as well as from alternative categorization approaches such as goal-based or causal-model approaches (Durand & Boulongne, 2017; Durand & Paolella, 2013). Given the dominant conceptualization of distinctiveness as deviation from an industry average (cf., Vergne & Wry, 2014, p. 73; also: Deephouse, 1996, 1999), I focus on the prototype as the most-average category member. I return to this point in the discussion.

2.2 | The effect of distinctiveness on competition

A central tenet of the resource-based view is that "uniqueness and not imitation provides firms with competitive advantage in acquiring resources" (Williamson, 2000, p. 33). Here, categories primarily function as arenas in which rivals struggle to defend contested positions (Porac et al., 1995). Although alignment to norms yields legitimacy, it thus also introduces competitive pressures among those that are similar—being in direct competition for resources, market share, and attention from the external environment (McNamara et al., 2003). This competition is the result of the combination of the average distance of the focal firm to other category members on strategic dimensions and the absolute number of firms competing with the firm for resource space (Baum & Mezias, 1992; see also: Deephouse, 1999, p. 151). Staking out distinct positions thus allows firms to locate themselves in underexploited niches with little competition while increasing the distance from others in the category (Porter, 1991).

The variation-restricting and clustering tendencies of categories (DiMaggio & Powell, 1983; Lounsbury & Rao, 2004; Zuckerman, 1999) imply that a disproportional number of firms will be positioned close to the center of a category. Indistinct firms are, therefore, similar to the most other firms, while also sharing a crowded market for resources and clients. The more a firm differentiates itself along one or multiple dimensions, the more it can move away from these central tendencies (Porac et al., 1995). This increases the distance to other category members and simultaneously reduces the number of rivals that share the firm's immediate resource space—leading to initial increases in distinctiveness quickly moving firms away from the crowded center. However, after a certain threshold is exceeded, further moves away from the center will do little in the way of reducing competition as the firm essentially stands to move from one more or less empty resource space to another. Therefore, distinctiveness first rapidly alleviates competitive pressures, but these reductions slow down once competition is effectively avoided.

Figure 1 illustrates these mechanisms, with the left panel showing an average category within which firms can position themselves along two dimensions (the argument can feasibly be extended to multidimensional space). Firms (shown using black squares) cluster at the center, which represents the prototypical most-average position as indicated by the intersection of the two dashed lines ($\mu 1$ and $\mu 2$ represent the average across all the positions in the category along strategic dimension 1 and 2, respectively). In general, the further the firm is from this average position in the category, the more distinctive the firm is. The dark grey area shows the range of acceptability (which is centered on the average position in the category) within which differentiation can occur without legitimacy loss (Deephouse, 1996, 1999). Light gray circles indicate the main competitive space of three illustrative firms: an indistinct, prototypical firm (shown with a dark grey diamond) that is positioned very close to the average; a moderately distinct firm (shown using a lighter grey triangle) that is positioned somewhat away from the average; and a distinct firm (represented by a white "plus") that is positioned far away from the average.

The indistinct firm is positioned well within the range of acceptability, such that is highly legitimate. The moderately distinct firm is positioned somewhat outside this range, making it less legitimate, while the distinctive firm is very far outside this range and thus very illegitimate. Each of these firms is in direct competition with firms positioned in their competitive space—indicated by the light grey circles for the highlighted firms. The indistinct firm shares competitive space with many other firms, the moderately distinct firm with six firms, and the distinctive firm with only one.

The prototypical firm positioned close to the average in the category attains the highest levels of legitimacy, but also faces the highest competitive pressures. In comparison, the highly distinctive firm is illegitimate yet faces little competition given its isolated position. The moderately distinctive

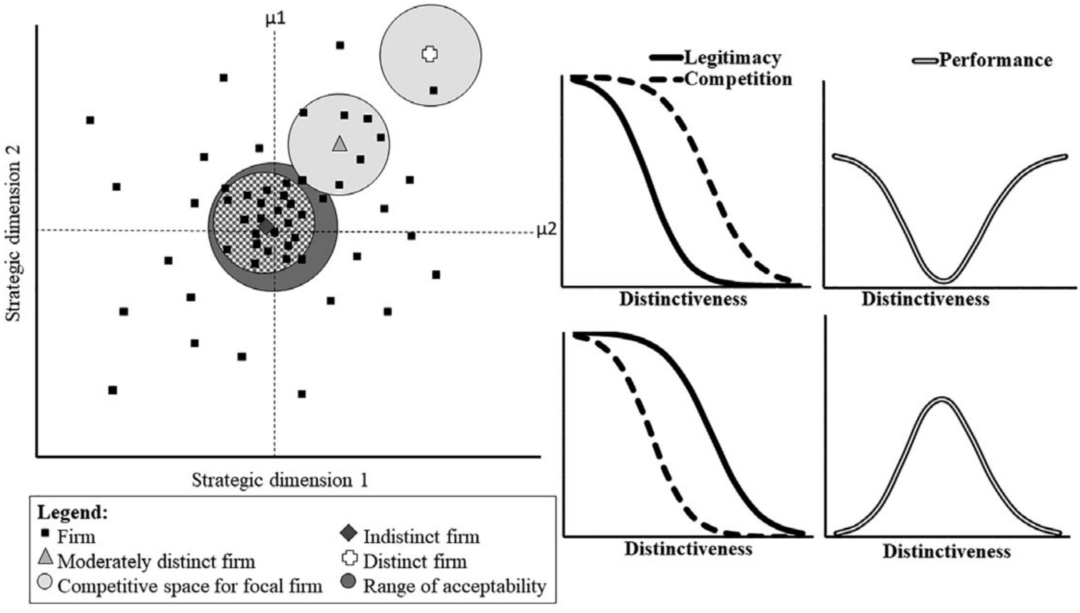

FIGURE 1 The theorized relationship between distinctiveness and legitimacy, competition, and performance with different assumed relative strengths

firm is neither (il)legitimate nor does it face exceptionally strong or weak competitive pressures. As developed above, it is expected that both legitimacy and competition drop rapidly between the positions of prototypical firm and the moderately distinct firm, while these drops level off between the moderately distinct firm and the highly distinctive firm. The right panel illustrates such S-shaped mechanisms (legitimacy with a solid line; competition with a dashed line)—resulting in the observed performance in an additive manner, as legitimacy can be seen as beneficial to performance while competitive pressures are costly to performance.[2]

A key insight that emerges from Figure 1 is that an average prediction about the observed relationship being a U-shape or inverted U-shape is not feasible. Indeed, the top half of the right panel of Figure 1 illustrate a scenario where the drop in legitimacy occurs before the drop in competitive pressures—resulting in a U-shape. In contrast, in the bottom half competition quickly drops as distinctiveness increases while legitimacy drops only later—yielding an inverted U-shape. This is because, under the assumptions developed above, the *relative* strength at each point of the curves determines what is observed rather than simply the existence of two countervailing forces. Given that relative strengths, therefore, determine what relationship is observed, it seems valuable to consider contingencies that shape when one mechanism obtains precedence over the other.

2.3 | Distinctiveness heterogeneity

So far, it has been assumed that categories do not differ in their composition, and in particular that firms cluster strongly around the average position in their category. However, categories *do* differ (Lounsbury & Rao, 2004; Zhao et al., 2017) and distinctiveness can be expected to be punished or

[2]I appreciate an anonymous reviewer's suggestions to explore S-shaped mechanisms. To allow for such S-shapes, I use the inverse logit function $\left(\frac{\exp(b_0+b_1X+b_2X^2)}{1+\exp(b_0+b_1X+b_2X^2)}\right)$. In the top panels, for legitimacy $b_0 = 4$, $b_1 = -12$, and $b_2 = 0$; for competition $b_0 = 6$, $b_1 = -10$, and $b_2 = 0$. In the bottom two, these coefficients are interchanged.

rewarded differently depending on the nature of the category. As comparisons to other firms form the basis of both the legitimacy and competition mechanisms, a natural contingency to consider is the degree to which *other* firms in the category are distinctive, themselves (Durand & Jacqueminet, 2015). Distinctiveness heterogeneity, defined as the degree to which firms in a category cluster around a single position, captures the variation in the positions of firms, and represents how common distinctiveness is in the category. This contingency in particular should affect both how acceptable "being different" is in the category while also being related to how crowded different competitive positions are—thus shaping both the legitimacy and the competitive pressure mechanisms driving the relationship between distinctiveness and performance.

