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RESEARCH ARTICLE

Categories and narratives as sources of distinctiveness: Cultural entrepreneurship within and across categories

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Abstract

Research Summary: Cultural entrepreneurship theory suggests that entrepreneurial narratives need to be optimally distinctive—neither portraying an offering as too similar to nor too distinctive from the conventions of its product category—for attracting superior demand. Building on and extending this literature, we propose that the benefits and downsides of a distinctive narrative fundamentally depend on a category's distinctiveness vis-à-vis alternative categories because distinctive categories (a) provide an important source of differentiation for their members and (b) disproportionally attract those audience members that highly value novelty. Our longitudinal study of 159,343 Airbnb listings in 45 categories strongly supports our hypotheses: the relationship between Airbnb listings' narrative distinctiveness and demand-side performance flips from an inverted U-shaped curve in indistinctive categories to a U-shaped curve in distinctive categories.

Managerial Summary: Entrepreneurs need to craft a compelling narrative around their offering to legitimate and differentiate it from competing offerings. In this article, we explore when and why entrepreneurs should craft narratives that portray their offerings as similar, moderately distinctive, or highly distinctive from other offerings. We study this question in the context of the Airbnb marketplace, in which Airbnb hosts compete with their respective accommodation listings. Our study shows that Airbnb listings in indistinctive categories attract most demand when their narratives portray them as moderately distinctive. In contrast, Airbnb listings in distinctive categories attract the most demand when their narratives portray them as either highly similar or highly distinctive from other listings in their category

KEYWORDS

categories, cultural entrepreneurship, narratives, novelty, optimal distinctiveness

1 | INTRODUCTION

How can entrepreneurs successfully attract customer demand for their offerings? In answering this question, cultural entrepreneurship theory highlights the tension between distinctiveness and similarity, emphasizing the importance of optimal distinctiveness (Lounsbury & Glynn, 2001, 2019). To achieve optimal distinctiveness, entrepreneurs need to sufficiently differentiate their offering while also sufficiently conforming to the conventions of their category to gain legitimacy (Deephouse, 1999;). A burgeoning literature at the intersection of strategic management and organization theory explores this tension between differentiation and conformity to theorize about the relationship between distinctiveness and demand-side performance outcomes in entrepreneurial market environments (Barlow, Verhaal, & Angus, 2019; Durand & Kremp, 2016; Taeuscher, Bouncken, & Pesch, 2021; Taeuscher & Rothe, 2021; Zhao, Ishihara, Jennings, & Lounsbury, 2018).

This line of research departs from the traditional strategic positioning literature in that it has focused on how symbolic forms of differentiation—such as the textual descriptions of mobile apps (Barlow et al., 2019) or entrepreneurial narratives in crowdfunding platforms (Taeuscher et al., 2021)—have important implications for performance above and beyond how product and portfolio characteristics situate a firm vis-à-vis competitors. Such symbolic forms of differentiation are particularly important in contexts in which hundreds or even thousands of offerings compete for consumers' attention. Rather than staking out and defending a market position vis-à-vis a small number of long-standing rivals, such environments require entrepreneurs to strategically deploy symbolic tools—such as narratives—to convey their offering's conformity and distinctiveness (Lounsbury & Glynn, 2001). Indeed, narratives represent one of the most important symbolic management tools to position an entrepreneurial offering, providing an important platform for conveying an offering's similarity and distinctiveness to key audiences (Martens, Jennings, & Jennings, 2007; Navis & Glynn, 2011; Wry, Lounsbury, & Glynn, 2011; Zhao, Ishihara, & Lounsbury, 2013).

In examining how narratives shape audiences' perception and evaluation of offerings' optimal distinctiveness, research to date has emphasized the central role of categories—a cognitive infrastructure that allows audiences to make sense of and evaluate otherwise unknown offerings (Glynn & Navis, 2013). As documented by two-stage models of evaluation (e.g., Zuckerman, 1999, 2016), categories shape audience evaluations because they provide a filtering mechanism through which audience members can easily preselect a set of options worthy of consideration (i.e., consideration set) before evaluating and comparing these preselected options more thoroughly (Urban, Hulland, & Weinberg, 1993). Categories also affect audience evaluations because they act as cognitive anchors for perceptions of offerings' conformity and distinctiveness (Zhao et al., 2017). Audiences generally infer an offering's distinctiveness by contrasting it with the prototypical offering in its category (Lounsbury & Glynn, 2001), and therefore, an effective narrative needs to position the offering as optimally distinctive vis-à-vis the prototypical offering in its category (Haans, 2019; Navis & Glynn, 2011; Taeuscher et al., 2021). Categories thus play a central role in the attainment of optimal distinctiveness because they serve audiences as cognitive filters to preselect offerings for consideration, and as cognitive anchors that subsequently shape evaluations of offerings' conformity and distinctiveness.

Categories may, however, also shape the attainment of optimal distinctiveness in a more direct way because membership in certain categories can—by itself—differentiate an offering from other offerings in its domain. This is because categories themselves are embedded in broader classification systems and differ in their *category distinctiveness*—defined as a category's relative position vis-à-vis other categories at the same horizontal level in its classification system (Lo, Fiss, Rhee, & Kennedy, 2020) and reflected in the uniqueness of a given category's prototype relative to the prototypes of other categories in the same classification system.[1] Categories can therefore also have a differentiating function whenever audience members attend to and evaluate offerings from more than one category, as can be the case in product category systems (Lancaster, 1966; Lounsbury & Rao, 2004).

Instead of purely serving as cognitive filters and anchors, we argue, product categories can become an integral part of audiences' perception and evaluation of an offering's distinctiveness. We thus propose that the distinctiveness of a category vis-à-vis other categories matters for the construction of an optimally distinctive narrative because category distinctiveness likely shapes how some audiences evaluate the distinctiveness of category members. By developing novel theory about the importance of category distinctiveness, a conceptual dimension that has been generally neglected in the literature, we aim to contribute to a richer, multilevel understanding of optimal distinctiveness (Bu, Zhao, Li, & Li, 2022; Zhao, 2022).

To this end, we integrate elements from category research as it relates to the distinctiveness of categories (Gehman & Grimes, 2017; Lo et al., 2020; Suarez, Grodal, & Gotsopoulos, 2015) with insights on audiences' heterogeneous evaluation of novelty (Cattani, Falchetti, & Ferriani, 2020; Cattani, Ferriani, & Allison, 2014; Pontikes, 2012; Taeuscher et al., 2021), and posit that category distinctiveness shapes category members' optimal distinctiveness in two important ways. First, distinctive categories might reduce the differentiation benefits of a distinctiveness-emphasizing narrative because membership in such a category already provides an important source of differentiation. Indeed, category research suggests that organizations can strategically claim and promote membership in a distinctive category to differentiate their

[1]The notion of *category distinctiveness* has some similarities but is conceptually distinctive from the notion of *category contrast*, as discussed in the ecological view on categories (Hannan et al., 2019). Category distinctiveness refers to categories' external position in the category system (based on differences in prototypical features), whereas category contrast refers to the degree of categories' overlap in terms of their members.

offering and convey its novelty (Gehman & Grimes, 2017; Granqvist, Grodal, & Woolley, 2013; Suarez et al., 2015).

Second, we propose that category distinctiveness also shapes the types of audience segments that primarily attend to and evaluate the members of that category. That is because audiences consist of multiple segments that differ in their valuation of novelty (Cattani et al., 2020); some audience segments highly value and actively seek novelty (e.g., in an offering), whereas others do not (Cattani, Ferriani, & Lanza, 2017). Focusing on consumers as the key audience, we distinguish novelty-seeking consumers—consumers who highly value novelty and therefore actively seek out novel offerings and experiences (Hirschman, 1980)—from mainstream consumers and propose that novelty-seeking consumers will more likely attend to offerings positioned in distinctive (versus indistinctive) product categories.

We thus propose that distinctive categories differ from indistinctive ones in that they differentiate their members to some degree vis-à-vis nonmembers (thus lowering the benefits of a moderately distinctive narrative), and more likely attract those audience segments that highly value novelty (thus accelerating the benefits of a highly distinctive narrative). Combining these theorized mechanisms with a graphical illustration, we propose that the commonly assumed inverted U-shaped optimal distinctiveness curve[2] will flip to a U-shaped curve in distinctive categories.

We test our predictions using the Airbnb marketplace as the empirical context. In this context, Airbnb hosts craft narratives to convey the distinctiveness of their accommodation listings to generate demand. The marketplace encompasses 45 different accommodation categories, ranging from categories with relatively indistinctive features (e.g., townhouses) to categories with high distinctiveness vis-à-vis other categories (e.g., houseboats). Given that Airbnb users generally do not limit their search to a single accommodation category before making a selection (Fradkin, 2017), our context differs from studies in which audiences primarily attend to the members of one single category (e.g., Zuckerman, 1999). In other words, Airbnb users evaluate and compare Airbnb listings across categorical boundaries, and Airbnb listings thus compete for consumer demand both within and across categories. The Airbnb marketplace therefore constitutes an ideal context for developing and testing a theory about how category distinctiveness shapes the optimal distinctiveness of narratives within and across categories.

Empirically, we compiled a novel dataset of all Airbnb accommodation listings offered in 12 major US markets, which consists of 425,857 observations for 159,343 Airbnb listings surveyed at 6-month intervals from July 2018 to July 2020. Our longitudinal models, analyzed with a generalized estimating equation (GEE) approach, provide strong evidence that the relationship between listings' narrative distinctiveness (assessed via content analysis) and demand (gauged by price premiums) is fundamentally contingent on categories' level of distinctiveness. Our findings have important implications for two-stage models of social evaluation because they imply that category distinctiveness may influence the types of audience segments that attend to a category, consequently shaping the norms, values, and expectations against which category members will be evaluated. We discuss the implications of our study for research on optimal distinctiveness, cultural entrepreneurship, and categories, as well as the practical implications for Airbnb hosts and entrepreneurs more generally.

[2]Optimal distinctiveness research conventionally assumes an inverted U-shaped relationship between distinctiveness and demand-side performance outcomes because the marginal benefits of differentiation are expected to exceed the marginal liabilities of nonconformity at low levels of distinctiveness and vice versa at high levels of distinctiveness.