2.4 | Distinctiveness in homogeneous categories

Homogeneous categories are characterized by highly similar and undifferentiated firms (Navis & Glynn, 2011), clustering closely around the average attributes that define the category. Figure 2 provides an illustration of such a category in two-dimensional space. In these contexts, there exists a salient view of what a firm in this category looks like and what it should be doing (Navis & Glynn, 2011; Zuckerman, 1999), yielding a narrowly defined range of acceptable behavior and making legitimate differentiation challenging (Deephouse, 1999). Indeed, audiences are prone to notice and question any deviation from the well-defined norms as represented by the prototypical, average, position (Lounsbury & Glynn, 2001; Navis & Glynn, 2011; Zuckerman, 1999). While conformity to these norms is highly legitimate (Deephouse, 1996), only minor deviations can, therefore, already be expected to yield a sharp drop in legitimacy—resulting in moderately distinctive firms facing nearly as strong legitimacy challenges as those that are highly distinctive, as shown in the right-hand panel of Figure 2.

Firms that position themselves within the narrow range of acceptability—and thus close to the prototypical average—simultaneously face conditions that resemble perfect competition as firms crowd around the same narrow space and thus compete for the same resources, clients, and audience

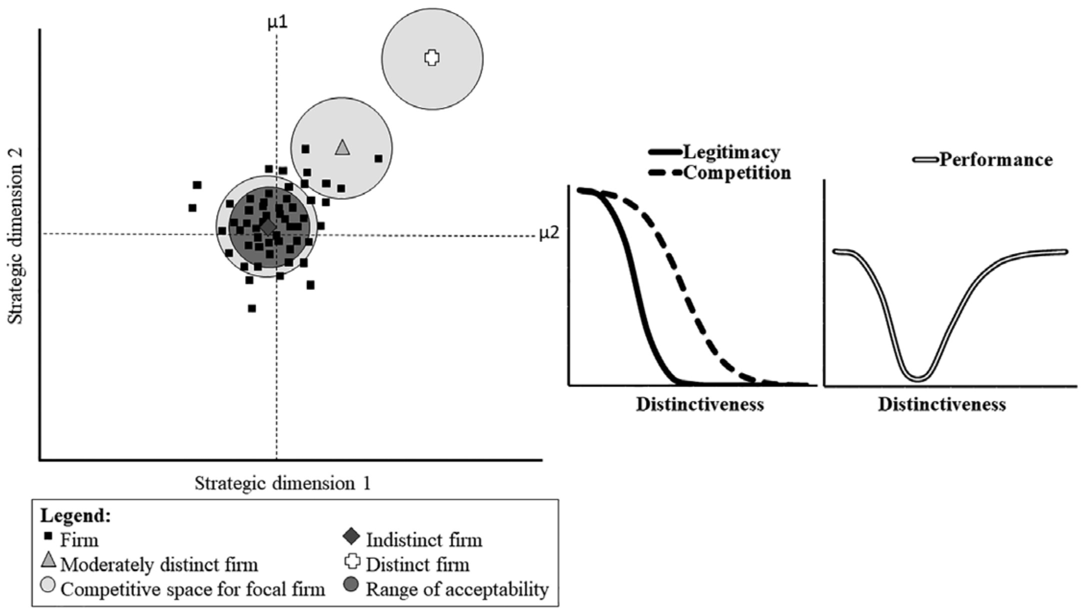

FIGURE 2 Theorized effects of distinctiveness in homogeneous categories

attention (Cennamo & Santalo, 2013; McNamara et al., 2003). The absolute number of firms with whom an indistinct firm competes is high, while the average distance to others is low, resulting in fierce competition at the center of the homogeneous category. However, compared to the quick drop in legitimacy, small deviations away from the center are unlikely to be sufficient to escape this strong competition. Specifically, small deviations maintain a non-negligible degree of overlap in resource space with central firms, requiring more substantive effort to tear away from competitive pressures, as shown in Figure 2 with a moderately distinct firm sharing competitive space with several firms positioned close to the center of the category. Once this competitive threshold is crossed, however, both average similarity and the number of rivals decrease quickly as the firm pulls away from the pack, allowing a rapid reduction in competition that again levels out once competition is finally avoided.

In sum, indistinct firms in homogeneous categories tend to be highly legitimate yet also suffer from fierce competitive conditions. Conversely, solitary firms can isolate themselves from competition, yet face major legitimacy challenges. Although highly indistinct and highly distinct firms each face their own challenges and reap their own benefits, firms that attempt to only marginally differentiate themselves bear the full brunt of the harmful forces while reaping few benefits, such that they are expected to accrue the lowest levels of performance. As illustrated in Figure 2, this pattern emerges from differences in the relative strengths of the two core mechanisms: initial drops in legitimacy are stronger than reductions in competition—resulting in an initial negative effect of distinctiveness on performance. However, once this effect levels off around moderate levels of distinctiveness, the key benefits of competition reduction start accruing and turn the observed relationship positive.

> **Hypothesis 1.** *The relationship between distinctiveness and performance is U-shaped in homogeneous categories.*

2.5 | Distinctiveness in heterogeneous categories

In contrast to homogeneous categories, heterogeneous categories consist of firms with widely varying positions (Navis & Glynn, 2011). Figure 3 illustrates such a context, where firms position themselves across the whole resource space—leading to little to no clustering around a single position. Compared to the homogeneous categories described above, I expect two major differences: the range of acceptable behavior shifts outwards and the effects of distinctiveness on both latent mechanisms are expected to weaken.

In heterogeneous categories, the average loses much of its informational value as it no longer represents the category ideal well (Lounsbury & Rao, 2004; Rosch, 1975). Because legitimacy reflects "cultural alignment" (Scott, 1995, p. 45), the firm in such categories needs to show how it is *different*, lest it is seen as uninteresting or boring (Lounsbury & Glynn, 2001). Firms in such categories face "differentiation imperatives" (Zuckerman, 2017, p. 35), resulting in the range of acceptable behavior moving away from the average attributes of the category and into a broader range of more distant attribute combinations. Although audiences are thus more likely to have a tolerance (or appetite) for more distinctive behavior (Zuckerman, 2017)—making atypical offerings more acceptable—it is unlikely that the range of acceptable behavior extends to infinity. Well-established difficulties in sense making of extremely unusual or equivocal positions can be expected to continue to raise doubts about the plausibility and comprehensibility of very distinct firms (Navis & Glynn, 2011). Thus, legitimacy in heterogeneous categories is maximized for those firms that adopt distinctive, but not excessively so, positions.