2 | THEORY AND HYPOTHESES

2.1 | Narratives as touchstones for legitimacy and differentiation

Consumers and other audiences are often unfamiliar with the specific features of an entrepreneurial offering, especially in a crowded marketplace where they lack prior experience with an offering. They therefore rely on information provided by the entrepreneur to alleviate information asymmetries and reduce uncertainty about an offering's features. Research on cultural entrepreneurship conceptualizes narrative as an important cultural tool that entrepreneurs use to gain audience support by communicating their offerings' similarity to and distinctiveness from a category's conventions (Lounsbury & Glynn, 2001, 2019; Martens et al., 2007; Navis & Glynn, 2010, 2011). Narratives do not need to accurately depict reality to be effective (Westphal & Zajac, 1998), and entrepreneurs can deploy narratives to strategically influence the degree to which audiences perceive their offering as similar to or distinctive from a categorical prototype (Lounsbury & Glynn, 2001). For instance, narratives can disproportionally emphasize a highly unusual feature of an offering or a unique aspect of the entrepreneur's identity to positively influence perceptions of the offering's distinctiveness. Some narratives may even provide a sort of façade (Abrahamson & Baumard, 2009) by packaging certain stylized dimensions of reality while hiding others to promote an offering to audiences (Giorgi, 2017). Therefore, narratives can differentiate an offering even if the offering's substantial features are largely aligned with a prototypical offering in a category.

Conversely, narratives can also stress an offering's conformity with the category's socio-cognitive conventions to gain legitimacy when the offering's other features cause illegitimacy concerns (Smith & Chae, 2016; Verhaal, Khessina, & Dobrev, 2015; Zhao et al., 2013). Hence, narratives provide entrepreneurs with an important tool for legitimating and differentiating their offerings (Lounsbury & Glynn, 2001; Navis & Glynn, 2011; Taeuscher et al., 2021); an optimal level of *narrative distinctiveness*—defined as the degree to which a narrative's content is distinctive from the content of a prototypical narrative in its category—is needed to reconcile these opposing demands.

2.2 | Social evaluations within and across categories

Similar to narratives, categories provide another central touchstone for perceptions of similarity and distinctiveness and therefore play a critical role in optimal distinctiveness research. Categories not only "provide a cognitive infrastructure that enables evaluations of organizations and their products, drives expectations, and leads to material and symbolic exchanges" (Durand & Paolella, 2013, p. 1102), but also represent important institutional resources that entrepreneurs draw on to legitimate and differentiate their offerings (Lounsbury & Glynn, 2001; Lounsbury & Rao, 2004; Navis & Glynn, 2010, 2011; Vergne, 2012).

An audience generally recognizes members of a category as such if they are sufficiently similar to the category's *prototype*—an abstract representation that encodes the average attributes of category members (Jones, Maoret, Massa, & Svejenova, 2012; Vergne & Wry, 2014). The general assumption is that audience members comprehend an otherwise unknown offering more easily if the offering resembles the prototype of an established category because this resemblance helps them to quickly and unambiguously recognize an offering as "one of those." At the same time, an offering needs to be differentiated to some degree from the category's prototype to match the specific preferences of some audience segments and therefore enhance its appeal to those segments. For instance, Cattani, Dunbar, and Shapira (2017) show how piano manufacturer Steinway & Sons has consistently attracted demand for their pianos by targeting virtuoso concert pianists—a consumer segment that highly values craftsmanship—and tailoring their differentiated offering to this segment.

The majority of optimal distinctiveness research to date has focused on examining how organizations manage this tension between conformity and differentiation within their specific categories (e.g., Barlow et al., 2019; Taeuscher & Rothe, 2021; Zhao et al., 2018). Prior research thus builds on the implicit assumption that a given category member (e.g., a product) primarily competes with other members of the same category. This assumption is informed by the observation that individuals are boundedly rational (March & Simon, 1958), and therefore necessarily rely on certain criteria and heuristics for efficiently screening a large number of potential options and filtering out those options that are worthy of consideration. Audience evaluations thus represent a two-stage process, in which audience members use certain minimum criteria as filtering mechanisms to preselect a limited set of options for consideration (filtering stage) before thoroughly evaluating these preselected options and selecting the best option among them (evaluation stage) (Gensch, 1987; Häubl & Trifts, 2000; Payne, 1976). In his influential work on security analysts' selection of stocks for coverage, Zuckerman (1999) proposed that conformity with a given category represents the central filtering mechanism through which audiences screen and filter available options for consideration.

The assumption that an audience primarily focuses their attention on a single category, and thus selects among options within that category has been documented across multiple contexts (e.g., Zuckerman & Kim, 2003). As Zuckerman (1999, p. 1401) argued, this implies that offerings need to sufficiently conform to a given category to be even considered by relevant audiences because they otherwise "stand outside the field of comparison and are ignored as so many oranges in a competition among apples." While the scope conditions under which this two-stage model of categorization and evaluation holds have not been fully specified, recent work suggests that there are situations where audiences may not limit their attention to a single category, highlighting that evaluation may occur across categories.

For instance, venture capitalists attend to entrepreneurial ventures from more than one market category when selecting ventures to fund (Pontikes & Barnett, 2017); thus, entrepreneurial ventures compete with entrepreneurial ventures from other market categories for venture capitalists' attention and investments. Similarly, consumers do not necessarily limit their attention to one single genre when choosing a restaurant, movie, or piece of music (e.g., Goldberg, Hannan, & Kovács, 2016); thus, such offerings often compete across different genre categories. In fact, scholarship on consumer behavior has maintained for several decades that in many product markets, consumers' decision-making typically involves the evaluation of offerings across product categories (Lancaster, 1966) because there often exists more than one product category that addresses consumers' needs and intended usage (Urban et al., 1993). In such contexts, members of a given category (e.g., a restaurant in the category of Italian cuisine) compete for audience members' consideration and selection with both other members of the same category (other Italian restaurants) and members of other categories (nonItalian restaurants).

In the next section, we develop context-sensitive predictions anchored in our empirical setting of the Airbnb marketplace. Context-sensitive theorizing is often useful for the construction of novel theory, as well as developing a deeper understanding of the scope conditions underlying existing claims (Eisenhardt, 1989). Nonetheless, our aim is to contribute to the development of more general theory about the attainment of optimal distinctiveness in contexts in which offerings face a meaningful level of cross-category competition—i.e., competition from members of other categories—in addition to the competition they face from other members within their own category.

2.3 | Optimal distinctiveness in the Airbnb marketplace

Today, Airbnb is the largest online marketplace for short-term accommodation rentals and has attracted more than 500 million consumers as users ("guests") since its launch in 2008 (Airbnb.com, 2019). Entrepreneurial individuals use Airbnb as "hosts" to generate revenue through short-term accommodation rentals (Slee, 2015). Airbnb strongly encourages these hosts to purposefully craft a narrative around their accommodation offering, which are prominently displayed on a listing's webpage, suggesting that "[a] great listing description is one of your best tools for securing bookings. [...] Your listing is where you market your space, and storytelling is a key part of great marketing. Often, the story you tell is about the experience you're offering guests" (Airbnb, 2020). The assumption that Airbnb users attend to these narratives during their evaluation is highly plausible because an accommodation booking represents a costly choice—Airbnb guests in the US pay $185 per night on average for their accommodations (Forbes.com, 2018)—and users thus spend considerable time evaluating and comparing potential accommodations (Fradkin, 2017).

Airbnb is similar to other online marketplaces, such as eBay, Etsy, Kickstarter, the Apple App Store, or Udemy, in that the marketplace provides an explicit classification system and asks hosts to self-categorize their offerings into one of these categories. In July 2018, Airbnb's classification system consisted of 45 different accommodation categories, including townhouses, barns, chalets, condominiums, tiny houses, castles, and tree houses. Research exploring consumers' browsing behavior in online marketplaces like Airbnb suggests that marketplace users generally do not limit their search ex ante to listings in one specific product category (Einav, Farronato, & Levin, 2015; Fradkin, 2017). However, this does not imply that consumers attend to *all* available product categories or *all* members of certain categories. Previous research rather suggests that consumers commonly apply multiple minimum criteria to screen and preselect offerings, including the offering's cognitive accessibility, social approval, and minimal fit with their preferences (Kovács & Sharkey, 2014). This assumption is in line with insights from browsing data of Airbnb users, which suggests that the majority of Airbnb users starts their search process by entering their target location, the number of guests, and travel dates into Airbnb's search engine (Fradkin, 2017). Users then attend to a subset of the available listings shown to them in response to their search request—typically those listings presented on the first page of search results—for evaluation. After they evaluated an initial subset of options, they commonly iterate between submitting new search requests with refined search filters (e.g., minimum star rating, neighborhood) and attending to a subset of the respective search results (Fradkin, 2017). The Airbnb marketplace therefore provides us with a very suited context to develop and test our hypotheses about how the distinctiveness of product categories shapes evaluations of optimal distinctiveness because Airbnb users generally do not limit their search to one specific accommodation category and Airbnb listings therefore compete across categorical boundaries.

Our theory extends the scope of previous optimal distinctiveness theorization in that we study the interplay between distinctiveness at two different levels: the level of Airbnb listings (i.e., category members) and the level of accommodation categories. We do so by drawing upon and further developing the notion of *category distinctiveness*—a concept recently suggested as a way to expand the scope of multilevel theorizing on categorization dynamics (Lo et al., 2020). Following Lo et al. (2020, p. 16), we define category distinctiveness as a category's "relative position in the broader classification and meaning system." According to this definition, a category becomes more distinctive if its prototype exhibits a higher distance to the prototypes of all other categories at the same horizontal level. In the context of the Airbnb marketplace, a category's distinctiveness is reflected in the degree to which its prototypical accommodation offering differs from the prototypical offerings of all other accommodation categories.

We subsequently examine how narrative distinctiveness affects consumers' relative demand for a listing. We focus our arguments on explaining the price premium that Airbnb hosts can command for their listings—an important indicator of the relative demand for a listing in our context, in which the supply of a given accommodation is fixed because only one customer can rent any given listing at a given time. Our focus on listings' relative demand, as expressed in price premiums as an observable consequence of demand heterogeneity, is in line with past optimal distinctiveness research (Barlow et al., 2019; Haans, 2019; Zhao et al., 2018); it also aligns with cultural entrepreneurship theory because it reflects Airbnb hosts' resource acquisition from the key audience—consumers. Our subsequent discussion is structured as follows: we first hypothesize on the relationship between listings' narrative distinctiveness and price premiums in indistinctive categories, and then discuss how this relationship changes under conditions of high category distinctiveness.

2.3.1 | Narrative distinctiveness and price premiums of Airbnb listings in categories with low distinctiveness

Drawing on the optimal distinctiveness literature, we expect that the relationship between a listing's narrative distinctiveness and price premium will be underpinned by both a positive (competitive benefits) and a negative (loss of legitimacy) mechanism. Airbnb, as an online marketplace, is prone to high market crowding and strong competitive intensity due to relatively low barriers to entry (Reuber & Fischer, 2011; Taeuscher, 2019). A given listing thus often competes against hundreds or thousands of other listings in the same market (i.e., city). Although competition is strong, previous research has indicated that the lodging industry provides varied opportunities for differentiation because consumers in this industry exhibit heterogeneous preferences (Canina, Enz, & Harrison, 2005; Chung & Kalnins, 2001). When competition is strong yet consumer preferences are heterogeneous, there are strong competitive benefits to differentiation (Hill, 1988). In crowded market environments, differentiation generally yields competitive benefits by attracting superior consumer attention (Pollock & Gulati, 2007; Rindova, Petkova, & Kotha, 2007). Moreover, differentiation allows hosts to command price premiums if it aligns their offering more closely with the unique preferences of a specific customer segment (Porter, 1980, 1991). For instance, a narrative that strongly emphasizes the host's passion for dogs may be perceived as particularly appealing to the customer segment of dog owners. Listings' narrative distinctiveness can therefore provide competitive benefits by attracting guests' attention and increasing the listing's appeal to specific customer segments.

While it is generally recognized that differentiation generates competitive benefits, the specific shape of this relationship may vary across contexts (Haans, 2019; Zhao et al., 2017). In the case of accommodation categories with low distinctiveness (i.e., indistinctive categories), we expect low marginal differentiation benefits at both low and high levels of narrative distinctiveness and high marginal benefits at moderate levels of narrative distinctiveness, leading to an S-shaped relationship between narrative distinctiveness and competitive benefits (Haans, 2019). This is the canonical finding in the optimal distinctiveness literature going back to Deephouse (1999) and is consistent with the two-stage model of evaluation (Zuckerman, 1999). We expect this relationship because (1) narrative distinctiveness only provides competitive benefits once it leads to a perceivable difference between an offering and the categorical prototype and (2) the competitive benefits of differentiation are generally bounded because further increases in narrative distinctiveness do not provide substantial additional benefits once a listing is already distinctive enough to stand out and closely match the preferences of a specific customer segment.

We also expect the relationship between narrative distinctiveness and loss of legitimacy to follow an S-shaped curve in indistinctive categories. As a listing's narrative starts to deviate from the prototypical narrative in its category, this initial slight deviation might still be in the “range of acceptability” (Deephouse, 1999) and may not immediately lead to a significant loss of legitimacy (Haans, 2019). Further increases in the level of narrative distinctiveness may, however, render the listing less appealing because mainstream consumers tend to dislike offerings that deviate too strongly from existing conventions in their category (Pontikes, 2012). However, once a narrative positions a listing far outside Airbnb guests' range of acceptability, further increases in narrative distinctiveness do not cause substantial additional penalties.

Thus, anchoring in previous optimal distinctiveness research, we assume that these two mechanisms have an additive effect on the price premiums that hosts can command for their listings (Deephouse, 1999; Haans, 2019; Taeuscher et al., 2021; Taeuscher & Rothe, 2021; Zhao et al., 2018). Figure 1a illustrates these mechanisms under conditions of low category distinctiveness. That is, in relatively indistinctive categories, we expect that the competitive benefits from a distinctive narrative exceed the opposing downside (loss of legitimacy) at low levels of narrative distinctiveness (due to the range of acceptability) and vice versa at high levels of narrative distinctiveness. To wit, in line with the default assumption in optimal distinctiveness research (Haans, 2019; Taeuscher & Rothe, 2021; Zhao et al., 2018), we predict that the relationship between a listing's narrative distinctiveness and its price premium follows an inverted U-shaped curve in categories with low distinctiveness, as illustrated in Figure 1b. Accordingly, we propose:

> **Hypothesis 1.** *In categories with low distinctiveness, there is an inverted U-shaped relationship between an Airbnb listing's narrative distinctiveness and its price premium.*

2.3.2 | Narrative distinctiveness and price premiums of Airbnb listings in categories with high distinctiveness

Anchored to our focus on narrative distinctiveness, we propose that category distinctiveness shapes the optimal level of narrative distinctiveness in two important ways. First, membership in distinctive categories can serve as an important source of differentiation for its category members vis-à-vis nonmembers of the category. Categories that are distinctive from other categories in their classification system provide their members with a useful resource to stand out (Lo et al., 2020). Moreover, the more distinctive a category, the more likely will audiences associate specific properties with the category (Lo et al., 2020) and consumers may therefore attend

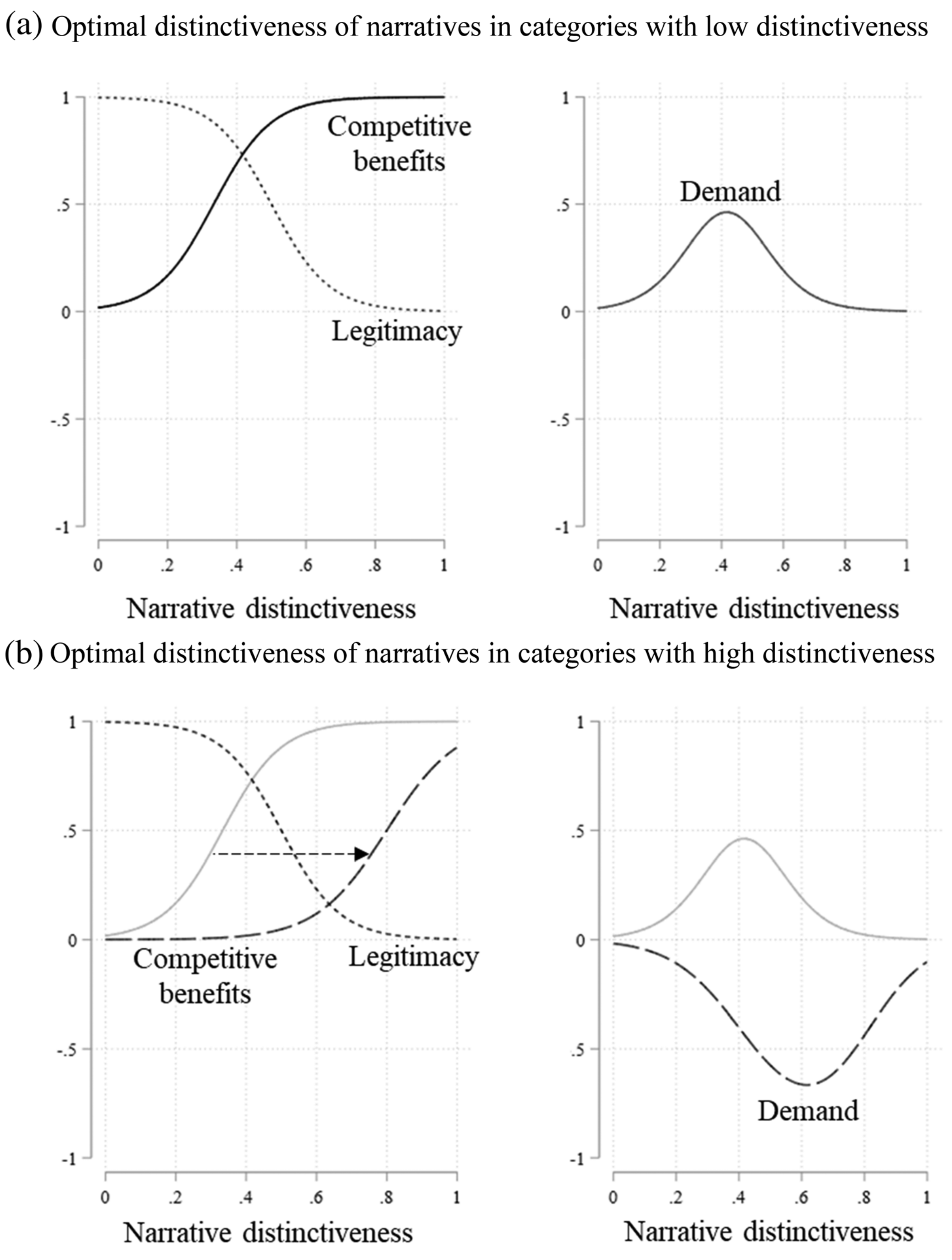

FIGURE 1 Illustration of theorized effect of narrative distinctiveness under conditions of low versus high category distinctiveness. (a) Optimal distinctiveness of narratives in categories with low distinctiveness. (b) Optimal distinctiveness of narratives in categories with high distinctiveness. For illustrative purposes, the plots for the individual mechanisms are specified as the inverse of the logit function of the equation $b0 + b1$ * Narrative distinctiveness + $b2$ * Narrative distinctiveness^2. We specified the beta coefficients for legitimacy in (a and b) as $b0 = 6$, $b1 = -12$, and $b2 = 0$. We specified the beta coefficients in (a) for competitive benefits as $b0 = -4$, $b1 = 12$, and $b2 = 0$, and the corresponding beta coefficients in (b) as $b0 = -8$, $b1 = 10$, and $b2 = 0$. The figure on the right-hand side of each panel represents the sum of both mechanisms. We subtracted 1 from the summed value to align the y-axes

to listings in a distinctive category because the category's unique properties closely match their preferences. Membership in a distinctive accommodation category (e.g., houseboats) may thus increase the likelihood that an audience segment with a specific set of preferences (e.g., accommodations with proximity to water) will select members of the distinctive category into its consideration set. A listing in a distinctive accommodation category may also more likely stand out from all available listings and may therefore be more cognitively accessible.

Findings in the category literature empirically support the assumption that a category can serve as a source of differentiation by showing that organizations are more likely to strategically promote their category membership to audiences when the category exhibits a high level of distinctiveness within their domain (Gehman & Grimes, 2017). Research on the emergence of new technologies and new categories similarly observes that producers of new technology products often strategically deploy category labels to convey their product's distinctiveness or novelty (Grodal, Gotsopoulos, & Suarez, 2015; Suarez et al., 2015; Zunino, Suarez, & Grodal, 2019).[3] For instance, many organizations strategically self-categorized into the nanotechnology category during the early 2000s—a category that was perceived as highly distinctive at the time—to signal their uniqueness and differentiate themselves within their respective industries (Granqvist et al., 2013).

If membership in a distinctive category already differentiates an offering to some degree, then, members of a distinctive category should gain lower competitive benefits from a distinctiveness-emphasizing narrative than those in indistinctive categories. In the Airbnb marketplace, this means that a moderately distinctive narrative may add no further competitive benefits in a distinctive category because members of such a category already match the preferences of specific consumer segments. The left plot in Figure 1b, therefore, illustrates the curve relating to competitive benefits as flat at low and moderate levels of narrative distinctiveness.