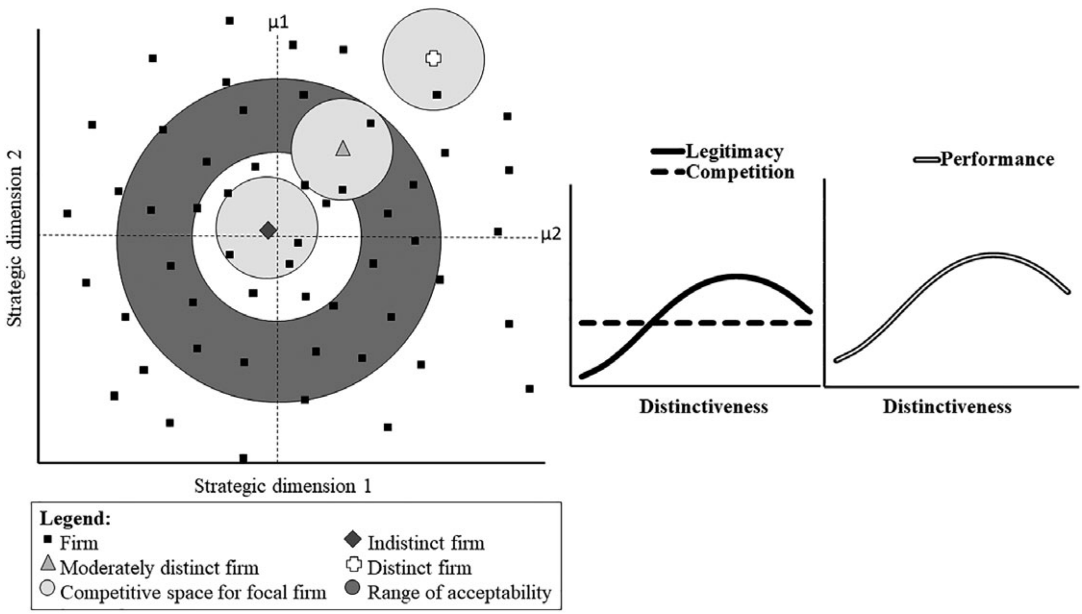

FIGURE 3 Theorized effects of distinctiveness in heterogeneous categories

At the same time, in contrast to homogeneous categories, it is unlikely that failure to meet the behavioral expectations in the category (by being too indistinct or too distinct) yields as strong implications for firms' legitimacy. In many ways, heterogeneous categories are akin to lenient categories (Pontikes & Barnett, 2015), which have less well-defined boundaries and are less constraining than more stringent categories. In such fuzzier categories, audiences are less likely to devalue deviance from the norms, as the boundaries present weaker schematization (Kovács & Hannan, 2010; Negro, Hannan, & Rao, 2010). Indeed, when classification systems themselves are weaker or in flux, normative pressures are likewise weakened (Ruef & Patterson, 2009). Thus, in more heterogeneous categories the range of acceptable behavior not only shifts outwards but positioning outside this range is also prone to lead to less-severe devaluation—as shown by the weaker overall curvature of the legitimacy mechanism in Figure 3.

Though distinctiveness enables firms to escape from strong competitive conditions in highly homogeneous categories, this function is likely lost entirely in more heterogeneous categories. Competition for customers and resources becomes spread across the category, rather than being focused at the center, reducing the number of unoccupied niches (Cennamo & Santalo, 2013). Figure 3 shows that the number of rivals becomes nearly identical for any given position implying that, *ceteris paribus,* competition becomes so diffuse than any firm shares resource space with some other firm, regardless of its specific position. Distinctiveness in such an environment, therefore, would only seem to serve as a way for the firm to position itself in one or the other location, rather than distancing itself from rivals, *per se*. This yields the straight line for the competition reduction mechanism illustrated in Figure 3.

As discussed earlier, a U-shaped effect is expected to emerge in homogeneous categories. In contrast, the changes in mechanisms set out above imply the existence of an inverted U-shaped relationship in categories that are heterogeneous, where firms are best off when adopting distinct enough identities to seen as legitimate yet not overly distinct so as to trigger difficulties in sense-making. In between these extremes—that is, more average categories—the observed effect of distinctiveness should be flatter. Thus, these arguments imply the following[3]:

Hypothesis 2. *The U-shaped relationship between distinctiveness and performance is flatter in more heterogeneous categories than in homogeneous categories.*

Hypothesis 3. *The relationship between distinctiveness and performance flips from a U-shape in homogeneous categories to an inverted U-shape in heterogeneous categories.*

3 | DATA AND METHODOLOGY

3.1 | Sample

I test my hypotheses by analyzing the websites of firms in the Dutch creative industries—shown in the Supporting Information (Appendix S1)—following a delineation by Statistics Netherlands (Braams & Urlings, 2010). This delineation contains both the more standard artistic industries but also more peripheral ones such as knowledge-based services, ensuring sufficient variation. This approach is chosen for a variety of reasons. Storytelling, identity, and image construction are crucial in the creative industries (Jones, Anand, & Alvarez, 2005) and websites serve as an important avenue for such positioning—the wide use and free accessibility fostering large-scale, cross-category data collection. The Dutch law requires anyone receiving more than symbolic compensation to be registered with the Chamber of Commerce, enabling identification of entities that may not be registered in other countries. As many firms in these industries are very small (OCW, 2016), it is also plausible texts are actually written by the firm owners.

Web-scraping methods were used on websites taken from a list of all unique Chamber of Commerce numbers with one of the creative industries as the primary industry. A valid domain was identified for 77,134 firms, and all texts on the front pages and on pages one click deeper on same domain were collected in July of 2014. Websites where the domain was still registered, but no longer in use, were manually removed. Texts were then cleaned by removing remaining code snippets, website-related words (such as "contact," "home," and "sitemap"), stop words in both Dutch and English (for instance, "the," "and," and "is"), filler words (e.g., "lorem ipsum" texts), and highly infrequent words (occurring in fewer than 500 websites). A set of 69,188 firms with cleaned, validated texts remained, consisting of 64,197,652 total and 6,602 unique words.

Given that there is no public information about the performance of these (predominantly private and small) firms, contact information was collected for a questionnaire. Parsing the websites identified 40,280 e-mail addresses. An "info@" address was estimated for the remaining 28,908 cases. External services validated the addresses, identifying 3,099 invalid addresses and 27,834 addresses of unknown validity (e.g., with "catch all" e-mail servers). Removing invalid addressed left 66,089 addresses contacted in March and April of 2015. Respondents were offered personalized reports and a chance to win one of 50 national museum subscriptions, and several industrial and professional associations promoted the study; 2,595 questionnaires were completed, yielding a 3.9% response rate. About 37% of those contacted opened the e-mail: taking this as the denominator, the response rate is

[3]Although support for H3 by definition would imply that H2 is supported, the converse does not need to be the case: e.g., a U-shaped effect in homogeneous categories may flatten out into a linear effect but not an inverted U-shape.

about 9.5%. After list wise deletion of missing or invalid observations, 2,279 respondents are used in the regression analyses. The "cold call" request, the many "info@" addresses with often unknown validity, and questionnaire fatigue mentioned by several respondents all suggest that this rate is acceptable.

To assess the extent of possible non-response bias, I first compared respondents (2,279 in total) with non-respondents (66,909 in total) on distinctiveness, distinctiveness heterogeneity, firm age, and number of employees (measurement of these variables is discussed, below). In spite of the large sample size, I find no significant differences on distinctiveness ($p = 0.259$), distinctiveness heterogeneity ($p = 0.128$), or firm age ($p = 0.839$) using *t*-tests. Tests of proportions for employee size brackets indicate that freelancers are over-represented (83.37% of respondents are freelancers, versus 75.22% of non-respondents, $p = 0.000$) and firms with two to 99 employees under-represented (*p*-values range from 0.000 to 0.038). Firms with 100+ employees are not over- or under-represented. I also compared early- and late respondents based on demographic variables that were specific to the questionnaire: 1,316 late respondents (57.74%) participated in the questionnaire after receiving a reminder (sent two weeks after initial contact). Early- and late-respondents do not differ in terms of revenues, respondent age, and education (*p*-values range from 0.315 to 0.890)—suggesting non-response bias may be limited.

I also compared the number of respondents and non-respondents from each of the 54 sampled four-digit industries using tests of proportions. The results are shown in Appendix S1. There are eleven industries with no survey respondents but with websites included in the topic model, which is likely the result of chance as none of the tests meet any conventional thresholds for statistical significance. In all, in particular the arts seem over-represented, while more peripheral industries such as "Knowledge-intensive services" (Braams & Urlings, 2010) are somewhat under-represented. The Dutch arts sector consist of a relatively larger proportion of freelancers than other creative industries (OCW, 2016), providing a partial explanation for the above differences in firm size. A second explanation may be that the associations which promoted the questionnaire are mainly active in the arts and other more core industries. Although I do not find evidence that respondents differ systematically from non-respondents on the three key dimensions of interest to this study (distinctiveness, distinctiveness heterogeneity, and revenues), the sample thus does over- and under-represent specific firm sizes and industries. As such, the results reported below are best interpreted with these differences in mind.

3.2 | Topic modeling methodology

I apply latent Dirichlet allocation (LDA), a generative probabilistic model for collections of texts (Blei, Ng, & Jordan, 2003), to the full set of websites to model firms' positioning. Topic modeling provides a methodology to discover and analyze latent themes underlying large databases of textual data by using documents and their words (which are observed) to learn the unobserved topic structure—consisting of the topics, the distribution of topics per document, and the distribution of words over topics. I show what a "topic" entails in my data further below.