Second, the distinctiveness of a category may also shape which audience segments will most likely attend to its members. There is growing recognition that audiences differ in their valuation of novelty (Cattani et al., 2014; Falchetti, Cattani, & Ferriani, 2021), where some audiences respond much more favorably than others to offerings perceived as distinctive and novel (Goldberg et al., 2016; Pontikes, 2012). Drawing on the observation that an audience "is never fully homogenous but usually consists of groups or segments that can embrace rather different standards and norms by which novelty is evaluated" (Cattani et al., 2020, p. 21), we propose that novelty-seeking consumers—individuals that have a high tolerance of nonconformity and highly value novelty in an offering—substantially differ from mainstream consumers in their evaluations. Most audiences likely consist of some novelty-seekers, but innovative platforms like Airbnb tend to attract a particularly large number of novelty-seeking consumers during their early lifecycle stages (Rietveld & Eggers, 2018). In fact, a survey-based segmentation study of Airbnb users suggests that around one in three Airbnb users can be characterized as "novelty seekers"—individuals who use the Airbnb marketplace to explicitly satisfy their desire for novelty (Guttentag, Smith, Potwarka, & Havitz, 2018). We propose that such novelty-seeking consumers will more likely attend to listings in distinctive rather than indistinctive categories because a category's distinctiveness may serve them as a filtering criterion for preselecting listings for consideration. This assumption is particularly plausible in our setting because online

[3]The focus of this line of research differs, however, from our focus in that we theorize about distinctiveness between established categories, whereas this line of research explores how alternative category labels compete for adoption during the emergence of a new technology or industry. In established categories, audiences can generally draw on institutionalized knowledge about categorical conventions and prototypes (based on category members' behavior) to infer a category's distinctiveness, whereas audiences may have to infer the distinctiveness of a newly emerging category from the perceived novelty, unfamiliarity or creativity of its label (Zunino et al., 2019).

marketplaces like Airbnb allow consumers to explicitly specify certain categories as filters during their search queries (Dinerstein, Einav, Levin, & Sundaresan, 2018). Contrary to mainstream consumers, who likely consider listings from both distinctive and indistinctive categories, we propose that novelty-seeking consumers will primarily consider listings from distinctive categories because categories' perceived novelty may represent an important filtering mechanism for this audience segment.

The proposition that novelty-seeking consumers will primarily attend to listings in distinctive categories has important implications for what constitutes optimal distinctiveness in such categories. Novelty-seeking audiences generally exhibit a high tolerance of nonconformity and ambiguity and tend to perceive distinctive offerings as particularly appealing (Taeuscher et al., 2021). For instance, crowdfunding projects perceived as highly novel have a high appeal to rewards-based crowdfunders (a novelty-seeking audience) and therefore, entrepreneurs attract most crowdfunding by crafting narratives that strongly emphasize distinctiveness (Taeuscher et al., 2021). Following the assumptions that novelty-seekers primarily attend to listings from distinctive categories and that highly distinctive offerings are most appealing to novelty-seekers, we propose that offerings in distinctive categories can attract substantial demand through narratives that strongly emphasize their distinctiveness and thus appeal to novelty-seekers. As such, we propose that a highly distinctive narrative can provide strong marginal benefits in distinctive categories because a listing perceived as highly novel will generate strong demand from novelty-seeking consumers. Figure 1b illustrates this assumption graphically. We illustrate this difference through the increase in competitive benefits at high levels of narrative distinctiveness (left plot).

In sum, we expect that a low and moderate level of narrative distinctiveness will provide no or limited competitive benefits in distinctive categories, whereas a high level of narrative distinctiveness will provide strong marginal benefits. The right plot of Figure 1b illustrates how the change in the latent mechanism regarding competitive benefits can flatten the optimal distinctiveness curve to such a degree that the inverted U-shaped curve flips to a U-shaped curve. Airbnb listings in distinctive categories will therefore attract most demand if they either emphasize their conformity with the categorical prototype (to appeal to mainstream consumers) or strongly emphasize their distinctiveness from the categorical prototype (to appeal to novelty-seeking consumers). Accordingly, we hypothesize:

> **Hypothesis 2.** *Under high category distinctiveness, there is a U-shaped relationship between an Airbnb listing's narrative distinctiveness and its price premium.*

3 | RESEARCH METHODS

3.1 | Study context and data

In compiling a sample of Airbnb listings to test our hypotheses, we started by selecting cities that were publicly recognized for their favorable (e.g., San Diego, Seattle) or unfavorable (e.g., Denver, San Francisco) short-term rental regulations.[4] The purpose of this initial selection was to ensure the diversity in regulatory institutions is represented within our sample. To

[4]To grade each city's regulatory favorability, we relied on the city evaluations by Moylan (2016), who systematically evaluated the regulatory institutions in 59 US cities. Evaluations of our sampled markets are reported in Appendix A1. It is noteworthy that several cities' regulations had changed by the time of analysis.

capture potential regional differences and geographic diversity, we next selected one major city from each of the nine regional divisions, as defined by the US Census Bureau (United States Census Bureau,). We focused on major cities to ensure there was a substantial degree of competition in each of the markets. Our final sample consists of all listings in 12 cities: Austin (Texas), Boston (Massachusetts), Columbus (Ohio), Denver (Colorado), Minneapolis (Minnesota), Nashville (Tennessee), New York City (New York), New Orleans (Louisiana), San Diego (California), San Francisco (California), Seattle (Washington), and Washington DC. Appendix 1 provides an overview of these markets.

We initially identified and collected data for all listings in these 12 markets in July 2018 and subsequently replicated our data collection in 6-month intervals (January 2019, July 2019, January 2020, and July 2020). Our main data source is the information provided on Airbnb listings' individual webpages. On Airbnb, each listing is presented on a publicly accessible webpage, which contains the listing's narrative description (including a name), information about the accommodation's amenities, standardized data points about the host and the accommodation, as well as previous guests' reviews and ratings. Using web-scraping surveys of all listings available in each of the selected markets at the time—provided by the non-profit project *InsideAirbnb.com*—we were able to capture these data points at scale. The number of available listings in these 12 markets increased from July 2018 to January 2020 (from 68,667 listings in July 2018 to 106,449 listings in January 2020), but fell back to 55,068 in July 2020—likely due to the travel restrictions related to the Covid-19 pandemic.

Our dataset covers all accommodation listings in the 12 markets that were listed during at least one of five points in time (i.e., one of our five survey periods) and consists of 180,786 unique listings and 523,352 survey observations. We excluded listings that required minimum stays of 30 days or more because such long-term rentals do not represent a valid option for most guests (N = 8,257). In line with previous optimal distinctiveness research (Barlow et al., 2019), we excluded listings offered by hosts with more than 10 listings because such hosts are normally existing businesses that use Airbnb as an additional sales channel and may thus pursue different performance objectives (N = 68,957 observations). We further excluded observations with self-descriptions of less than 50 characters (N = 8,769) because such listings do not allow for meaningful content analysis. An initial review of the data also revealed outliers in terms of listings' price per night; we eliminated listings that exceeded the sample's average price by more than 10 times to avoid any bias from these listings (N = 8,331). Finally, we excluded observations with missing data (N = 3,181), including 23 observations with implausible survey data in respect to listings' category membership. The final sample consists of 159,343 unique listings and 425,857 survey observations.

3.2 | Dependent variable

Our dependent variable is the *price premium* of each Airbnb listing. Ideally, we could have access to data on each listings' revenue generation within a given period, but we are not aware of any online marketplaces that publish financial performance metrics at the level of individual producers or listings. Studying the performance of listings within online marketplaces therefore requires researchers to identify context-specific proxies. Prior studies of the Airbnb marketplace have focused on listings' price per night as the most suited proxy for the "success" of Airbnb listings (Edelman & Luca, 2014; Ert & Fleischer, 2019; Ert, Fleischer, & Magen, 2016; Kakar, Voelz, Wu, & Franco, 2018; Wang & Nicolau, 2017). The idea is that Airbnb accommodations have a fixed capacity because hosts can only rent an accommodation unit to one customer at a time (even though a customer can consist of several individuals). Heterogeneity in guests' demand for a listing therefore manifests itself primarily in the price a host charges for a listing.

This assumption is particularly plausible in our context because Airbnb provides hosts with a sophisticated price-setting algorithm ("Smart pricing") that automatically sets a listing's price to maximize a listing's revenue generation in light of the observed demand for the listing. All else being equal, a higher price therefore indicates higher demand for a listing. However, prices also reflect the attractiveness of a particular geographic area, and they are systematically higher in some geographic areas than others. We therefore constructed a measure of price premium that represents the degree to which a listing's price exceeds the average price in that geographic area. Airbnb already classifies listings into "neighborhoods," and we used this classification as the basis for standardizing prices by the local price level. We calculated price premium by standardizing listings' price per night within a given neighborhood and observation time.

Specifically, we subtracted the average price per night in a listing's neighborhood at a given time from the listing's price per night at that time, and divided the measure by the standard deviation of the price per night in the neighborhood at the time. Standardizing within each observation time further allowed us to net out any seasonal price fluctuations when calculating a listing's price premium. A price premium of 0 indicates that a listing charges a price that aligns with the average price per night in the neighborhood at the time, and a price premium of 1 indicates that a listing demands a price that is one standard deviation above the neighborhood's average price at the time.

3.3 | Independent variables

Narrative distinctiveness captures the degree to which the content of a listing's narrative deviates from the content of the prototypical narrative in the listing's category. For each listing, we considered the listing's name, summarizing the description of the accommodation offering, and description of the accommodation space as parts of its narrative. We followed previous research (Haans, 2019; Taeuscher et al., 2021) and used latent Dirichlet allocation (LDA), which is the most commonly applied topic modeling technique (Hannigan et al., 2019), to develop our measure of narrative distinctiveness. This approach allowed us to identify common topics used by Airbnb hosts to describe their accommodations and to subsequently represent each narrative as a probabilistic vector of these topics. We calculated a separate topic model for each observation time to account for potential changes in the narrative content over time and to account for the entry and exit of listings. In other words, for each observation period we constructed a text corpus that consisted of the textual narratives of all listings in the selected markets over that observation period.[5]

We chose a model with 25 topics after comparing the results of topic models with 25, 50, 75, and 100 topics in terms of their interpretability. Previous optimal distinctiveness studies have specified their topic models to 100 topics (Haans, 2019; Taeuscher et al., 2021). We

[5]Our topic modeling procedure followed recent practice (Haans, 2019; Taeuscher et al., 2021). Specifically, we cleaned our text corpus by removing nonalphanumeric characters and highly generic words, focusing on nouns, adjectives, verbs, and adverbs, eliminating words with fewer than 10 occurrences in the entire corpus of all texts in our sample, and stemming the words. In the process of data cleaning, we also identified a small number of narratives that used a language other than English and excluded them from the text corpus.

therefore started our search process with 100 topics but found that this number yielded too many indistinguishable topics since narratives in our context broadly relate the same type of offering (accommodation rental) rather than offerings across multiple industries. We subsequently compared the topic-keyword matrices for topic models with 100, 75, 50, 25, and 10 topics and found that the model with 25 topics provided the best balance between interpretability and distinctiveness between topics. We also compared the alternative topic models with regard to their perplexity score and log-likelihood—two commonly used measures of model fit, where a lower perplexity score and a higher log-likelihood indicate a higher model accuracy (Hannigan et al., 2019). These technical indicators of model fit suggested that the model with 10 topics would lead to the most accurate topics. However, qualitative analysis of the 10-topics solution revealed that this model yielded less meaningful topics than the 25-topics solution. Therefore, we opted for the 25-topics solution, but nevertheless confirmed our regression results with alternative topic models (see Section 4.2). We developed all our topic models using Python's *Gensim* package. Appendix A2 presents the 10 most representative words for each of the 25 topics in the selected topic model.