A key benefit is that LDA does not require classification by humans (infeasible given the number of websites and the unknown nature of the topics of interest), instead having structure emerge from the data. One crucial human choice when using LDA is the number of topics to be estimated by the algorithm. The few fit measures that exist in the literature tend to produce excessively large number of topics which do not correspond well with human interpretation (Chang, Boyd-Graber, Gerrish, Wang, & Blei, 2009). Thus, I follow recent practice (Kaplan & Vakili, 2015), and set the number of topics to 100—balancing between having too many topics to be interpretable and too few to allow meaningful variation. Results are robust to a range of alternative topic numbers (reported below). I

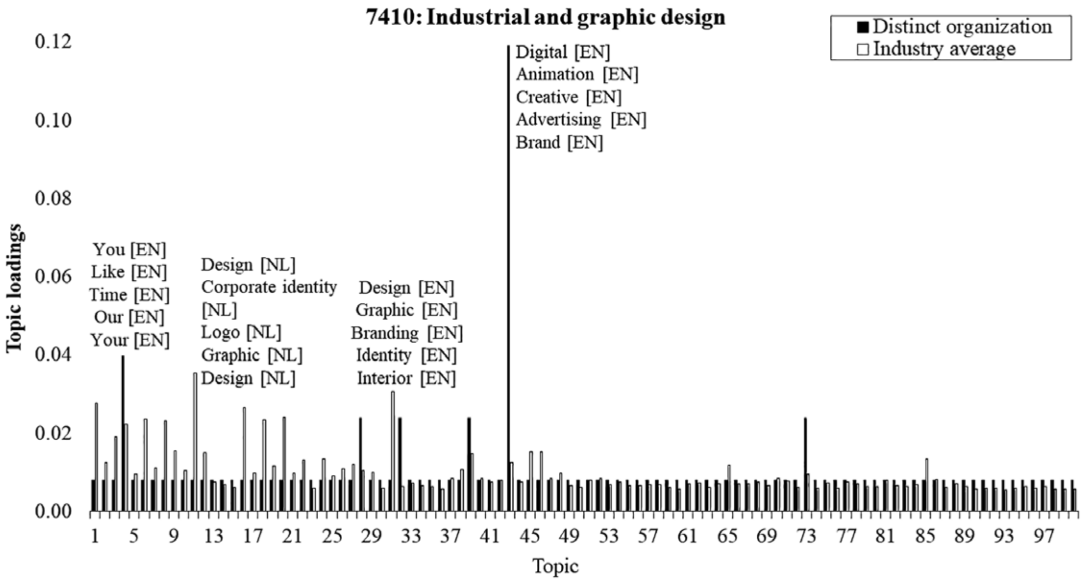

FIGURE 4 Topic distributions for the industrial and graphic design industry

use the Gibbs sampling algorithm and follow prior work in setting the topic smoothing parameter α to 0.5 and the term smoothing parameter β to 0.1 (Griffiths & Steyvers, 2004).

The LDA model is able to identify a wide variety of topics, capturing many dimensions along which firms can position themselves. Appendix S1 provides an overview of all topics. Some topics that emerge are clearly centered on services (one topic [51] consists of "training," "course," "trainings"), while others are more centered on the individuals that make up the firm (e.g. [24]: "my," "story," "inspiration").[4] Some topics emphasize location ([81]: "eindhoven," "tilburg," "maastricht"), while yet others are more anchored in a specific industry ([32]: "video," "film," "animation"). As such, the topic model seems to capture well the different elements of categories as the symbolic and material attributes of products, firms, and industries that are both shared among actors and that distinguish these entities from others (Douglas, 1986; Durand & Thornton, 2018; Zerubavel, 1991).

Figure 4 illustrates the average topic distribution over the 100 estimated topics for the industrial and graphic design industry, together with the topic distribution of one distinctive firm in my data. On average, firms in this industry tend to have the highest topic weights for a topic centered on words such as "design," "corporate identity," "graphic." I returned to the websites of several highly average firms, finding them to indeed be very similar. For example, one average firm stated that "[Company name] offers professional and affordable graphical solutions for companies and firms in any industry. I distinguish myself through my forward-looking vision and the finding of smart solutions that work." Compared to these firms, the distinctive firm shown in Figure 4 emphasizes a topic around "digital," "animation," and "creative." This freelancer defines himself "as a creative, multi-disciplined, ambitious, international, easy-going, self-motivated, and determined person" and "a digital creative." In describing what sets him apart from others, this individual highlighted skills in video editing, arguing that "film and animation are a very powerful tool to tell a story." The topic model

[4]I show translations of Dutch words but did not translate content in the analyses. The topic model deals well with the multilingual nature of some of the data, with some topics being a mix of Dutch and English words very close in meaning. The use of non-native content may also be a way to take a distinct position, which my approach allows for.

thus seems to model the (in)distinctiveness of firms well, making it suitable for further use in regression models.

3.3 | Measures

3.3.1 | Dependent variable

Respondents were asked to indicate in which of the following brackets their total *revenues*, in Euro, earned during the past year fit: no revenues (value zero); 1–12,499 (one); 12,500–24,999 (two); 25,000–49,999 (three); 50,000–99,999 (four); 100,000–149,999 (five); 150,000–249,999 (six); 250,000–499,999 (seven); 500,000–999,999 (eight); 1,000,000-4,999,999 (nine); and more than 5,000,000 (ten). Respondents were asked to categorize their revenues, as pretests showed that they tended to be unaware of their exact revenues—potentially resulting in missing values or attrition if respondents are unwilling to look up or share exact financial information. Revenues are an especially appropriate measure of performance in the creative industries, rather than an indicator of size, as these consist predominantly of small firms and freelancers. The creative industries also host much non-profit activity, such that focusing on profits would result in the omission of this group.

3.3.2 | Independent variables

Distinctiveness is computed as $\sum_{T=1}^{100} \mathrm{ABS}\left[\left(\theta_{T,i} - \overline{\theta}_{T,I}\right)\right]$, where $\theta_{T,\ i}$ indicates firm *i*'s weight for topic *T* and $\overline{\theta}_{T,I}$ indicates industry *I*'s average weight for topic *T*. For every firm, the sum of absolute deviations from the industry-average over every topic is calculated. Primary four-digit industry codes are used for these calculations, thus taking the industry to be representative of the category which the firm predominantly operates in (see, for example, Lounsbury & Rao, 2004; Zuckerman, 1999). This measure mirrors measures of strategic deviation (Deephouse, 1999) or strategic distinctiveness (Miller et al., 2018) and I include its square to test for curvilinearity.

Distinctiveness heterogeneity is the sum of standard deviations of the topic weights over every topic: $\mathrm{heterogeneity}_I = \sum_{T=1}^{100} \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} \left(\theta_{T,i} - \overline{\theta}_{T,I}\right)^2}$, where *N* is the number of firms with a website in industry *I*. Industry-specific spreads in each topic's usage are thus calculated and summed up. Art galleries and architecture are among the most homogeneous industries; film production and photography are moderately heterogeneous, while industrial design and the performing arts are very heterogeneous. This variable is similar to Lounsbury and Rao's (2004) measure of category heterogeneity, and is interacted with distinctiveness and its square.

3.3.3 | Control variables

At the industry level, to ensure that density dependence effects are not driving the effects of interest (Hannan & Freeman, 1977), I control for the total firms in the industry, divided by 1,000 ("*density*," also including its square). Moreover, I control for the change in density ("*density-change*," as compared to the prior year) because industries with high turnover in the number of firms may see a greater inflow of novel positions. I also control for the main types of creative industries as delineated by Statistics Netherlands (Braams & Urlings, 2010): the arts, taken as the baseline category; media and entertainment, creative business services, knowledge-intensive services, creative retailing, and other creative industries—with the latter two combined into a single category due to the small number of firms in my sample in creative retailing) to correct for systematic differences in the nature of work in these industries.

A few large firms may dominate the market space—thus altering the space available for more or less distinctive behavior. Because the creative industries are predominantly labor-rather than capital-intensive, I take the average employee value of the firm's employee size bracket (discussed below) to represent each firm's number of employees (e.g., the class two to four employees becomes three) and calculate the total number of employees active in each industry at the time of sampling. Then, I summed up the squares of each firm's market share to calculate "*market concentration.*" Moreover, to account for differences in the resource space of each industry, I calculated niche width using each firm's topic distribution with the Simpson index of dissimilarity of the grades of membership defining the niche (Hsu, Hannan, & Koçak, 2009; Kovács & Hannan, 2010; Negro et al., 2010; Paolella & Sharkey, 2017) to obtain the "*average niche width*" in the category. Increases in average niche width decrease the advantage that a more specialist position would have (Kovács & Hannan, 2010; Negro et al., 2010)—thus potentially confounding effects of distinctiveness, as well.

At the level of the firm, I control for "*organizational niche width*" (as discussed above), to ensure that the effects of distinctiveness are not confounded by differences in the extent to which the firm is more or less specialized (Hsu et al., 2009; Kovács & Hannan, 2010; Negro et al., 2010; Paolella & Sharkey, 2017)—with more specialized firms potentially also being more distinctive in nature. I also control for the number of "*employees*," obtained from the Chamber of Commerce, which divides firms into size classes: 1 employee (i.e., freelancers), 2–4 employees, 5–9 employees, 10–19 employees, 20–49 employees, 50–99 employees, and 100–199 employees (the largest category in my sample). Although results are robust to using a linear specification with values 1 through 7, I use a more flexible specification by utilizing employee size dummies. Because the models (discussed below) do not converge with the full set of dummies included, I combined the five classes with less than 50 observations into a new "5–199 employees" bracket, with 62 observations. The group of freelancers is the baseline category. I also control for "*firm age*," as firms of different ages may face differing pressures to conform to the norms of the industry.

The following variables originate from the questionnaire: because younger individuals may be more inclined to deviate from the norms in one's industry, I control for "*respondent age.*" For similar reasons, the respondent's gender (1 for *female*, 0 for male), and dummies for the respondent's level of *education* (high school, the baseline category; vocational; polytechnic; university; PhD) are included. I also control for how important three artistic *goals* are (on a seven-point scale): (a) producing innovative work, (b) artistic freedom, and (c) expanding the art form (adapted from Voss, Cable, & Voss, 2000), as respondents may be working "for art's sake" and thus may be both more distinctive and less concerned with monetary outcomes (Caves, 2000). For similar reasons, I control for whether or not it has a *creator* role (Caves, 2000; with creators likely emphasizing the unique aspects of themselves and their own work more than those firms that engage in more "humdrum" manufacturing or service work) as well as a measure of *creative personality* (the Creative Personality Scale; Gough, 1979), as creativity is particularly crucial for performance and may correlate with distinctiveness, as well (Caves, 2000).

To control for differences in activities, I control for whether or not the firm was the respondent's *sole income* source (as respondents for whom the firm's activities are secondary might differ systematically from others in the way they describe their activities), as well as an indicator for whether or not the firm has any *exporting* activities (as differentiation strategies tend to be bolstered by having international experience; McKnight & Zietsma, 2018). For similar reasons, respondents were asked to indicate whether their firm was mostly *cost-driven*, or whether it focused on value creation. To account for potential differences in the innovativeness of the firm's activities (which might be more distinctive in nature), respondents were also asked to indicate the extent to which they focused on existing versus "*new products*" and existing versus "*new clients*" (ranging from zero for existing to one for new products/clients).

3.4 | Model

The ordered, discrete nature of the revenues classes leads me to utilize partial proportional odds logistic regression (Williams, 2016).[5] Technical details underpinning this model are shown in Appendix S1. As there are too few observations per bracket for the full model to estimate 10 full equations (the number of outcome values minus one), I combined the revenues brackets into more balanced brackets: 0–12,499 Euro, 12,500–24,999 Euro, 25,000–49,999 Euro, 50,000–99,999 Euro, and 100,000+ Euro, implying that the model estimates a set of four equations. Standard errors are clustered at the four-digit industry level to account for a lack of independence of observations within industries. I also estimated an OLS regression model, a Poisson regression model, and the naïve ordered logistic regression model using the full set of eleven revenues brackets and employee size brackets. Appendix S1 shows these results, confirming that the results are not driven by these changes to the data nor the choice of model.

4 | RESULTS

Appendix S1 contains descriptive statistics and correlations. In all, correlations between variables are minor and the size of the sample should yield sufficient statistical power, such that multicollinearity does not appear to be a major issue. Models are robust to excluding several variables that exhibit collinearity with the focal variables, such as organizational niche width (correlated with distinctiveness) and density (correlated with distinctiveness heterogeneity) as well as to variables being mean-centered.[6]

Table 1 contains the results of the regression model. This table is structured based on the four equations that are estimated by the model, which represent each of the cumulative logit models that are simultaneously estimated (here: the lowest revenues bracket versus the four highest, the two lowest revenues brackets versus the three highest, et cetera). Intuitively, the sign and size coefficients shown in Table 1 can be interpreted as corresponding to the effect the variable has on the probability of moving to a higher revenues bracket. For example, a positive coefficient in the left-most panel implies a negative effect on the probability of being in the lowest revenues bracket and a positive effect on being in the second-lowest revenues bracket; a positive coefficient in the second equation a negative effect on being in the second-lowest bracket and a positive effect on the chance of being in the middle bracket, et cetera. The technical description in Appendix S1 provides exact information for how to interpret the coefficients from these tables via a calculation example. For space reasons, it also provides a full discussion of the effects of the different control variables in the different equations.

The model shows that all coefficients involving distinctiveness are highly significant ($p = 0.000$) and consistent across equations. Before turning to formal statistical tests, the two leftmost panels of

[5]I appreciate an anonymous reviewer's suggestion to utilize this model.

[6]Exploratory analysis suggested by an anonymous reviewer regressing distinctiveness heterogeneity on all category-level variables shows that density does not significantly predict heterogeneity ($p = 0.362$). This model, available upon request, has an R^2 of 0.387 with 54 observations corresponding to each industry. Density-change positively predicts heterogeneity (coef. = 0.193, $p = 0.058$); concentration negatively predicts heterogeneity (coef. = −1.025, $p = 0.000$); creative business services are more heterogeneous than the "other" industries (coef. = 0.234, $p = 0.098$).