When listing an accommodation on Airbnb, hosts are asked to self-categorize their listings into one of 45 categories (e.g., *Bungalow*, *Aparthotel*, *Treehouse*). The implicit assumption underlying our measure of narrative distinctiveness is that Airbnb hosts can theoretically draw on 25 different topics to construct a narrative for their listing and can differentiate the narrative by drawing on topics that are rather uncommon in the listing's category or by refraining to draw on topics that are highly representative for the category (i.e., most commonly used). Following recent optimal distinctiveness studies (Haans, 2019; Taeuscher, 2019), and additionally incorporating a temporal dimension, we calculated narrative distinctiveness of a listing as follows:

$$\sum_{T=1}^{25} abs\left(\Theta_{T,i,t} - \overline{\Theta}_{T,c,t}\right),$$

where $\Theta_{T,i,t}$ refers to listing i's weight for topic T at time t, and $\overline{\Theta}_{T,C,t}$ refers to the average weight for topic T in accommodation category c at time t. For each category, we calculated the average topic weights based on all available listings in that category, not just those included in our regression sample. A listing's narrative distinctiveness was thus measured by the absolute distance between the weight of a topic in the listing's narrative (at the time) and the category's prototypical narrative at the time (measured by the average topic share across all listings in the category period), summed over all 25 topics. A narrative distinctiveness of 0 indicates that a listing's narrative draws on all topics with exactly the same weights as the prototypical narrative in its category at the time. Appendix A3 provides examples of narratives with low, moderate and high distinctiveness.

Category distinctiveness refers to the degree to which a given category's prototypical features differ from the prototypical features of other categories in the same classification system. We measured category distinctiveness based on categories' prototypical amenities because different accommodation categories are generally associated with a different set of amenities. For instance, the *Aparthotel* category is relatively similar to the *Apartment* category; listings in either category generally provide a kitchen but do not provide a pool or gym. The two categories differ, among others, in that listings in the Aparthotel category generally include breakfast, whereas listings in the Apartment category generally do not. We exploited the fact that Airbnb provides a comprehensive list of accommodation-relevant amenities and requires each host to specify in a standardized format which of these amenities are provided by their listing. In total, we observed 56 different amenity types during our observation period, including tangible (e.g., pool) and intangible (e.g., self-check-in) features of the accommodation service.

To infer a category's prototype (in terms of amenities), we calculated each category's average share of listings that offered a respective amenity in a given period. Categories' average amenity shares can broadly indicate the probabilities at which users may reasonably expect listings from a given category to provide certain amenities. We therefore represented each category period as a probability vector of amenities based on the relative share of listings in that category offering the amenity at the time. We then calculated the cosine distance between two categories *c* and *d* over all 56 amenities as $\sum_{A=1}^{56} cosine\left(\overline{\Theta}_{A,c} - \overline{\Theta}_{A,d}\right)$, where $\overline{\Theta}_{A,c}$ refers to category *c*'s probability of amenity A, and $\overline{\Theta}_{A,d}$ refers to category *d*'s probability for amenity A. This approach allowed us to estimate the cosine distance between each unique category pair (e.g., Aparthotel versus Apartment). We subsequently calculated a given category's *category distinctiveness* as the median distance between the focal category and each of the other 44 categories. The measure therefore represents the degree to which a given category differs from the other 44 categories in terms of their prototypical amenities. A high level of category distinctiveness implies that the prototypical amenities of a given category substantially deviate from the prototypical amenities of other categories.[6] For ease of interpretation, we also created a dummy variable—*distinctive category*—which we coded as 1 for category periods in which category distinctiveness is larger than the median level of category distinctiveness at the time, and 0 otherwise.

3.4 | Control variables

We included variables to control for potential confounding effects at the level of (a) categories, (b) listings, (c) hosts, (d) markets, and (e) neighborhoods. Category coherence and category density represent two category-level controls. We controlled for category coherence because listings' membership in coherent categories may facilitate guests' comprehension of these listings (Lo et al., 2020), and such categories may provide more leeway for differentiation (Haans, 2019). In our context, we measured *category coherence* as the average degree to which all narratives within a category are similar to the categorical prototype in terms of the category's five most representative topics. The underlying idea is that each category may be characterized by a small number of highly representative topics, and a category is more coherent if a large share of its members align their narrative contents with these highly representative topics. We therefore identified the five most representative topics in a given category period and subsequently calculated the average absolute distance between the category period's average topic probabilities and each category member's topic probabilities, summed over the five identified topics. We subtracted the resulting value from 1 to transform the distance measure into a measure of coherence, where higher values indicate higher levels of category coherence. We further controlled for *category density*, measured as the natural logarithm of the number of available listings in a category period, to capture differences in the demand and competition within different

[6]We also measured the distances between-category pairs as (a) Euclidean distances and (b) absolute distances, and (c) further calculated category distinctiveness as a category's mean (instead of median) distance across category pairs. We further calculated each of these alternative distance measures based on categories' median share of each amenity (i.e., 1/0). The measures are highly correlated, and choosing a different measure does not change our results. In our results section, we also present robustness tests in which we calculated a measure of category distinctiveness based on average topic shares in category periods (i.e., based on categories' prototypical narratives).

categories. Since these two control variables showed a strong negative correlation, we orthogonalized them and included the orthogonalized measure of category density.

We followed previous Airbnb studies (Ke, 2017; Zervas, Proserpio, & Byers, 2021) and included 11 listing-level controls: review count, rating, amenities count, room type, guests included, number of bathrooms, minimum nights, instant booking, verification required, cancellation policy, and narrative length. Review count and rating are two important reputation signals in online marketplaces (Taeuscher, 2019). *Review count* was captured by the logged number of guest reviews that a listing received up until the given period. *Rating* was measured by previous guests' evaluation of the accommodation. Airbnb is similar to other online marketplaces in that guests rate listings on a scale of one to five stars. Since listings without any reviews naturally lack this data point (Airbnb only displays average ratings once a listing has received at least three reviews), we transformed the numerical rating into a categorical variable to prevent loss of these observations. Our categorical variable of *rating* consists of four levels: "none," "low" for numerical ratings below the sample's 25th percentile, "moderate" for values between the 25th and 75th percentiles, and "high" for values above the 75th percentile. We further included the variable *amenities count*, which captures the number of different amenities provided by a given listing. *Room type* was a categorical variable that refers to whether hosts rent out an entire unit, a private room in a shared unit, or a bed in a shared room (Ke, 2017). *Guests included* was measured as the number of guests that can stay at a listing during the accommodation period at no additional cost. We further included *number of bathrooms*, a count measure of the number of bathrooms offered in the accommodation, as a proxy for the accommodation's size. We initially also controlled for the *number of bedrooms*, but preliminary analysis suggested that number of bathrooms and number of bedrooms are highly correlated. We included *minimum nights* to capture the minimum number of nights for which guests need to book a listing because some hosts require guests to stay for more than one night. Airbnb hosts further specify whether guests can instantly book a listing without prior inquiry (*instant booking)* and whether guests are required to first verify themselves by phone before being able to book the listing (*verification required*). We controlled for both in our models. *Cancellation policy* affects the degree of ease with which guests can cancel a booking and was operationalized as a categorical variable based on Airbnb's classification (flexible, moderate, strict, and super strict). We also included *narrative length*, the logged number of characters in a listing's description, to net out heterogeneity in narratives' lengths.

We further included seven host-level controls: host listings count, host identity verified, host photo, host response time, superhost, gender, and race. We first controlled for hosts' number of Airbnb listings (*host listings count*) because hosts with a larger portfolio may be more experienced in offering high-quality accommodation service. Conversely, guests may perceive accommodations as more authentic if they are provided by hosts who only offer one or a few listings (Guttentag et al., 2018). *Host identity verified* is a dummy variable indicating whether a host has been formally verified by Airbnb through one of several verification methods. *Host photo* indicates whether a host provided a photo in his or her profile. *Response time* indicates how quickly a host responds to booking requests on average. Airbnb displays one of five value labels to codify hosts' response time (e.g., "within an hour"), which we used to construct host response time as a categorical variable. Airbnb visibly marks hosts as "superhost" if they have received a minimum of 10 bookings, have a response rate of 90% or higher, have received five stars in at least 80% of reviews, and have never canceled a booking (Airbnb, 2019). We followed previous research and included *superhost* as a binary measure to indicate a host's superhost status (Ke, 2017; Proserpio, Xu, & Zervas, 2018). Previous research suggested that Airbnb guests may systematically discriminate hosts based on their gender and/or race (Edelman, Luca, & Svirsky, 2017). Airbnb does not explicitly display information about a host's gender or race, but guests can generally infer this information from the hosts' photos and first names (Edelman et al., 2017). We therefore leveraged hosts' first names to infer their gender and race. Detailed coding procedures are presented in Appendix A4. Gender was coded as categorical variable ("female"; "male"; and "not available"), so was race ("Black"; "Hispanic"; "White"; "other"; and "not available").

We included a dummy for each market (i.e., city) to net out inter-market heterogeneity in accommodation demand and supply or regulatory differences between these markets. At the level of neighborhoods, we controlled for *price level in neighborhood*—the natural logarithm of the average price per listing in a given neighborhood—to account for differences in the attractiveness of neighborhoods. We further controlled for *density in neighborhood*, a count measure of all Airbnb listings in given neighborhood, to further control for heterogeneity in local levels of competition. To control for temporal and seasonal dynamics, we further included dummies for each of the years and dummies for each season in which we surveyed the Airbnb marketplace.

3.5 | Model

Our dataset consists of a panel of Airbnb listings with up to five repeated observations per listing. We estimated our main models using the generalized estimating equation (GEE) approach—an extension of generalized linear models for panel data (Ballinger, 2004; Liang & Zeger, 1986). The GEE approach allowed us to account for the correlation between the repeated measurements over time, estimate population-averaged parameters (as opposed to listing-specific parameters), and specify the models to the most appropriate correlation structure. In doing so, the GEE approach provided the most efficient and unbiased parameter estimates for our panel data (Hardin & Hilbe, 2013). Our dependent variable, *price premium*, is continuous and follows a normal distribution. We therefore specified the GEE model with a Gaussian distribution and an identity link function.