TABLE 1 Generalized ordered logistic regression results

	(R1) v (R2; R3; R4; R5)			(R1; R2) v (R3; R4; R5)			(R1; R2; R3) v (R4; R5)			(R1; R2; R3; R4) v (R5)		
	Coeff.	***SE***	***p***	**Coeff.**	***SE***	***p***	**Coeff.**	***SE***	***p***	**Coeff.**	***SE***	***p***
Distinctiveness	−25.61	(5.70)	[0.000]	−25.61	(5.70)	[0.000]	−25.61	(5.70)	[0.000]	−25.61	(5.70)	[0.000]
Distinctiveness^2	15.94	(3.47)	[0.000]	15.94	(3.47)	[0.000]	15.94	(3.47)	[0.000]	15.94	(3.47)	[0.000]
Distinctiveness × heterogeneity	13.79	(3.28)	[0.000]	14.09	(3.25)	[0.000]	13.99	(3.18)	[0.000]	12.62	(3.24)	[0.000]
Distinctiveness^2 × heterogeneity	−8.48	(2.00)	[0.000]	−8.66	(1.97)	[0.000]	−8.60	(1.91)	[0.000]	−7.83	(1.95)	[0.000]
Heterogeneity	−6.49	(1.20)	[0.000]	−6.07	(1.12)	[0.000]	−5.13	(1.15)	[0.000]	−4.95	(1.07)	[0.000]
(Density/1,000)	0.08	(0.04)	[0.075]	0.08	(0.04)	[0.075]	0.08	(0.04)	[0.075]	0.08	(0.04)	[0.075]
(Density/1,000)^2	−0.00	(0.00)	[0.116]	−0.00	(0.00)	[0.116]	−0.00	(0.00)	[0.116]	−0.00	(0.00)	[0.116]
Density-change	−0.67	(0.16)	[0.000]	−0.67	(0.16)	[0.000]	−0.67	(0.16)	[0.000]	−0.67	(0.16)	[0.000]
Media and entertainment	−0.38	(0.20)	[0.054]	−0.24	(0.23)	[0.291]	0.25	(0.27)	[0.369]	0.24	(0.32)	[0.453]
Creative business services	0.11	(0.12)	[0.375]	0.30	(0.13)	[0.023]	0.57	(0.20)	[0.004]	0.53	(0.29)	[0.062]
Knowledge-intensive services	0.14	(0.19)	[0.454]	0.38	(0.20)	[0.063]	0.82	(0.27)	[0.003]	0.83	(0.28)	[0.003]
Other industries	−0.69	(0.24)	[0.005]	−0.34	(0.34)	[0.330]	0.47	(0.33)	[0.149]	0.51	(0.51)	[0.325]
Market concentration	−1.26	(2.55)	[0.622]	−3.11	(2.56)	[0.224]	10.09	(6.51)	[0.121]	14.46	(6.11)	[0.018]
Average niche width	−10.46	(7.04)	[0.138]	−10.46	(7.04)	[0.138]	−10.46	(7.04)	[0.138]	−10.46	(7.04)	[0.138]
Niche width	1.02	(1.22)	[0.400]	1.02	(1.22)	[0.400]	1.02	(1.22)	[0.400]	1.02	(1.22)	[0.400]
Two to four employees	0.52	(0.21)	[0.012]	0.84	(0.15)	[0.000]	1.48	(0.12)	[0.000]	1.79	(0.18)	[0.000]
Five to 199 employees	1.83	(0.88)	[0.039]	2.64	(0.60)	[0.000]	2.45	(0.64)	[0.000]	4.09	(0.66)	[0.000]
Firm age	0.10	(0.01)	[0.000]	0.07	(0.01)	[0.000]	0.07	(0.01)	[0.000]	0.05	(0.01)	[0.000]
Respondent age	0.00	(0.00)	[0.885]	0.00	(0.00)	[0.885]	0.00	(0.00)	[0.885]	0.00	(0.00)	[0.885]
Female	−0.79	(0.10)	[0.000]	−0.79	(0.10)	[0.000]	−0.79	(0.10)	[0.000]	−0.79	(0.10)	[0.000]
Education: vocational	−0.11	(0.24)	[0.642]	0.12	(0.18)	[0.528]	−0.35	(0.14)	[0.016]	−0.19	(0.23)	[0.418]
Education: polytechnic	0.02	(0.15)	[0.889]	0.02	(0.15)	[0.889]	0.02	(0.15)	[0.889]	0.02	(0.15)	[0.889]
Education: university	−0.18	(0.18)	[0.328]	−0.18	(0.18)	[0.328]	−0.18	(0.18)	[0.328]	−0.18	(0.18)	[0.328]
Education: PhD	−0.64	(0.30)	[0.031]	−0.64	(0.30)	[0.031]	−0.64	(0.30)	[0.031]	−0.64	(0.30)	[0.031]
Goals: innovative work	−0.01	(0.05)	[0.875]	0.03	(0.05)	[0.512]	0.17	(0.04)	[0.000]	0.28	(0.06)	[0.000]

TABLE 1 (Continued)

	(R1) v (R2; R3; R4; R5)			(R1; R2) v (R3; R4; R5)			(R1; R2; R3) v (R4; R5)			(R1; R2; R3; R4) v (R5)		
	Coeff.	***SE***	***p***	**Coeff.**	***SE***	***p***	**Coeff.**	***SE***	***p***	**Coeff.**	***SE***	***p***
Goals: artistic freedom	−0.20	(0.04)	[0.000]	−0.20	(0.04)	[0.000]	−0.20	(0.04)	[0.000]	−0.20	(0.04)	[0.000]
Goals: expanding art form	−0.08	(0.04)	[0.035]	−0.08	(0.04)	[0.035]	−0.08	(0.04)	[0.035]	−0.08	(0.04)	[0.035]
Creator role	0.06	(0.15)	[0.678]	−0.33	(0.19)	[0.079]	−0.68	(0.12)	[0.000]	−1.13	(0.17)	[0.000]
Creative personality	0.06	(0.01)	[0.000]	0.06	(0.01)	[0.000]	0.06	(0.01)	[0.000]	0.06	(0.01)	[0.000]
Sole income source	1.68	(0.07)	[0.000]	1.68	(0.07)	[0.000]	1.68	(0.07)	[0.000]	1.68	(0.07)	[0.000]
Exporting	0.29	(0.06)	[0.000]	0.29	(0.06)	[0.000]	0.29	(0.06)	[0.000]	0.29	(0.06)	[0.000]
Cost-driven	−0.33	(0.07)	[0.000]	−0.37	(0.12)	[0.002]	−0.27	(0.13)	[0.039]	−0.63	(0.18)	[0.000]
New products	−0.37	(0.15)	[0.012]	−0.37	(0.15)	[0.012]	−0.37	(0.15)	[0.012]	−0.37	(0.15)	[0.012]
New clients	−0.69	(0.23)	[0.003]	−0.85	(0.30)	[0.004]	−0.34	(0.23)	[0.138]	−0.36	(0.28)	[0.190]
Intercept	21.83	(6.87)	[0.001]	19.98	(6.73)	[0.003]	16.11	(6.81)	[0.018]	15.33	(6.73)	[0.023]

Notes: Standard errors are clustered at 4-digit industry. $\chi^2[41] = 126{,}981.14$, $p = 0.000$; Log pseudolikelihood = −2,680.37; No. of observations = 2,279. R1: Revenues = 0–12,499; R2: Revenues = 12,500–24,999; R3: Revenues = 25,000–49,999; R4: Revenues = 50,000–99,999; R5: Revenues = 100,000+.

Figure 5 illustrate, respectively, the predicted probabilities of belonging to the lowest and highest revenues brackets across the range of distinctiveness at low (mean minus 1.5 standard deviation), medium (average), and high (mean plus 1.5 standard deviation) distinctiveness heterogeneity. The inverted U-shaped solid black curve in the left-most panel shows that moderate distinctiveness—corresponding to roughly average levels of distinctiveness—yields the highest probability of belonging to the lowest revenues bracket in homogeneous categories compared to either high or low distinctiveness. Similarly, in the middle panel this curve is U-shaped and shows moderate distinctiveness yielding the lowest probability of being in the highest revenues bracket: moderate distinctiveness is sub-optimal in homogeneous categories—consistent with Hypothesis 1.

Testing Hypothesis 1 more formally, I find that the slope of the solid black curve in the left-most panel of Figure 5 is positive and significant (0.266, $p = 0.000$) at the 1st percentile of distinctiveness while it is negative and significant at the 99th percentile (−0.287, $p = 0.000$). The maximum of this relationship occurs at distinctiveness with a value of 0.747, where the probability of belonging in the lowest revenues bracket equals 0.307 (see Appendix S1 for information on how to calculate these probabilities). For comparison, distinctiveness 1.5 standard deviations below or above this maximum yields a probability of 0.212 (the curve is symmetric around the turning point). As distinctiveness ranges from 0.254 to 1.987, with an average of 0.879, this maximum indeed occurs at moderate levels of distinctiveness— having moderate distinctiveness in homogeneous categories substantially increases the probability that the firm attains the worst possible performance.

In contradistinction, in the middle panel of Figure 5 (showing the probability of being in the highest revenues bracket) the slope of the curve for homogeneous categories is negative and significant (−0.281, $p = 0.000$) at the 1st percentile of distinctiveness while it is simultaneously positive and significant at the 99th percentile of distinctiveness (0.942, $p = 0.000$). The minimum of this relationship occurs at a distinctiveness value of 0.792, where the probability of being in the highest revenues bracket equals 0.135. Distinctiveness 1.5 standard deviations above or below this minimum results in a probability of 0.217, meaning that the chance of attaining the best possible performance is much higher for firms with either high or low distinctiveness than for those with moderate distinctiveness.

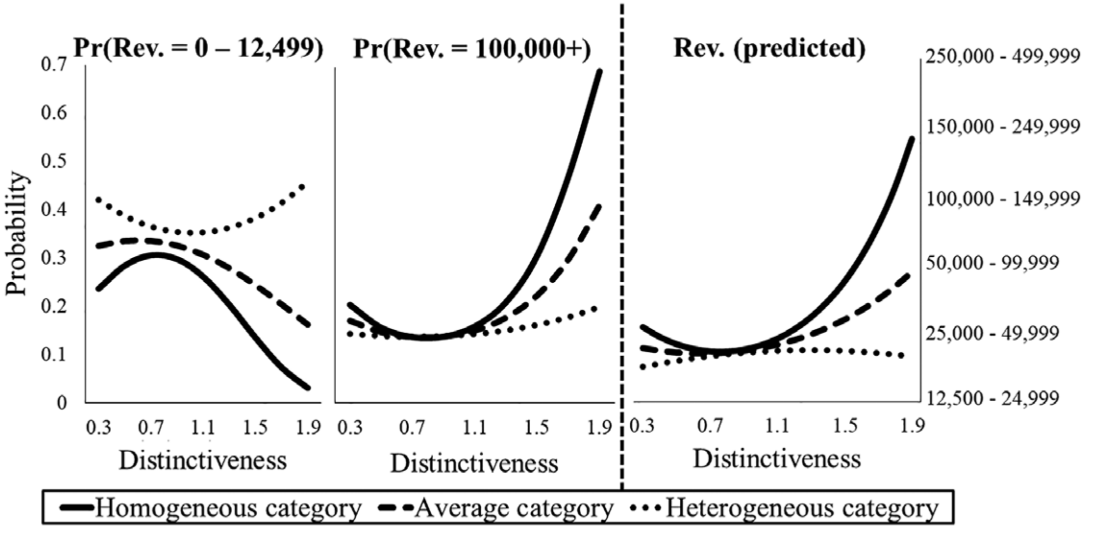

FIGURE 5 The distinctiveness-revenues relationship in homogeneous, average, and heterogeneous categories. The two leftmost panels show the predicted probabilities of being in the lowest and highest revenues bracket, respectively, based on Table 1. The rightmost panel illustrates predicted revenues based on a Poisson regression for the full revenues variable

In all, this strongly confirms a U-shaped effect of distinctiveness on performance in homogeneous categories and supports Hypothesis 1.

Consistent with the theorized flattening of the curve, all equations show a strongly negative and significant interaction term between distinctiveness squared and distinctiveness heterogeneity—indicating that the U-shape is flattened by distinctiveness heterogeneity (Haans et al., 2016). To test this, I compare the slopes of the curves in homogeneous and heterogeneous categories (shown using the solid and dotted curves, respectively) at one standard deviation to the left of each curves' turning points. In heterogeneous categories, the turning point in the left-most panel occurs at distinctiveness of 1.017, while in the middle panel it occurs at distinctiveness equaling 0.712. These comparisons confirm that the effect of distinctiveness on revenues flattens as heterogeneity increases (difference in slopes equals 0.335, Chi-squared[1] = 27.40, p = 0.000 in the left-most panel; 0.177, Chi-squared [1] = 10.85, p = 0.001 in the middle panel). Hypothesis 2 is strongly supported, as the U-shape that is present in homogeneous categories significantly flattens out as distinctiveness heterogeneity increases.

A necessary condition for a shape-flip as hypothesized in Hypothesis 3 is that a significant (and meaningful) inverted U-shaped effect is present at high values of the moderator (Haans et al., 2016). It is clear that for the highest revenues bracket, no inverted U-shaped effect of distinctiveness is present in heterogeneous categories as the slopes at the 1st and 99th percentile of distinctiveness are insignificant (p = 0.524 and 0.381, respectively). Hypothesis 3 is not supported and the role of distinctiveness heterogeneity is only to flatten—but not flip—the U-shaped effect of distinctiveness on performance that's observed in homogeneous categories.

To elucidate the monetary implications of the effects, the rightmost panel of Figure 5 shows the results for a Poisson regression estimated using the full revenues variable.[7] It is clear that deviating far from the category's norms pays tremendously in homogeneous categories, with those at the high end of the distinctiveness range having predicted revenues between 150,000 and 249,999 Euro—substantially larger than the 25,000–49,999 Euro for indistinct and moderately distinct organizations. As the curve flattens, the gains to conformity decrease somewhat, while vertical differences between the curves at moderate distinctiveness are nearly non-existent (that is, absolute performance for moderately distinctive firms is roughly the same across categories). Most pronounced is the drop in revenues when comparing highly distinctive firms in homogeneous categories with such firms in average and heterogeneous categories, for whom predicted revenues are between 50,000–99,999 Euro and between 12,500–24,999 Euro, respectively. Considering that half of entrepreneurs in the Dutch creative industries have a total annual income lower than 30,000 Euro (OCW, 2016)—a pattern also observed in my data with 50.81% of respondents having lower than 24,999 Euro of revenues—it is clear that the economic value of being different changes dramatically as a function of distinctiveness heterogeneity.

4.1 | Robustness checks

I conducted a number of analyses to verify the identified relationship, all shown in full in Appendix S1. First, I checked whether the results are robust to alternative topic numbers (50, 75, 125, or 150 topics) and find that the results are unchanged with any of these alternatives. Then, I performed analyses where the dependent variable was replaced by one where the numeric values of the full

[7]Ordered logistic regression disallows assessing economic magnitude—being only concerned with the probability of belonging to the revenues brackets. However, the revenues brackets are also not truly of a count-nature, such that these results—based on the Poisson model reported in Appendix S1—need to be interpreted with caution.

revenues brackets were divided by the numeric values of the full employee classes. The purpose of this was to get closer to a ROA-type variable by directly adjusting the revenue variable for number of employees. The results, estimated using OLS regression, remain entirely consistent with those reported above. I also re-ran all analyses after removing firms from industries for which I identified a website for fewer than 100 firms in the full website sample, as the distinctiveness and heterogeneity variables may be less precise or less meaningful for very small industries. This change affected 10 firms in the regression sample, and their omission did not affect the results. To assess the influence of outliers, I winsorized distinctiveness and heterogeneity at the 1st and 99th percentile: all results persist when doing so.

Because the distinctiveness measure is unable to distinguish between firms that are highly distinctive on one dimension versus more moderately distinctive on many, I generated an alternative distinctiveness measure that sums up the absolute differences between the absolute distances from the mean for all pairwise combinations of topics, divided by the number of topics.[8] Specifically, this variable is operationalized as $\left(\sum \text{ABS}\left[\text{ABS}\left[\left(\theta_{T,i}-\overline{\theta}_{T,I}\right)\right]-\text{ABS}\left[\left(\theta_{S,i}-\overline{\theta}_{S,I}\right)\right]\right]\right)/100$ for all pairwise combinations of topics T and S. While the current distinctiveness measure assigns the same value to firms with equal distances from the average across many topics (e.g., ten absolute deviations of 0.02) and firms with very large differences along one topic (e.g. an absolute deviation of 0.2 for one topic but zero for all others), this operationalization discounts the former firms. The results are unchanged when replacing the original distinctiveness measure in the regression model, therefore suggesting that the results are not changed when correcting for firms differentiating themselves in more or less focused ways.[9]

Finally, the current distinctiveness measure might be confounded by differences in conventionality (an alternative form of conformity, being the selective adoption of highly salient and expected attributes: Durand & Kremp, 2016) rather than alignment (which the current measure of distinctiveness captures the inverse of). I calculated the sum of positive deviations from the three topics with the highest average topic loadings in the industry, thus capturing the extent to which firms over-emphasize important topics in their category. For instance, as per Figure 4, in the industrial and graphic design industry the three most important topics are topics 1, 11, and 20. The highly distinctive firm in Figure 4 is unconventional, as it has lower-than-average emphasis on all these topics (yielding a score of zero). In contrast, if it had very high emphasis on topics 1, 11, and 31, it would be classified as both distinctive as well as highly conventional. The effects of distinctiveness are unchanged when controlling for this variable, suggesting conventionality is not driving the effects.