The consistency of parameter estimates in GEE models do not depend on the specified correlation structure, but choosing an appropriate correlation structure increases the efficiency of model estimates (Ballinger, 2004). We used the quasi-likelihood under the independence model criterion (QIC) statistic, as implemented in the *qic* Stata module (Cui, 2007), to compare the efficiency of different correlation structures. Estimating the QIC statistic revealed that an independent correlation structure led to more efficient parameter estimates than models specified with an autoregressive, unstructured, or exchangeable correlation structure. Specifying our correlation structure as independent also allowed us to include listings with only one observation in our estimations. We specified our models with heteroscedasticity-robust standard errors and reported significance levels based on Huber–White robust standard errors to control for potential heteroscedasticity across panels. This approach allowed us to further account for the repeated observation structure of our data, which is equivalent to clustering by listings (Wooldridge, 2010).

4 | RESULTS

4.1 | Main results

Table 1 provides descriptive statistics and the correlation matrix for our regression sample. The correlation table shows that narrative distinctiveness is not significantly correlated with category distinctiveness. Category distinctiveness has a slightly negative correlation with our control variables of category coherence and category density.[7] The mean value of price premium is slightly below zero because we calculated price premium based on *all* available listings in a neighborhood at the time, but excluded listings with price outliers from the regression sample (see Section 3.1).

Model 1 of Table 2 includes narrative distinctiveness and control variables to test for a potentially linear effect of narrative distinctiveness on price premium. The positive coefficient suggests that narrative distinctiveness, on average, has a positive effect on listings' price premium. Model 2 adds the quadratic term of narrative distinctiveness (*Narrative distinctiveness^2)* to test for a curvilinear relationship between narrative distinctiveness and price premium. The low statistical significance of narrative distinctiveness and narrative distinctiveness^2 in Model 2 suggests that the relationship between narrative distinctiveness and price premium follows neither a consistently U-shaped nor inverted U-shaped relationship over the entire data range. A formal test, using STATA's *utest* module (Lind & Mehlum, 2010), also rejects the alternative hypothesis that narrative distinctiveness has a consistently U-shaped or inverted U-shaped effect on price premium over the entire data range.

Hypotheses 1 and 2 stated that the relationship between listings' narrative distinctiveness and price premium follows an inverted U-shaped relationship (U-shaped relationship) in categories with low (high) distinctiveness. Model 3 adds interactions between-category distinctiveness and the single and squared term of narrative distinctiveness to model the relationship under varying levels of category distinctiveness. To illustrate the relationship, we post-estimated price premium at different levels of narrative distinctiveness (within the sample's 1st and 99th percentile) and category distinctiveness (median and one standard deviation below/above the median). The plot in Figure 2 suggests that the relationship between narrative distinctiveness and price premium strongly depends on the level of category distinctiveness. The plot shows that the relationship follows an inverted U-shaped relationship under conditions of low category distinctiveness. An increase in category distinctiveness flattens the inverted U-shaped curve to the degree that the curve flips into a slightly U-shaped relationship at a moderate level of category distinctiveness and a clearly U-shaped relationship at high levels of category distinctiveness. At above-average levels of category distinctiveness, increases in narrative distinctiveness have a negative effect on price premium until the narrative exceeds a moderate level of narrative distinctiveness, and a positive effect once the narrative already exhibits above-average levels of distinctiveness. The plot provides strong evidence in support of our hypothesized relationships.

While there exists no test statistic to formally test for a flip from inverted U to U-shaped curve, such a shape-flip can be seen as an extreme case of curve-flattening. Hence, formal support for the hypothesized and visualized curve-flipping effect comes from the interaction term between narrative distinctiveness^2 and category distinctiveness. A curve-flattening effect would formally exist if the coefficient of this interaction term is positive and statistically significant (Haans, Pieters, & He, 2016). The interaction term in Model 3 is indeed positive and the low *p*-value and narrow standard errors suggest that this relationship is statistically significant. Model 3 therefore provides formal support for the curve-flattening effect that is necessary for an inverted U-shaped curve to flip into a U-shaped curve. Formal exploration of the curve's shape

[7]It is important to note that the presented correlations and model coefficients for category-level measures (category distinctiveness, category coherence, category density) are based on our listing-level dataset and therefore only allow limited interpretation of their direct effects on price premium.

TABLE 1 Descriptive statistics and correlation table

	Variable	Mean	*SD*	Min	Max	1	2	3	4	5	6	7
1	Price premium	−0.05	0.80	−2.37	27.15	1.00						
2	Price (ln)	4.85	0.79	0.00	7.73	0.67	1.00					
3	Narrative distinctiveness	1.15	0.22	0.00	1.90	−0.01	−0.02	1.00				
4	Category distinctiveness	0.05	0.01	0.04	0.48	−0.06	−0.06	0.00	1.00			
5	Distinctive category (dummy)	0.55	0.50	0.00	1.00	−0.10	−0.13	0.05	0.66	1.00		
6	Category coherence	0.49	0.05	0.15	1.00	−0.01	0.02	0.08	−0.02	−0.15	1.00	
7	Category density	10.12	1.30	0.00	11.11	−0.01	−0.05	0.13	−0.16	0.30	−0.44	1.00
8	Review count	2.43	1.69	0.00	6.86	−0.13	−0.17	−0.22	−0.04	−0.05	0.03	−0.12
9	Amenities count	19.68	7.64	0.00	47.00	0.09	0.14	−0.24	−0.17	−0.22	0.10	−0.18
10	Guests included	1.87	1.69	1.00	35.00	0.28	0.31	−0.12	−0.14	−0.18	0.02	−0.05
11	Bathrooms	1.32	0.69	0.00	50.00	0.36	0.42	−0.05	−0.22	−0.31	0.01	−0.07
12	Minimum nights	4.47	7.35	1.00	30.00	−0.02	−0.03	0.00	0.03	0.01	−0.05	0.01
13	Instant booking = 1	0.42	0.49	0.00	1.00	−0.01	0.02	0.00	−0.03	−0.05	0.05	−0.05
14	Phone verification = 1	0.03	0.16	0.00	1.00	0.00	0.00	−0.06	0.00	−0.01	0.01	−0.01
15	Narrative length	1,107.53	665.05	51.00	4,098.00	0.02	0.02	−0.55	−0.05	−0.09	0.07	−0.13
16	Host listings count	1.10	0.45	0.69	6.86	0.00	0.01	−0.01	0.06	−0.02	0.04	−0.09
17	Verified = 1	0.51	0.50	0.00	1.00	−0.02	−0.03	−0.08	0.00	0.01	−0.01	0.01
18	Photo = 1	1.00	0.05	0.00	1.00	0.00	−0.01	−0.01	0.00	−0.01	0.01	−0.01
19	Superhost = 1	0.32	0.47	0.00	1.00	−0.05	−0.05	−0.18	−0.09	−0.13	0.07	−0.16
20	Density in neighborhood	1,006.62	1,192.66	1.00	4,569.00	−0.02	0.06	0.01	0.04	0.16	−0.03	0.14
21	Price level in neighborhood	4.88	0.39	3.00	6.96	−0.06	0.44	−0.01	−0.01	−0.08	0.05	−0.10

	8	9	10	11	12	13	14	15	16	17	18	19	20	21
8	1.00													
9	0.41	1.00												

TABLE 1 (Continued)

	8	9	10	11	12	13	14	15	16	17	18	19	20	21
10	0.15	0.30	1.00											
11	−0.07	0.19	0.35	1.00										
12	−0.09	−0.03	−0.03	0.01	1.00									
13	0.06	0.13	0.05	0.03	−0.07	1.00								
14	0.11	0.04	0.02	0.00	0.04	−0.06	1.00							
15	0.41	0.41	0.19	0.06	0.01	0.00	0.10	1.00						
16	0.03	0.09	0.06	0.08	0.06	0.08	0.03	0.08	1.00					
17	0.15	−0.01	0.01	−0.04	0.02	−0.18	0.09	0.12	−0.05	1.00				
18	0.02	0.01	0.01	0.00	0.00	−0.01	0.00	0.02	0.00	0.05	1.00			
19	0.50	0.40	0.13	0.01	−0.05	0.05	0.05	0.32	0.03	0.08	0.03	1.00		
20	−0.14	−0.13	−0.07	−0.04	−0.04	−0.02	−0.01	−0.07	−0.04	−0.01	−0.01	−0.13	1.00	
21	−0.05	0.09	0.07	0.15	0.00	0.03	0.01	0.02	0.05	−0.01	−0.01	0.02	0.15	1.00

Note: Values for *Category density* before orthogonalization.

TABLE 2 Results of GEE models estimating price premium of Airbnb listings

DV: *Price premium*	Model 1			Model 2			Model 3			Model 4		
	Coef.	*SE*	*p*	*Coef.*	*SE*	*p*	*Coef.*	*SE*	*p*	*Coef.*	*SE*	*p*
Narrative distinctiveness	0.02	0.008	0.021	0.05	0.052	0.292	1.44	0.236	0.000	0.28	0.093	0.003
Narrative distinctiveness^2				−0.02	0.023	0.497	−0.63	0.108	0.000	−0.12	0.041	0.004
Narrative distinctiveness × category distinctiveness							−24.99	4.164	0.000			
Narrative distinctiveness^2 × category distinctiveness							11.09	1.909	0.000			
Distinctive category = 1										0.13	0.063	0.034
Narrative distinctiveness × distinctive category = 1										−0.48	0.112	0.000
Narrative distinctiveness^2 × distinctive category==1										0.21	0.049	0.000
Category distinctiveness	−2.01	0.247	0.000	−2.01	0.247	0.000	11.38	2.202	0.000			
Category coherence	0.74	0.056	0.000	0.74	0.056	0.000	0.73	0.055	0.000	0.35	0.057	0.000
Category density	0.01	0.003	0.000	0.01	0.003	0.000	0.01	0.002	0.000	0.02	0.003	0.000
Review count	−0.06	0.002	0.000	−0.06	0.002	0.000	−0.06	0.002	0.000	−0.06	0.002	0.000
Rating: None	0.23	0.008	0.000	0.23	0.008	0.000	0.23	0.008	0.000	0.23	0.008	0.000
Rating: Average	0.05	0.004	0.000	0.05	0.004	0.000	0.05	0.004	0.000	0.05	0.004	0.000
Rating: High	0.07	0.005	0.000	0.07	0.005	0.000	0.07	0.005	0.000	0.07	0.005	0.000
Amenities count	0.00	0.000	0.000	0.00	0.000	0.000	0.00	0.000	0.000	0.00	0.000	0.000
Room type: private room	−0.46	0.004	0.000	−0.46	0.004	0.000	−0.46	0.004	0.000	−0.48	0.005	0.000
Room type: shared room	−0.49	0.005	0.000	−0.49	0.005	0.000	−0.49	0.005	0.000	−0.50	0.005	0.000
Room type: hotel room	−0.62	0.022	0.000	−0.62	0.022	0.000	−0.62	0.022	0.000	−0.62	0.022	0.000
Guests included	0.06	0.003	0.000	0.06	0.003	0.000	0.06	0.003	0.000	0.06	0.003	0.000
Number of bathrooms	0.33	0.017	0.000	0.33	0.017	0.000	0.33	0.017	0.000	0.32	0.017	0.000
Minimum nights	−0.01	0.000	0.000	−0.01	0.000	0.000	−0.01	0.000	0.000	−0.01	0.000	0.000
Instant booking = 1	−0.01	0.004	0.007	−0.01	0.004	0.007	−0.01	0.004	0.006	−0.01	0.004	0.016
Verification required = 1	0.04	0.011	0.000	0.04	0.011	0.000	0.04	0.011	0.000	0.04	0.011	0.000

TABLE 2 (Continued)

DV: *Price premium*	Model 1			Model 2			Model 3			Model 4		
	Coef.	*SE*	*p*	*Coef.*	*SE*	*p*	*Coef.*	*SE*	*p*	*Coef.*	*SE*	*p*
Cancellation policy included	Yes			Yes			Yes			Yes		
Narrative length	0.00	0.000	0.071	0.00	0.000	0.069	0.00	0.000	0.061	0.00	0.000	0.082
Host listings count	−0.02	0.004	0.000	−0.02	0.004	0.000	−0.02	0.004	0.000	−0.02	0.004	0.000
Host identity verified = 1	0.01	0.004	0.002	0.01	0.004	0.002	0.01	0.004	0.002	0.01	0.004	0.004
Profile photo = 1	−0.05	0.036	0.131	−0.05	0.036	0.130	−0.05	0.036	0.131	−0.05	0.036	0.143
Superhost = 1	−0.01	0.004	0.001	−0.01	0.004	0.001	−0.01	0.004	0.001	−0.01	0.004	0.001
Female	0.04	0.007	0.000	0.04	0.007	0.000	0.04	0.007	0.000	0.04	0.007	0.000
Male	0.01	0.007	0.437	0.01	0.007	0.438	0.01	0.007	0.422	0.01	0.007	0.443
Race: Black	0.02	0.008	0.012	0.02	0.008	0.012	0.02	0.008	0.011	0.02	0.008	0.015
Race: Hispanic	0.01	0.008	0.422	0.01	0.008	0.422	0.01	0.008	0.412	0.01	0.008	0.411
Race: White	0.03	0.008	0.000	0.03	0.008	0.000	0.03	0.008	0.000	0.03	0.008	0.001
Race: other	−0.01	0.012	0.209	−0.01	0.012	0.211	−0.02	0.012	0.190	−0.02	0.012	0.155
Price level in neighborhood	−0.34	0.006	0.000	−0.34	0.006	0.000	−0.34	0.006	0.000	−0.33	0.006	0.000
Density in neighborhood	0.00	0.000	0.000	0.00	0.000	0.000	0.00	0.000	0.000	0.00	0.000	0.000
Market dummies included	Yes			Yes			Yes			Yes		
Quarter dummies included	Yes			Yes			Yes			Yes		
Year dummies included	Yes			Yes			Yes			Yes		
Constant	0.74	0.060	0.000	0.72	0.066	0.000	−0.02	0.138	0.912	0.75	0.077	0.000
Observations	425,857			425,857			425,857			425,857		
Number of listings	159,334			159,334			159,334			159,334		
Wald x^2	33,195.16			33,196.26			33,215.82			33,169.11		
p	.000			.000			.000			.000		

Note: GEE models are estimated using all listing observations in July 2018, January 2019, July 2019, January 2020, and July 2020 in the 12 selected markets. Models are specified with Gaussian distribution, identity link function, and independent correlation structure. The standard errors are estimated using a robust estimator.

flip suggests that the curve flips at a category distinctiveness of 0.056, a level that aligns very closely with the sample's mean (0.055) and median (0.054) levels of category distinctiveness.

Comparing the curves in Figure 2 at each given level of narrative distinctiveness, we find that a moderate level of narrative distinctiveness has, ceteris paribus, a more positive effect on price premium in categories with low category distinctiveness than in categories with high distinctiveness. This finding further supports our proposition that the benefits of moderately distinctive narratives are weaker for listings in distinctive (versus indistinctive) categories. The figure further shows that high narrative distinctiveness is associated with a strong marginal increase in predicted price premiums in categories with high distinctiveness—in comparison to a marginal decrease in the expected price premium in categories with low distinctiveness—and therefore suggests that a strongly distinctive narrative is more beneficial in distinctive (versus indistinctive) categories.

In Model 4, we replaced the continuous variable category distinctiveness by the corresponding dummy variable—distinctive category—and interacted this dummy variable with the single and squared term of narrative distinctiveness. The model similarly shows a positive and statistically significant interaction effect between narrative distinctiveness^2 and distinctive category, adding further support to the theorized moderation effect. A respective plot based on the binary classification of categories into distinctive and indistinctive ones confirms the effect presented in Figure 2: the relationship between narrative distinctiveness and price premium follows an inverted U-shaped curve in indistinctive categories and a U-shaped curve in distinctive categories.

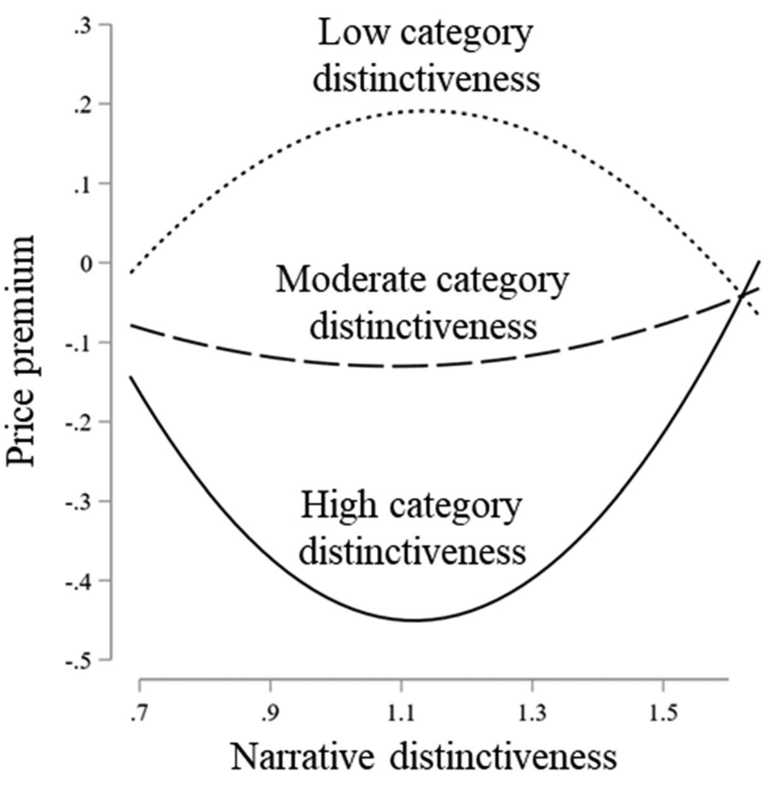

FIGURE 2 Estimated effect of narrative distinctiveness on price premium at different levels of category distinctiveness. The plot represented the predicted price premium at different levels of narrative distinctiveness (1st to 99th percentile) and category distinctiveness (median and 1 *SD* below/above the median; based on unique category periods). The model is estimated based on main Model 3 of Table 2

4.2 | Robustness tests

We conducted various robustness tests to confirm the reliability of our main findings. To do so, we focused on four key choices that may have influenced our results. First, we validated that our findings do not change with different parameter choices for our topic model, particularly in terms of the specified number of topics. Our findings were fully replicated if we specified our models to 10 or 50 topics.

Second, we validated whether our findings are robust if we predicted the natural logarithm of a listing's price per night—*price (ln)*—instead of its price premium. Appendix A5, which presents alternative GEE models predicting price (ln), provides strong support for our main findings. Our findings were also replicated when we standardized price premium to the entire sample of listings rather than a given neighborhood.

Third, we validated that our findings are consistent if we excluded listings from categories with very low category density; this is to verify that our results are not driven by systematic differences in the density of categories because categories with only a few listings may provide more leeway for differentiation. Excluding listings from categories with less than five listings at a given time ($N = 66$) fully confirms our findings.

Fourth, we further tested the robustness of our main relationship by constructing alternative measures of category distinctiveness. Appendix A6 presents models with alternative measures of category distinctiveness. Models 1 and 2 in Appendix A6 confirm that our findings are not sensitive to the chosen distance measure through which we calculate distances between each category pair. The respective models confirm that our findings do not change if we measure inter-category distances as Euclidian or absolute distances (rather than cosine distances). Model 3 in Appendix A6 further confirms that our results do not change if we measure category distinctiveness as a given category's average (rather than median) distance from each of the other categories. Model 4 in Appendix A6 presents findings for an alternative measure of category distinctiveness based on the median availability (instead of mean availability) of each amenity across all listings of a given category. The measure thus represents categorical prototypes as vectors of 56 binary variables (for 56 amenities), where each binary amenity variable is either 1 if the majority of listings in a category offers the amenity, or 0 otherwise. The measure consequently represents category distinctiveness as the median cosine distance between a given category's vector of binary amenity variables and the respective vectors of each other category. Model 5 in Appendix A6 presents findings based on an alternative approach to operationalize category distinctiveness, in which we calculated inter-category distances based on categories' prototypical narratives (rather than prototypical amenities). Analogous to our main measure, this measure represents median cosine distances between a given category's vector of topic probabilities and each of the other categories' topic probability vectors. These robustness tests fully confirm our main results at a high level of statistical significance and therefore provide strong additional support for our hypotheses.

4.3 | Supplemental analyses

This section presents findings from supplemental analyses about the size of our identified moderation effect, as well as additional evidence supporting the assumption that Airbnb users attend to multiple categories. We quantified the size of the effect of narrative distinctiveness on price premium in distinctive versus indistinctive categories based on the results of Model 4 of Table 2. Results are presented in Appendix A7. To compare the relative effect of narrative distinctiveness, we predicted price premiums at different levels of narrative distinctiveness at low and high category distinctiveness, and subsequently calculated the relative increase/decrease in predicted price premiums between these scenarios. In indistinctive categories (i.e., distinctive category = 0), we find that a standard deviation increase in narrative distinctiveness increases the expected price premium by 41.1% if the narrative has a low distinctiveness (one standard deviation below mean), but decreases the price premium by 10.9% if the narrative is already moderately distinctive and by 57.2% if the narrative is already distinctive (one standard deviation above mean). In distinctive categories (i.e., distinctive category = 1), the same standard deviation increase in narrative distinctiveness decreases the expected price premium by 0.2% for narratives with low distinctiveness and increases the expected price premium by 8.1% and 17.8% if the narrative exhibits a moderate or high level of distinctiveness.