5 | DISCUSSION AND CONCLUSION

One of the core paradoxes at the intersection of strategic management and organization theory is how firms should manage the competing pulls towards conformity through isomorphic pressures with the competitive push towards differentiation to attain competitive advantage (Deephouse, 1999; Zhao et al., 2017; Zuckerman, 2016). Prior work on the relationship between distinctiveness and performance has come to seemingly contradictory arguments and conclusions, ranging from inverted U-

[8]I thank an anonymous reviewer for highlighting this characteristic of the distinctiveness measure.

[9]I also investigated whether this issue is salient for heterogeneity. Several homogeneous categories have one topic with substantial variation, suggesting heterogeneity emerges predominantly from having consistently higher topic spreads. I constructed a measure that sums up the absolute differences between the standard deviations for all pairwise topic combinations. The model does not converge when replacing the heterogeneity measure, likely because it correlates highly with average niche width (−0.680). However, results are robust to controlling for this measure.

shaped to U-shaped effects. This study was therefore driven by the question of whether and under what conditions moderate distinctiveness is optimal. Analyses combining a topic model of 69,188 organizational websites in the Dutch creative industries with a questionnaire with 2,279 respondents show that a strong U-shaped effect of distinctiveness on revenues exists in homogeneous categories, which flattens out and disappears in more heterogeneous categories. The performance implications of distinctiveness for a focal firm thus depend crucially on how widespread distinctiveness is, at the level of the category.

Recent work emphasizes that it is "both timely and important to synthesize the literature on optimal distinctiveness" (Zhao et al., 2017, p. 108). Though there is agreement in the literature regarding the existence of two fundamental mechanisms driving the distinctiveness-performance relationship, I find clear disagreement on their *exact* nature. This study provides a formalization of each mechanism that is able to flexibly accommodate seemingly incommensurable views (e.g., Deephouse, 1999; Jennings et al., 2009; McNamara et al., 2003), and shows how the existence of these countervailing forces is not a sufficient condition for either a U-shape or an inverted U-shaped effect of distinctiveness to emerge. Instead, it highlights the importance of contingencies altering which mechanism dominates at specific levels of distinctiveness. In so doing, this formalization contributes to the rapidly growing literature on optimal distinctiveness (see Zhao et al., 2017; Zuckerman, 2016 for recent reviews) by baring its "essential structure or morphology" (Hunt, 1991, p. 159) and aiding both more precise theory development by incorporating how incentives for differentiation and conformity shift depending on context (McKnight & Zietsma, 2018; Miller et al., 2018).

By relaxing the assumption that categories cluster around the average, this study also offers valuable new insights regarding the boundary conditions of the conceptualization of the prototype as the most-average firm (Durand & Paolella, 2013; Vergne & Wry, 2014). Although the results do not show the theorized inverted U-shaped effect of distinctiveness in highly heterogeneous categories, they instead suggest that both legitimacy- and competition-related pressures weaken to such an extent that distinctiveness as distance-from-the-average loses its performance implications altogether in heterogeneous categories. This therefore suggests that there is no strong imperative—either for conformity to or differentiation from the average—in heterogeneous categories and that audiences may hold different theories of value that determine what offerings are attractive to them in such categories (Paolella & Durand, 2016; Zuckerman, 2017).

Taken as such, I view my findings as consistent with recent work on categories highlighting the importance of alternative categorization approaches, such as a goal-based approach (Durand & Boulongne, 2017; Durand & Paolella, 2013), or alternative benchmarks such as the most salient or exemplar member of a category (Vergne & Wry, 2014; Zhao, Ishihara, Jennings, & Lounsbury, 2018). At the same time, my results clearly show that the prototype-as-average approach has strong explanatory power in homogeneous categories—where the average tends to be more meaningful, to start. Therefore, it complements prior work by identifying conditions under which the average *does* serve as a powerful categorization tool. It would be interesting for future research to study whether or not alternative approaches become more dominant in heterogeneous settings, whether or not the average-as-prototype dominates other reference points in homogeneous categories, or whether alternative approaches operate simultaneously to the prototype-as-average. Such comparative insights would further the accumulation of knowledge about the role of different (types of) reference points for optimal distinctiveness. Certainly, it is unlikely that strategic positioning is a complete free-for-all in heterogeneous settings.

More generally, this study contributes to the literature on distinctiveness by bringing to the forefront within-category heterogeneity. The cross-level mechanisms identified in this study add to recent calls to shift neoinstitutional theory to study variability rather than isomorphism, with an emphasis on more intensive dialogue with strategic management (Deephouse, 1999; Durand & Jacqueminet, 2015; Zhao et al., 2017). By bringing in work on heterogeneity in categories (Kovács & Hannan, 2010; Negro et al., 2010; Pontikes & Barnett, 2015; Ruef & Patterson, 2009), I further emphasize the value of considering categories as a bridge between perspectives (see also; Durand & Thornton, 2018).

In terms of limitations of this study, the theoretical development underpinning this study was built on an explicit "between-firm" and "between-category" theorization as well as cross-sectional analyses, therefore abstracting from temporal considerations and enabling only limited causal insights. Though this approach usefully simplified the theorization process, studying the interplay between firm level adjustments in positioning and subsequent changes in category level makeup over time provides a prime candidate for further exploration. At the firm-level, I am unable to account for a substantial degree of unobserved heterogeneity because of my cross-sectional approach. For example, it may be that firms' positions have been the result of firm-specific optimization paths—even for those with relatively poor performance compared to other firms. Although I control for many factors, further work taking a longitudinal empirical approach could account for time invariant unobserved heterogeneity and therefore investigate within-firm developments in distinctiveness and performance over time—in turn also allowing for a much more fine-grained set of theoretical mechanisms that may be investigated using such an approach. At the level of the category, homogeneous categories should become increasingly heterogeneous if more firms stake out the apparently profitable distinct positions in such categories, yet the results suggest that the effects of such distinctiveness also disappear as heterogeneity increases—begging the question of whether occupying such a position is worthwhile in the long run. Thus, longitudinal work would open up major extensions to my cross-sectional arguments both at the firm- and category-level.

It also remains an open question to what extent these results are generalizable to other countries as well as other (types of) industries. Indeed, my analyses were based on a single country (the Netherlands) and only on the creative industries. Although the sample of creative industries was wide—including for example both the classic artistic industries as well as more economically focused industries—the majority of these industries are nevertheless service-based and knowledge intensive. Moreover, the artistic nature of most activity in these industries is rather unique (Caves, 2000), although the act of creation is common in more business domains and many creative industries also have much in common with other domains (Haans & van Witteloostuijn, 2016). Although the theorized mechanisms and fundamental ideas of this paper should be general enough so as to be applicable to other types of industries and countries, this nevertheless would be very interesting to put to the test in further work.

Though this study's application of topic modeling to organizational websites enabled novel cross-category comparisons, one could also pose that much of what is being said on these websites may simply be rhetoric. However, in the creative industries "all work of cultural industries, in some way or the other is preoccupied with claims to authenticity" (Jones et al., 2005, p. 893), and websites in particular allow firms to make such claims. Considered as such, rhetoric rather than actual behavior may be what matters most in these industries. Moreover, many of the claims made are relatively easily verifiable—e.g. educational background, place of operation, products and services offered—suggesting that the texts studied here do capture real differences between firms. Nevertheless, rhetoric versus actual behavior may matter differently for legitimacy versus competition and in different contexts, such that further study is warranted to investigate effects of different sources of distinctiveness on firms' performance and in different contexts.

Being different from competitors is a key recommendation in strategic management. This paper has questioned the implicit assumption that the benefits and costs of being different can be evaluated independent of the firm's context by incorporating the degree to which differentiation is commonplace in one's market category. In so doing, it offers an important step in developing a more fine-grained understanding of the performance effects of distinctiveness and advances understanding of the cross-level interactions between firm-level differentiation and category-level contingencies. My results show that distinctiveness can indeed have tremendous returns for firms—but only when very few other firms in one's category are different, themselves, and only when taking distinctiveness to very high levels. Moreover, distinctiveness has no effect on performance when being different is the norm. By empirically identifying conditions under which the recommendation to differentiate holds merit, this study therefore highlights the importance of moving further towards a more comprehensive theory of optimal distinctiveness.

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