We aimed to empirically validate our theory's underlying assumption that Airbnb users do not have a clear preference for one specific category and therefore do not limit their attention to the listings of one single category. To validate this assumption, we collected additional data to construct a user-level dataset. We exploited the fact that the majority of Airbnb users provide online reviews after they stayed at an accommodation (Fradkin, Grewal, Holtz, & Pearson, 2015; Zervas et al., 2021) and Airbnb presents these reviews with the respective user's name and unique identifier on a given listing's webpage. Web-scraping surveys of all online reviews for all listings in our sample allowed us to identify all unique users that left at least one review for one of the sample listings. Users' unique identifiers subsequently allowed us to identify all listings reviewed by each given user and therefore provided us unique insights into the heterogeneity of listings reviewed (and therefore necessarily booked) by individual users. In total, we collected 5,694,543 unique online reviews for 117,989 unique listings from our sample, provided by 4,446,569 unique users. Due to our interest in the heterogeneity of individual users' category choices, we focused on those 808,287 unique users (18.2%) that have reviewed at least two different sample listings.

If our assumption is true, then a substantial share of these users should have reviewed listings from more than one category. Among these 808,287 users, we find that 559,317 (69.2%) have reviewed listings from more than one category. Assuming that review-providing users do not substantially differ from users that do not provide reviews, this finding suggests that the majority of Airbnb users that stayed in more than one listing have stayed in listings from more than one accommodation category. The plot presented in Appendix A8 further suggests that the number of categories from which an Airbnb user chooses accommodations increases proportionally with the user's number of reviewed accommodations. These user-level data provide strong support for our assumption that individual Airbnb users do not limit their attention to one specific accommodation category. Appendix A9 provides further supplemental analyses based on Airbnb users' online reviews.

5 | DISCUSSION AND CONCLUSION

Our theory and findings most directly contribute to cultural entrepreneurship theory and the burgeoning literature on optimal distinctiveness (Barlow et al., 2019; Bu et al., 2022; Haans, 2019; Taeuscher et al., 2021; Taeuscher & Rothe, 2021; Zhao et al., 2017; Zhao et al., 2018). Specifically, we propose and demonstrate that the optimal level of distinctiveness within a given category is shaped by the category's distinctiveness vis-à-vis other categories within its category system. By theorizing about how categories' distinctiveness shapes the optimal level of intra-category distinctiveness, our study takes a first step toward a multilevel theorization of optimal distinctiveness. This is an important step since optimal distinctiveness theory essentially transcends across different levels of analysis (Zhao, 2022), but research engaging this multilevel conceptualization of optimal distinctiveness remains rare (see Bu et al., 2022 as an exception).

By highlighting category distinctiveness as an important boundary condition for the attainment of optimal distinctiveness, our study advances the emerging line of research that theorizes about the conditions under which distinctiveness will be (most) beneficial for demand-side performance outcomes (Haans, 2019; Taeuscher & Rothe, 2021; Zhao et al., 2018). For instance, Haans (2019) demonstrated that the optimal firm positioning differs between industry categories in which competitors choose relatively homogenous positions near the category's prototype—thereby providing more leeway for differentiation—and industry categories in which competitors occupy relatively heterogeneous positions. Focusing on product categories' development stage, Zhao et al. (2018) showed that the optimal distinctiveness of products' positioning changes as categories become more established. Studying optimal distinctiveness in the strategic positioning of multi-sided platforms (Rietveld & Schilling, 2021), Taeuscher and Rothe (2021) showed how affiliations with high-status organizations—an important source of legitimacy in platform markets—can alleviate platforms' pressure for conformity and therefore increase the effectiveness of a moderately distinctive positioning. We complement these studies by theoretically and empirically demonstrating how category distinctiveness affects the theorized benefits of (intra-category) distinctiveness to such a degree that the distinctiveness-performance relationship can flip from an inverted U-shaped to a U-shaped curve.

Our findings further advance cultural entrepreneurship theory, which emphasizes how entrepreneurial narratives represent an important tool for entrepreneurs in their effort to gain attention and support from resource-providing audiences (Lounsbury & Glynn, 2001, 2019), by adding empirical weight to the claim that the conformity and distinctiveness conveyed in entrepreneurial narratives shape performance outcomes (Lounsbury & Glynn, 2001; Navis & Glynn, 2011). Yet, our study theoretically and empirically complicates this claim by demonstrating that what constitutes an optimally distinctive narrative depends on the level of distinctiveness of the category in the broader categorization system. This finding complements and extends previous studies on the performance implications of entrepreneurial narratives (Martens et al., 2007; Navis & Glynn, 2010; Zhao et al., 2013) by highlighting how narrative distinctiveness is dependent upon categorical context. Our study thus suggests an important new direction for research on how the nature of categories shapes the sources and effectiveness of entrepreneurial narratives.

Our theory and findings also contribute to the literature on categories, particularly as it relates to the evaluative and competitive consequences of category membership (Cattani, Porac, & Thomas, 2017; Gehman & Grimes, 2017; Paolella & Durand, 2016; Pontikes, 2018; Pontikes & Barnett, 2017; Suarez et al., 2015; Zuckerman, 1999). Drawing on the two-stage evaluation framework, prior research commonly assumes that categories represent the primary filtering mechanism through which audiences pre-select a set of potential options for consideration (Phillips & Zuckerman, 2001; Zuckerman, 1999, 2016). Implicit in these theories is that members of the relevant audience limit their attention ex ante to one specific category and therefore only consider offerings that sufficiently conform to the conventions of this category. We highlight that such an assumption may not hold up in all contexts. Drawing on consumer research (Lancaster, 1966; Ratneshwar & Shocker, 1991; Urban et al., 1993), we proposed that consumers commonly preselect offerings from multiple product categories for consideration whenever there exists a meaningful level of substitutability between product categories—that is, when consumers perceive multiple product categories as suited for addressing their context-specific needs. Our supplemental analyses of individual Airbnb users' booking choices strongly supported this assumption by showing that 69.2% of Airbnb users with multiple bookings chose listings from more than one category; thus, our study provides clear evidence that audiences do not necessarily limit their attention to any single category. Our study therefore advances category research by outlining an important boundary condition under which social evaluations likely take place both within and across categorical boundaries.

By uncovering this boundary condition, we highlight how category-level characteristics may shape performance outcomes. We extend the proposition that categories can serve as a source of differentiation for their members (Gehman & Grimes, 2017) by showing how a distinctive category can enable its members to stand out and differentiate an offering in a crowded domain. We further argued that novelty-seekers—characterized by a high tolerance of nonconformity and a high appreciation of novelty and distinctiveness (Taeuscher et al., 2021)—are more likely attracted to distinctive rather than indistinctive categories. The proposition that distinctive categories may attract audiences with a particular appreciation of novelty is highly consequential because it implies that category distinctiveness may generally shape the composition of a category's audience, including their norms, values and expectations, and consequently determines the effectiveness of category members' strategies and symbolic tools. These theoretical propositions advance understanding about the implications of category distinctiveness (Lo et al., 2020) and can help bring categories to the foreground in theories of differentiation and competitive advantage (Cattani, Porac, & Thomas, 2017).

Empirically, we also provide a novel contribution to the category literature by developing the first empirical measure of category distinctiveness, providing a starting point for research accumulation on how category distinctiveness determines a category's viability and explains the emergence, survival, and decline of categories (Gehman & Grimes, 2017; Lo et al., 2020; Navis & Glynn, 2010). Our measure effectively deals with the challenge that categories within a classification system often differ on many dimensions by representing each category as a vector of prototypical attributes—an operationalization that can be easily adjusted to the relevant product, market, or organizational attributes in different contexts. Category research can draw on our newly developed measure to conduct category-level analysis and explore how the distinctiveness of categories shapes their emergence, survival, or decline (Grodal et al., 2015; Lo et al., 2020; Suarez et al., 2015).

There also exist varied opportunities to build on our theory and measurement approach to study firms' strategic categorization. Among others, our study may open up new directions for research on firms' strategic selection of categories and category labels (Granqvist et al., 2013; Pontikes, 2018; Zunino et al., 2019), category promotion (Gehman & Grimes, 2017), category spanning (Paolella & Durand, 2016) or category innovation (Pontikes, 2022). Our study focused on established product categories but future research may also explore how category distinctiveness affects members' legitimation during category emergence (Navis & Glynn, 2010, 2011; Ozcan, 2018). If a category is not yet established, high category distinctiveness may counteract the legitimation of the category (Lo et al., 2020) and membership in such a category may therefore threaten category members' legitimacy. While we focused on how category distinctiveness shapes the benefits of differentiation at the level of individual offerings, we believe that it would also be fruitful to study how firms can diversify into categories with certain levels of distinctiveness to cultivate particular styles over time (Formilan, Cattani, & Ferriani, 2021), providing yet another opportunity of differentiation at the firm level.

We believe that our study suggests the fruitfulness of developing further research on how organizational processes and outcomes are variably shaped by different kinds of audiences (e.g., novelty-seekers, experts) and category schemes (e.g., products, industries, organizations). This extends recent work that has increasingly recognized that audiences differ in their norms, expectations, and valuation of novelty (Cattani, Ferriani, & Lanza, 2017; Cudennec & Durand, 2022; Falchetti et al., 2021; Fisher, Kuratko, Bloodgood, & Hornsby, 2017; Pontikes, 2012; Taeuscher et al., 2021), highlighting how an audience's heterogeneity with respect to members' valuation of novelty may lead to fundamentally different performance outcomes across categories. This proposition has important implications because it suggests that organizations and offerings within the same domain may be evaluated against systematically different norms, values, and expectations. Moreover, by pointing to important differences between-category schemes—such as product categories (Lounsbury & Rao, 2004), genres (Hsu, 2006), and industry categories (Zuckerman, 1999)—our study can also lay the foundation for future research that fully appreciates the heterogeneity in category schemes and their implications for a variety of organizational phenomena. We therefore encourage future research to more closely examine how different audience segments and different kinds of category schemes shape organizational processes and outcomes, including organizations' legitimation and resource acquisition.

Our propositions and empirical findings have important practical implications for Airbnb hosts and entrepreneurs more broadly. Our postestimations demonstrate that narratives have a substantial effect on the demand for and performance of entrepreneurial offerings, suggesting that an optimally distinctive narrative provides entrepreneurs with an effective tool for attracting superior demand to their offering. The degree to which entrepreneurs should emphasize their offering's similarity to or distinctiveness from the conventions of their product category substantially depends on the category's distinctiveness. In indistinctive categories, they should craft narratives with moderate levels of distinctiveness in order to balance the demands for conformity and differentiation. In distinctive categories, entrepreneurs can attract the highest demand if they craft narratives that either position their offering as very similar to or highly different from the category's prototypical offering. Jointly, our findings can help entrepreneurs and managers to successfully legitimate and differentiate their offerings to ultimately achieve superior performance.

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DATA AVAILABILITY STATEMENT

Research data are not shared.

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